CONTEXT-AWARE AND TIME-AWARE INDOOR EVACUATION

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Department of Infrastructure Engineering
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Haifeng Zhao: Context-Aware and Time-Aware Indoor Evacuation
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ABSTRACT

Upon sudden occurrence of disasters such as fire, earthquakes, or floods, evacuation is the first and foremost needs to get people out of the disaster area. Context awareness and time awareness is of significant importance especially for such a life-critical activity as evacuation.

Current indoor evacuation prominently relies on stationary exit signage and emergency maps for providing recommended escape routes. However, such signage or maps are static and reflect no updating of the environment. Consequently, it is inevitable that the recommended routes may have been blocked by the disaster. An evacuee that follows such a route will have to seek alternative routes, wasting time or in the worst case failing the evacuation. Full awareness of the indoor structures as well as the real-time risk of the buildings to be evacuated from is supposed to be beneficial. In order to achieve a full awareness of the real-time situation of the environment, the omnipresent sensors in modern buildings and the pervasively used mobile devices are potentially to be utilized. By integrating sensors and the building structure, real-time risk information of the environment can be monitored and evacuees are kept updated with the real-time information. Personalized evacuation route based on the real-time situation of the environment can be provided to each evacuee via their mobile devices. A framework integrating sensing and routing has been provided in this thesis. As the first contribution of this thesis, the framework integrating sensing and routing has been investigated via simulation and experiment; results indicate that such centralized evacuation facilitated with full situation awareness is capable of saving more lives in evacuation than without such centralized evacuation framework. Taking fires as example, the evolution of a fire disaster is a spatio-temporal process, and its impact on the evacuation route graph is also spatially and temporally evolving. Any real-time conditions of the environment at a specific time instance is just a snapshot of the changing conditions of the environment. An evacuation route based on the real-time conditions of the environment at a current time instance only guarantees that this route is safe at the current time instance, but may be blocked in the next moment, in which case a new evacuation route based on real-time information will need to be computed. The changes of a planned evacuation lead to a waste of time, and in the worst case, causes failing in the evacuation. Taking the temporal differences of the situation awareness into consideration, an optimal evacuation route should guarantee the passability not only at the current moment but also in the near future. This thesis then integrates timing, and also tests whether foresight is beneficial for evacuations. The second contribution of this thesis is to verify that integrating timing with prediction generally improves
evacuation performance, and the improvement shows an dependence on the accuracy of the prediction.

Centralized evacuation systems are of high efficiency because of their global situational awareness; however, such centralized evacuation systems share at least three shortcomings. First, the central infrastructure may not always exist in an arbitrary building. Second, either the communication channels between the central infrastructure and sensors, or the communication channels between the central infrastructure and mobile devices may be blocked due to a failure or damage of the central infrastructure. Third, such centralized evacuation systems are building specific so that the central infrastructure as well as the settings of the mobile devices are not seamlessly transferable to another building. Decentralized evacuation has been proved to be effective for evacuation in the absence of any central infrastructure or in case that the centralized evacuation systems collapse. Decentralized evacuation is also superior in its scalability and robustness against any failure of the central infrastructure.

To investigate decentralized evacuation it is assumed that no central infrastructure is available. Evacuees are supposed to have full awareness of the environment before disasters but only rely on self-exploration and peer-to-peer communication via a (hand-held or head-held) mobile device when the disaster happens. Without real-time updating from a central infrastructure, situation awareness of the environment is prone to being out of date. Decision making in a possibly changed environment without awareness of the time when that knowledge is lastly updated is problematic. This thesis contributes to situational awareness by developing a time-aware routing model, fading memory, for decision making in dynamically changing environments. Fading memory values not only the knowledge that has been acquired but also the time when that knowledge was lastly updated by trusting more the knowledge recently explored and less the knowledge explored a long while ago. This thesis tests this model; experiment results indicate this mechanism generally benefits evacuation performance.

In addition to the unreliability of the out-of-date knowledge, what makes decentralized evacuation more challenging is that people are sometimes required to evacuate a place which they are unfamiliar with and have incomplete awareness of the environment before the event. Decentralized evacuation in unfamiliar environment is challenging in that it involves not only a critical evaluation of the acquired knowledge but also an exploration of the unknown environment if no evacuation route can be derived from existing knowledge. Relaxing the constraint of a full awareness of the environment before the disaster is of significant value in that the mobile device will rely on no infrastructure and is thus safe to be seamlessly transferred to arbitrary environments. A decentralized evacuation paradigm with incomplete prior knowledge has been developed and a fading memory model for evacuation with incomplete prior knowledge has been verified to be beneficial for decentralized evacuation, which composes the fourth contribution of this thesis.
In a decentralized evacuation paradigm, evacuees are guided by smartphones acquiring environmental knowledge and risk information via exploration and knowledge sharing by peer-to-peer communication. Peer-to-peer communication, however, relies on the chance that people come into communication range with each other. This chance can be low. To bridge between people being not at the same time at the same places, this thesis then suggests information depositories at strategic locations that collect the knowledge acquired by the smartphones of evacuees passing by, maintain this information, and convey it to other passing-by evacuees. Experiments implementing these depositories in an indoor environment show that integrating depositories improves evacuation performance: It enhances the risk awareness and consequently increases the chance that people survive and reduces their evacuation time. For evacuating during dynamic events, deploying depositories at staircases has been shown more effective than deploying them in corridors.

Overall, this thesis contributes to both centralized and decentralized evacuations from context-awareness and time-awareness perspectives. The main research method is to use agent-based simulation to simulate the complex evacuation process embedded with different evacuation strategies so as to analyze and compare the system behavior, while leaving aside any study of human behavior. Strategies that have been investigated include whether a context-awareness generated by integrating sensor graphs and route graph benefits evacuation outcome, whether prediction benefits evacuation outcome, whether trusting less the aged knowledge leads to better decision making in dynamic environments, and whether an information depositories benefit evacuation outcomes. Such strategies have been verified here to be effective for evacuation; they also have valuable implications on a broad range of activities in dynamic environments.
DECLARATION

This is to certify that:

1. the thesis comprises only my original work towards the PhD except where indicated in the Preface,

2. due acknowledgment has been made in the text to all other material used,

3. the thesis is fewer than 100,000 words in length, exclusive of tables, maps, and bibliographies.

Melbourne, Australia, July 2017

Haifeng Zhao
This thesis is based on published work from my PhD research during candidature. Some ideas and figures have appeared previously in the following publications:

**JOURNAL ARTICLES**


**PEER-REVIEWED CONFERENCE ARTICLES**


**ARTICLES UNDER REVIEW**

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ACRONYMS

GiScience  Geographic Information Science
GIS   Geographic Information Systems  
CFD   computational fluid dynamics  
RFID  radio frequency identification  
STRA  Sensor Tracking and Risk Aware  
EF    Exact Foresight  
CF    Conservative Foresight  
NF    No Foresight  
DeptSt Depositories at Staircases  
DeptCr Depositories at Corridors  
BLIND a blind evacuation strategy  
STATIC a static evacuation strategy  
NoDepot Evacuation without Depositories  
WSN   wireless sensor network  
MWSN  mobile wireless sensor network  
NRS   Node-Relation-Structure
INTRODUCTION

In case disasters strike, such as earthquakes, fire or other sudden threats to safety, one of the foremost needs is to get people out of the disaster area. Evacuation is a significant measure of response in disaster management, where spatial and temporal knowledge has not been sufficiently leveraged.

1.1 BACKGROUND AND PROBLEM STATEMENT

While more buildings are built in order to accommodate a rapidly growing world population, the development of evacuation is stagnant. Current evacuation support facilities are still limited to stationary exit signs and emergency maps for providing recommended escape routes, which are static and reflect no updating of the environment. The omnipresent sensors in modern buildings and the pervasive use of smart mobile phones exhibit largely unexplored potential for more real-time context aware evacuation. To bridge this gap, the first research question of the thesis is

RQ1: How to achieve real-time context aware evacuation by using the sensors and mobile devices? Is it advantageous compared to static evacuation manner?

With real-time conditions of the environment being monitored by the sensor system, the computed evacuation route is always guaranteed to be the best solution considering the current circumstances. However, the dynamic event as well as the evacuation is a spatial and temporal process, whose impact on the environment is also spatially and temporally evolving. How many people can be successfully evacuated is the output of an integral of all real-time decision making. A real-time route is only guaranteed to be a best route for a snapshot of the process in the temporal dimension, but the route may not be the optimal route for the whole process. Considering the temporal dimension of the process and looking forward, an optimal evacuation route should also involve decision making based on the state of the environment in the upcoming moments of the process, which has never been addressed in previous study. Since the future state of the environment is not likely to be acquired, a possible manner for timing is using prediction, which leads to the second research question of this thesis:

RQ2: Can integrating timing derive even better evacuation performance than real-time context aware evacuation, for example, using prediction?

Both of the previous evacuation manners belong to the centralized evacuation realm, which requires central infrastructures to collect the information from sensors and communicate with mobile devices. Such central evacuation systems share at least three shortcomings:
• First, the central infrastructures are prone to be damaged or destroyed during the disaster. Neither of the previous two centralized systems can avoid breaking down if the central infrastructures are damaged.

• Second, such centralized evacuation systems and supporting infrastructure may be lacking in many buildings.

• Third, different buildings have their specific spatial connectivity and infrastructure, thus a central infrastructure and mobile device application for a specific building may not seamlessly work in other buildings.

Decentralized evacuation management is scalable and robust against infrastructure failure, and has been proven to be an effective manner in case of collapse of the centralized evacuation system. In decentralized evacuation, without the real-time updating, all the knowledge are out of date and may only be valid in the past due to the dynamic of the event. Decision making with the possibly changed environment and outdated knowledge without considering its validity is problematic. To bridge the gap of the unreliability of out-of-date knowledge in decentralized evacuation case, the third research question of this thesis is

RQ3: How to model the time-awareness in decentralized evacuation management? Is it advantageous to consider the age of knowledge than without considering the age of knowledge, for example, trusting more the recent exploration and less the knowledge that has been explored a long while ago?

Apart from the unreliability of knowledge, another challenge for decentralized evacuation management is the lack of global knowledge of the environment. Not all buildings are guaranteed to greet the new enterer with a complete map. People may be required to be evacuated from environments which they are not familiar with or even have no knowledge of. In this case, evacuation routes are computed based on unreliable and incomplete knowledge. Decentralized evacuation with incomplete prior knowledge is challenging in that it involves not only a selection of the acquired knowledge but also an exploration of the unknown environment. The evacuation outcome becomes a combination of an exploitation of existing knowledge and an exploration of incoming knowledge. However, up to now no research has considered both the uncertainty and the incompleteness of knowledge in decentralized evacuation. To bridge this gap and to test whether trusting less the aged knowledge is also an appropriate model in this case, the fourth research question of this thesis will be

RQ4: How to manage the unreliability and incompleteness of knowledge in decentralized evacuation management? Is trusting less the aged knowledge still advantageous? What the evacuation paradigm operates in this case?

In decentralized evacuations, evacuees are guided by their smartphones that are acquiring environmental knowledge and risk information as the evacuees explore the environment. These smartphones
are sharing their collected knowledge by peer-to-peer communication with other smartphones within short-range radio communication range. Decentralized evacuation has the advantage that no further infrastructure is required, i.e., it is applicable in any environment. In simulations, it has proven to work well where there are good chances that evacuees come into communication range with each other. In reality, however, the chance that evacuees encounter may be low due to spatio-temporal constraints, especially in less occupied environments. The success of a single evacuee depends on up-to-date knowledge of the dynamics in the environment. To bridge the spatial and temporal gaps in the communication of single evacuees in decentralized evacuations, the fifth research question of this thesis is

RQ5: How to effectively maintain the spatial and temporal information of the dynamic environment within the environment? How to robustly keep evacuees updated?

Addressing the aforementioned research questions will lead to more efficient evacuation performance in both centralized and decentralized manners. Approaches are potentially to be found from the context-aware and time-aware perspective.

1.2 RESEARCH OBJECTIVES AND APPROACH

This research aims to achieve optimal evacuation strategies by leveraging the space and time concepts in Geographic Information Science (GIScience).

Modern buildings are fully equipped with different kinds of sensors such as temperature sensors, smoke detectors and movement sensors. These devices can be efficiently utilized if integrated with the omnipresent availability of smart phones. It is possible that this real-time data be collected, analyzed and provide a context-aware situation for each occupant via smart phones. In case of emergency, real-time, location-based and personalized evacuation routes can be generated based on this real-time global information. Since this envisioned strategy has great potential to significantly improve evacuation guidance service by providing personalized shortest and safer evacuation routes, the first objective of this thesis is:

Objective 1: Proposing and evaluating methods that integrate sensing and routing to provide real-time and context aware evacuations.

Hypothesis 1: Integrating sensing and routing can save more evacuees compared with evacuation assisted only by static exit signs.

Real-time information is insufficient for a process like evacuation. The safest and fastest route should be considered based on the overall spatio-temporal information including the dynamic behavior of the catastrophic event. One way to get the whole spatio-temporal situational awareness of emergencies is through prediction. The prediction-based shortest route is generated taking timing into consideration. The shortest route derived from knowledge with ideally accurate prediction should outperform the one that derived without prediction, which lead to the second objective of this thesis:
Objective 2: Aiming at the dynamics of events in centralized evacuation, investigating whether foresight is an effective example of timing in indoor evacuation to improve centralized evacuation.

Hypothesis 2: That the integration of time in evacuation facilitates risk-aware and time-aware evacuation planning, which improves both evacuation times and the number of saved lives significantly.

In view of the unreliability of knowledge during evacuation in a dynamic environment, a fading spatial memory model can be proposed that enables time-awareness for evacuation route planning. Fading spatial memory model critiques the validity of spatial knowledge from the temporal perspective, trusting less the older knowledge for decision making in a dynamically changing environment. Since evacuation with incomplete maps as prior knowledge is a challenge in itself, at this step, it is assumed that each person is familiar with the environment or has a complete map of the environment by the time of evacuation. The third objective of this thesis is:

Objective 3: Developing a fading memory model for a time-aware evacuation support system by devaluing the aged information in acquired knowledge.

Hypothesis 3: Fading memory is beneficial for agents’ decision making in a dynamic environment.

However, in practice people may be required to evacuate an area that they are not familiar with. A full knowledge of the environment may either be unavailable, or depends on certain service infrastructures which may either be unavailable or can easily get damaged in the disaster. Relieving the constraint of complete prior knowledge is of significant value because in this case no infrastructure of a particular environment is required so that an evacuation system can be transferable for different environments and is thus more robust. So the fourth objective of this thesis is:

Objective 4: Developing and evaluating a paradigm for decentralized evacuation management based on fading memory for generic environments and varying prior knowledge.

Hypothesis 4: When complete prior knowledge is unavailable, fading memory improves the evacuation performance in decentralized evacuation services.

To bridge the spatial and temporal gaps in the communication of single evacuees in decentralized evacuations, and inspired by ants that communicate by pheromone traces that keep being updated by passers-by, this thesis suggests information depositories in the field for decentralized evacuation. Information depositories enable the environment to maintain information and interact with passing-by evacuees. They record and update the environmental and risk information deposited by passing-by evacuees, and provide this information to later passers-by. They are sharing points in the environment for evacuees passing the same location at different times, enabling asynchronous communication (Harvey and Macnab, 2000; Raubal, Miller, and Bridwell, 2004). Thus information depositories add to peer-to-peer communication, and therefore are expected to produce better evacuation outcomes. Thus the fifth objective of this thesis is:
Objective 5: Developing information depositories for efficient collaborative mapping of the dynamic environment, and verifying that integrating dynamic sensors and information depositories benefits decentralized evacuation.

Hypothesis 5: Even a small number of information depositories will enhance risk awareness of evacuees and improve the evacuation results.

Research Objective 1 and Objective 2 belong to the realm of centralized evacuation, while research Objective 3, Objective 4 and Objective 5 belong to the realm of decentralized evacuation. The aforementioned objectives directly lead to the major contributions that this thesis provides for the research domain of both centralized and decentralized evacuation.

1.3 RESEARCH SCOPE

The scope of this thesis is to explore optimal conceptual models for indoor evacuation from the space and time perspective of GIScience.

First, this research focuses on pedestrian evacuation from an indoor environment. A typical indoor environment is the indoor space of an office building. Thus this research leaves apart evacuation in an outdoor environment. For example, massive evacuations in an urban scale by private or public transportation due to earthquake or bush fires, are out of the scope of this research.

Second, this research focuses on the evacuation strategies under emergency situations. In particular, it considers the emergency dynamics and their impacts on the evacuation scenario. Evacuation strategies are evacuated under such situation that is continually changing by the emergency dynamics. The emergency dynamics and the evacuation process are part of an evacuation scenario, and will be simulated. However, this research will not focus on the realistic reproduction of the emergency dynamics; there is rich literature doing this. For example, developing a sophisticated computational fluid dynamics (CFD) model of fire-driven fluid flow, or emulating the crowd behaviors such as herding behavior and socio-psychological aspects such as panic, are not considered in this research. Instead, this research develops conceptual evacuation strategies that are prone to save more people or reduce the evacuation time, if the evacuees follow the directions as suggested by proposed strategies. The model and evacuation strategies consider general pedestrians in an indoor environment, which are not constrained in their mobility, i.e., excluding groups of pedestrians with particular requirements as disabled people or patients that need to be taken care of. Such group of people may also benefit from the developed method in this thesis though.

Third, this research provides a conceptual framework for each evacuation strategy, while it leaves aside the implementation of specific technologies. A conceptual framework may involve modules such as indoor localization and indoor navigation, the sensing of emergency dynamics, the risk assessment and risk prediction, and the ad-hoc communication between wireless sensors. For example, exist-
ing technologies for indoor localization include QR codes, radio frequency identification (RFID), dead-reckoning and pattern-recognition. This research will not limit the evacuation strategy to specific implementations of different technologies, rather, it provides a framework, and only assesses the viability of such technologies. Any existing or emerging technologies can be plugged in to implement the framework.

Last, this research aims to optimize the evacuation process from the space and time perspective in GIScience. In particular, it emphasizes the context awareness and time awareness of evacuation knowledge. In this research, context awareness specifically refers to two aspects of awareness: the original spatial connectivity in an indoor environment, and the perceived or sensed risk introduced by the emergency dynamics. Time awareness refers to the time when that context awareness has been lastly updated. Optimizing the evacuation process by adjusting the design of a building is out of the scope of this research.

### 1.4 SIGNIFICANCE OF THE STUDY

*The first major contribution relates to the research area of centralized evacuation management.* A real-time context-aware evacuation system for buildings is proposed. This part of research has been presented in GIScience 2014 (Wang et al., 2014), to which my contribution is about 25%, i.e., to implement real-time context aware evacuation in simulation and to verify that the proposed context-aware method is capable of saving more evacuees. The system has been implemented with agent-based simulation tool – Repast Simphony. A five level departmental building has been adopted as the sample evacuation environment. Three evacuation strategies have been compared:

2. Static. Evacuation with knowledge of only the start location of emergency.
3. Blind. Evacuation with no awareness of the start location of emergency.

Results show that integrating sensing and routing is capable of saving more people and shortening the evacuation time.

An integration of sensor graphs and route graphs allows a situation- and risk-aware indoor evacuation planning. In this prior work, evacuation risk had been considered statically in the evacuation planning: In the iterative route planning throughout the evacuation, at each iteration step the current situation as reported by the sensors had been taken into account. This strategy, although reflecting best current knowledge, does not yet take into account the dynamic behavior of most emergency events.

*The second contribution relates to the dynamics in evacuation, more precisely, that foresight in centralized evacuation can improve the evacuation
performance. An integration of building sensor information with indoor route graphs for the purpose of real-time evacuation planning is proposed. This integration allows dynamic risk assessment by prediction, for both the sensor graph and the route graph, and thus enables evacuation route planning aware of predicted risks. The model assumes a dynamic sensor graph according to building monitoring systems and varying sensor states over time. A dynamic risk assessment mechanism evaluates the risks as the event is predicted to progress. This part of research has been published in Fire Safety Journal (Wang, Zhao, and Winter, 2015), to which my contribution is about 33%, i.e., to implement a context-aware and time-aware evacuation system and to verify via experiments that accurate prediction is an approach to improves the evacuation results, saving more people.

The third contribution relates to the task of decentralized evacuation management. Considering the temporal dimension and looking backward, the knowledge of the environment in decentralized evacuation for decision making is always out of date, and thus should be critiqued and examined. A fading memory model, a mechanism trusting more the knowledge recently explored while less the knowledge explored a long while ago, is proposed. A decentralized paradigm has been developed for applying such mechanism. In this paradigm, each evacuee is assumed to be acquainted with the environment before the event: they have complete knowledge of the (static) route graph. In addition, this experiment assumes that during an event, people acquire knowledge and update their memory applying the two mechanisms:

- People acquire updated knowledge of the environment upon a physical encounter with a changed environment.
- People acquire updated knowledge of the environment upon an encounter with fellow evacuees by exchanging their mutual time-stamped knowledge.

Experiments indicate this mechanism benefits evacuation performance when evacuees are familiar with the environment, or from application perspective when their mobile devices can be greeted with a complete map of the building when they enter the environment (Zhao, Ronald, and Winter, 2015; Zhao and Winter, 2016). Decentralized evacuation process is in this case with complete knowledge of the structure of the building but only unreliable update about changes and thereafter the accessibility of the space introduced by the dynamics of the event. Whether the mechanism of fading memory still improves evacuation performance requires investigation.

The fourth contribution is to verify that even with incomplete prior knowledge the mechanism of fading memory is still advantageous. It challenges the validity of spatial knowledge during evacuation, and improves the existing decentralized evacuation method with a fading memory concept. Albeit challenging, relieving the prior condition of a complete map is of significance in that the mobile device will in this case rely on no infrastructure and thus can be used in any building. Since fading memory with incomplete prior knowledge works independent
from the structure of an environment, an evacuation problem of similar properties in outdoor environments such as forests or street networks is also promising to be improved by this method. The result of fading memory with incomplete prior knowledge has implications on a broad spectrum of applications, and the mobile device installed with this decentralized evacuation system potentially benefits evacuation in arbitrary buildings even without support of external infrastructure.

A decentralized evacuation paradigm has also been developed. In this paradigm, each evacuee is equipped with one mobile device, which facilitates trajectory recording before the event and also communication and route calculation during the event. The evacuation process with this mobile device involves two iteration steps. The device firstly tries calculating a route based on existing knowledge, where time-awareness has been considered to avoid potential risk. Then if a route is not available, the device suggests exploration of the environment with heuristics.

Combining the third and fourth contribution, decentralized evacuation will benefit from trusting more recently updated knowledge and less the knowledge acquired a long while ago, independent from the prior knowledge of the agents. Based on this conclusion, applying fading memory in decentralized evacuation is suggested, and because of its independence from any central infrastructures, can be transferable to any other environment, e.g., being applied to different buildings without revision of the system.

The fifth contribution is to verify that integrating information depositories in decentralized evacuation is beneficial. Information depositories enable the environment to maintain information and interact with passing-by evacuees. They record and update the environmental and risk information deposited by passing-by evacuees, and provide this information to later passers-by. Experiments verify that even a small number of information depositories make a difference if these depositories are deployed at strategic locations such as staircases.

### 1.5 Structure of the Thesis

The thesis is organized as follows. Chapter 2 provides an overview of the state-of-the-art research about evacuation. Chapter 3 addresses RQ1 and achieves Objective 1 by developing a centralized evacuation model that integrates sensing and routing for context-aware evacuation. Experiments suggests that the model is benefiting evacuation (Wang et al., 2014).

Chapter 4 addresses RQ2 and achieves Objective 2, by providing an integration of building sensor information with indoor route graphs for the purpose of real-time evacuation planning. This integration allows dynamic risk assessment by prediction, for both the sensor graph and the route graph, and thus enables evacuation route planning aware of predicted risks. The model assumes a dynamic sensor graph according to building monitoring systems and varying sensor
states over time. Sensor states are then propagated to a dynamic route graph through the building with regard to passability of edges at different time instance, using a risk model that quantifies risks of an impact on evacuation (Wang et al., 2014).

Knowledge of dynamic environments expires over time, thus, using static maps of the environment for decision making is problematic. Chapter 5 addresses RQ3 and achieves Objective 3, the results of which has been published in Zhao, Ronald, and Winter (2015) and Zhao and Winter (2016). This chapter suggests a fading memory model for mapping dynamic environments: a mechanism to put less trust on older knowledge in decision making. The model has been assessed by simulating indoor evacuations, adopting and comparing various strategies in decision making. Results suggest that fading memory generally improves this decision making.

When people have to evacuate, their prior knowledge of the environment is in most cases incomplete. Chapter 6 addresses RQ4 and achieves Objective 4, suggesting a decentralized paradigm that facilitates time-aware and risk adverse evacuation. The experiment suggests that fading memory improves the evacuation performance in decentralized evacuation services. The proposed paradigm with fading memory is a more effective and robust method than without fading memory.

Chapter 7 addresses RQ5 and achieves Objective 5. To bridge the gap of knowledge sharing among evacuees in decentralized evacuation, this chapter develops information depositories, which enhances the context awareness and time awareness of evacuees. Experiments with a sample implementation of the model suggest the advantage of the proposed model.

Chapter 8 presents a discussion of the research in this thesis. Chapter 9 concludes the findings of this thesis and provides outlooks for future work.
Evacuation is the overarching task for disaster management (Richter et al., 2013; Gan et al., 2016), which generally relocates people from a risky area to safe areas due to emergencies, such as fire, a gas leak, a hurricane, or an earthquake (e.g., D’Orazio et al., 2014; Bernardini, Quagliarini, and D’Orazio, 2016). The area at threat in emergencies can be an office building, a theater, a railway station (e.g., Davidich et al., 2014; Wan, Sui, and Yu, 2014), a shopping mall, or an urban region (e.g., Zhang and Chang, 2014; Goerigk, Grün, and Heßler, 2014; Pillac, Van Hentenryck, and Even, 2016). Evacuation scenarios include precautionary scenarios and life-saving operations (Hamacher and Tjandra, 2002). Precautionary scenarios compare the estimation of the evacuation time and the hazard propagation time. They are part of the preparedness (in the disaster management cycle). Life-saving operations occur when evacuees are in and around the damaged area. They are part of the response (Figure 1). Research on evacuation can be divided into three streams: (a) the study of human behavior and crowd dynamics, (b) the development of descriptive models to represent pedestrian dynamics as realistically as possible, and (c) determining optimal evacuation plans or design solutions (Vermuyten et al., 2016). Most of the research falls under the first two categories.

Figure 1: Disaster management cycle (Alexander, 2002).


2.1 EVACUATION MODELS

Alvear et al. (2014) identified three purposes of evacuation models: (a) performance-based analysis for new and existing buildings in order to evaluate the design and evacuation procedures (e.g., Tang and Ren, 2012; Shi et al., 2012), (b) forensic analysis to reconstruct historical evacuation processes in order to analyze possible failures and inefficiencies (e.g., Sivers et al., 2016), and (c) management during evacuation procedures (e.g., Feng and Miller-Hooks, 2014). The detailed assessments of the existing modeling approaches and simulation models can be found in the literature (Gwynne et al., 1999; Zheng, Zhong, and Liu, 2009; Hamacher and Tjandra, 2002; Duives, Daamen, and Hoogendoorn, 2014; Sakour and Hu, 2017).

Evacuation models can be roughly categorized into microscopic models and macroscopic models, which simulate crowd movement in emergency situations with different levels of abstraction. Macroscopic models, (e.g., Li and Ozbay, 2014; Liu, Lai, and Chang, 2006; Kimms and Maassen, 2012; Abdelgawad and Abdulhai, 2009; Chalmet, Francis, and Saunders, 1982; Kisko and Francis, 1985; Bretschneider and Kimms, 2011), formulate the evacuation process as an aggregate. They are typically deployed to find lower bounds of evacuation times without considering the individual behavior of evacuees, and accordingly are mainly used for regional evacuation planning. Microscopic models (Klüpfel et al., 2001; Lox, 1998) consider each evacuee as a separate entity, and thus are typically used for evacuation planning in smaller urban areas and indoor environments.

2.1.1 Microscopic models

Examples of microscopic models are cellular automata models (e.g., Kirchner and Schadschneider, 2002; Varas et al., 2007; Shi, Ren, and Chen, 2009; So and Daganzo, 2010; Koo et al., 2013; Jian et al., 2014; Bandini, Mondini, and Vizzari, 2014; Ji et al., 2014; Davidich et al., 2014; Huang et al., 2016; Lima and Oliveira, 2017), lattice gas models (e.g., Guo, Huang, and Sadek, 2013), social force models (e.g., Helbing, Farkas, and Vicsek, 2000; Ha and Lykotrafitis, 2012; Hou et al., 2014; Yang et al., 2014; Wan, Sui, and Yu, 2014), motion planning with velocity obstacles (e.g., Fiorini and Shiller, 1998; Berg, Lin, and Manocha, 2008), agent-based models (e.g., Goetz and Zipf, 2012; Sánchez et al., 2016; Yin et al., 2014), game theoretic models (e.g., Zheng and Cheng, 2011; Mesmer and Bloebaum, 2014; Eng, 2016), approaches based on experiments with animals (e.g., Saloma et al., 2003; Fourcassie et al., 2002; Lin et al., 2016; Parisi, Sorin, and Josens, 2015), and hybrid models (e.g., Kneidl, Hartmann, and Bormann, 2013).

Cellular automata models and lattice gas models partition the space into grids or hexagons. Evacuees are supposed to move from one cell to another. A social force model was first proposed by Helbing and Molnar (1995), describing pedestrians as particles that are subject to forces of attraction and repulsion. Helbing, Farkas, and Vicsek (2000)
then developed another social force model to study the collective phenomenon of escape panic, where a mixture of socio-psychological and physical forces was assumed, which includes interaction forces, body force and siding friction force. Velocity obstacle models have been originally developed for robot motion planning. They assume that other robots in the environment maintain their current velocity and thus may define velocity obstacles; such models enable a robot to plan for collision avoidance. Agent-based models describe the evacuation system by simulating each evacuee (or a household (Yin et al., 2014)) as an autonomous agent with certain behavior and situated in an environment, and studying the emergent system behavior. In contrast, approaches based on experiments with animals study escape dynamics with real biological agents such as mice (Saloma et al., 2003) or ants (Fourcassie et al., 2002; Lin et al., 2016; Parisi, Soria, and Josens, 2015). Hybrid models combine the previously mentioned microscopic models to benefit from their advantages and to avoid their drawbacks.

This thesis focuses on simulating the heterogeneous characters of each evacuee and their interactions by using an agent-based model. Each evacuee acts as an autonomous agent which independently explores the environment and acquires different knowledge.

2.1.2 Macroscopic models

In contrast to microscopic models describing the crowds as discrete individuals, macroscopic models treat the crowd as a continuous medium characterized by averaged quantities such as density and velocity (Luh et al., 2012; Twarogowska, Goatin, and Duvigneau, 2014). Fluid dynamic models are the most recognized macroscopic models (Hughes, 2002; Huang et al., 2009), which use the analogy of fluid dynamics to describe the crowd flow in the form of partial differential equations (Yang et al., 2015). Fluid-dynamic models and social force models are continuous in space and time, compared to cellular automata models and lattice gas models, where space and time are discrete (Zheng, Zhong, and Liu, 2009). Agent-based models can have both continuous and discrete representations in space and time.

2.1.3 Indoor environment and emergency event

Since many outdoor concepts of routing networks are not suitable for indoor environments, indoor routing models have been presented, such as a representation in Indoor Geography Markup Language (IndoorGML) (OGC, 2013), navigation graph (Yang and Worboys, 2015), and the Node-Relation-Structure (NRS) (Lee and Kwan, 2005).

The microscopic model in this thesis is based on a continuous indoor routing graph. Discrete geometries of indoor routing are an area of research in itself. Most of the emerging 3D building modeling stan-
Standards, such as CityGML\(^1\) (Kolbe, 2008), KML\(^2\), and IFC\(^3\), the data model used in BIM, represent geometries, cartographic and semantic information about indoor space. Only IndoorGML\(^4\), an application schema of GML suggested as an OGC standard\(^5\), focuses on modelling indoor spaces for navigation purposes. However, while the development of this standard is progressing, this thesis has used Stahl’s method to derive indoor route graphs (Munzer and Stahl, 2011; Stahl, 2010; Stahl, 2008; Stahl and Schwartz, 2010a). Alternative graph-based models for indoor navigation have been suggested as well, such as (Stoffel, Lorenz, and Ohlbach, 2007; Stoffel, Schoder, and Ohlbach, 2008; Yang and Worboys, 2015; Liu and Zlatanova, 2012; Liu and Zlatanova, 2015; Goetz and Zipf, 2011; Nagel, 2014), or grid-shaped graphs (Tan et al., 2014). The actual choice of a graph model has no impact on the theoretical contribution of this thesis.

Furthermore, while other papers have integrated dynamic event spreading in their cellular automata models (e.g., Shi, Ren, and Chen, 2009), this thesis integrates dynamic event spreading through the (also discrete) sensor graph. However, it does so in order to predict future states of the event and anticipate the impact on evacuation planning. The microscopic model in this thesis focuses on system behavior, in contrast to other papers that focus on evacuee behavior. This prediction of future states’ impact on route planning is possible by starting out from an integrated sensor and route graph (Wang et al., 2014), or a multilayered graph integrating a topographic space layer and a sensor space layer (Nagel, 2014).

The purpose of the microscopic model introduced in this thesis is to provide an effective approach to map dynamic sensor monitoring systems with building environment through real-time sensor graphs and route graphs, but not to discuss the nature of emergency event itself or congestion avoidance model. Thus, the event and congestion risk calculation in this model could be replaced by any other existing event spreading model or congestion model. This model tends to provide risk-aware evacuation routes for evacuees to help them stay away from danger as soon as possible.

2.1.4 Regional evacuation

In contrast to building evacuation, other research deals with optimizing traffic during evacuations on an urban scale (So and Daganzo, 2010; Daganzo and So, 2011). So and Daganzo (2010) proposed a decentralized strategy that evacuated the maximum number of people at all times. Feng and Miller-Hooks (2014) proposed a network optimization-based methodology to support crowd movement during large public gatherings held in venues such as complex buildings, transportation stations, football stadiums, and commercial malls. Yin

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\(^1\) [http://www.citygml.org/](http://www.citygml.org/)
\(^4\) [http://www.opengis.net/doc/IS/indoorgml/1.0](http://www.opengis.net/doc/IS/indoorgml/1.0)
\(^5\) [http://www.opengeospatial.org/projects/groups/indoorgmlswg](http://www.opengeospatial.org/projects/groups/indoorgmlswg)
et al. (2014) presented an agent-based travel demand modeling system to generate household activity-travel plans for hurricane evacuation simulation, in which each agent represented a household. They considered the ultimate evacuation trips of a household as the result of a series of demands and the thereafter decisions, such as whether to evacuate, when, to where, by which mode, as well as pre-evacuation preparation activities such as purchasing fuel and food, or family gathering. Another model addressing the simulation of pre-evacuation behavior has been studied by Lovreglio, Ronchi, and Nilsson (2015), who adopted Random Utility Theory.

There are many similar features between traffic management strategies and indoor evacuations when integrating timing such as congestion avoidance and real-time data tracking. Many of these models go back to cellular automata as well (Nagel and Schreckenberg, 1992). In recent years, the method called Cell-Transmission-Model (CTM) proposed by Daganzo (Daganzo, 1994) has been picked up to develop various traffic assignment or evacuation planning models (e.g., Kimms and Maassen, 2012). The basic idea of CTM is to divide space into cells which are the basic unit to analyze the in- and out-flow per period to control the congestion problem and to limit travel time. Liu, Lai, and Chang (2006) proposed a cell-based graph model to capture critical characteristics associated with the evacuation operation for computing the optimal starting time and routes for the people in each evacuation zone. However, traffic management strategies can always rely on real-time traffic information from GPS, in contrast to indoor evacuation strategies.

Compared with indoor evacuation which involves pedestrians, evacuation planning in urban areas involves different tasks: such as deciding shelter locations, routing for public transport and for individual traffic simultaneously (Goerigk, Grün, and Heßler, 2014). A review of highway-based evacuation modeling and simulation has been provided as well (Murray-Tuite and Wolshon, 2013). Lim, Baharnemati, and Kim (2016) assume the availability of real-time traffic information, proposing an evacuation reroute planning approach, which combines a network preprocessing algorithm and a network flow optimization model. Evacuation planning is challenging because of the uncertainty of demand. Pourrahmani, Delavar, and Mostafavi (2015) propose a fuzzy credibility theory and genetic algorithm for evacuation vehicle routing problem. Gan et al. (2016) provide an evacuation model for road network by using a close coupling of simulation and optimization. The method leads to improved results than ad-hoc evacuation; however, the improvement can be highly influenced by the density of evacuees and road network topology. Considering the transportation network capacity, Shahabi and Wilson (2014) combines descriptive and prescriptive approaches for urban evacuation routing. By contrast, to relax the assumption that evacuation demand as well as road capacities are assumed to be known with certainty during evacuations, Ng and Lin (2015) suggest an intuitive idea of demand inflation and capacity deflation, which ensures an priori confidence, but the amount of inflation and defla-
tion might be much more than necessary. To overcome the congestion in free-flow models, one strategy is to increase the capacity by reversing the direction of certain lanes (Kim and Jun, 2008). However, contraflow lanes are only applicable for roads with multiple lanes (Gan et al., 2016) and selecting contraflow roads is by itself NP-Hard (Pillac, Van Hentenryck, and Even, 2016). Pillac, Van Hentenryck, and Even (2016) divide the evacuation planning into two separate iterative steps: the generation of evacuation routes and the scheduling of the evacuation. Evacuating population exposed to flood hazards has been studied (Alaeddine et al., 2015; Masuya, Dewan, and Corner, 2015). Montz and Zhang (2015) provide a regional evacuation model focusing on the traffic assignment calibration and network flow validation.

2.1.5 Crowd behaviors

Typical phenomena that can be reproduced in simulations include kin behavior, arching, effect of obstacles, jamming, friction effects, clogging, “freezing by heating”, “faster-is-slower”, counterflow, choking flow, mass behavior, pushing behavior, panic propagation, impatience, repulsion behavior, competitive behavior, queuing behavior, and herding behavior (Zheng, Zhong, and Liu, 2009). Zheng, Zhong, and Liu (2009) identified two reasons that may cause people being injured or killed during evacuations: either due to failing to evacuate timely, or due to the crowd’s behavior such as shuffling, pushing, crushing, and trampling. Sivers et al. (2016) argued that most models for evacuation dynamics consider individuals as particles, so they added social identity to pedestrian simulation. They take helping others as an example to investigate whether psychological models and computer models of pedestrian motion can be combined so that simulation results correspond to observations from crowd psychology. Davidich et al. (2014) found that standing pedestrians affect crowd dynamics strongly and should be considered when designing critical infrastructures such as railway stations. Kneidl, Hartmann, and Borrmann (2013) developed a hybrid model which combines a dynamic navigation field with a navigation graph. Space and time are discretized using cellular automata, which act as the underlying grid for constructing the navigation field. The dynamic navigation field employs the analogy of an expanding wave which estimates the travel times of pedestrians traveling between an origin and a given destination considering congestions. Such a dynamic navigation field allows evacuees (a) to follow a direction which is subject to minimization of estimated travel times, and (b) to steer around congestions even when the congestions are not visible from their actual position. However, Kneidl, Hartmann, and Borrmann (2013) aimed to provide a realistic simulation of crowd dynamics rather than optimizing evacuation routes, so they also added a navigation graph constructed on top of the scenarios’ geometry which acts as a visibility graph to help distinguish between visible and invisible areas.
Compared with evacuation models and crowd dynamics, evacuation optimization has received less attention from researchers. A recent review of optimization models for evacuation problems has been provided (Vermuyten et al., 2016).

The purpose of evacuation optimization is to improve the evacuation process, aiming at two objectives: reducing the number of deaths and accelerating the evacuation process (Gan et al., 2016). Research efforts for evacuation optimization fall into two categories: either to improve the evacuation process by improving the environmental factors (e.g., optimizing the room structures, finding the optimal number, width and placement of doors), or by improving the route choice of evacuees (Merkel, 2014).

Optimization models gravitate to graphs to represent the routes available to pedestrian evacuees (García-Ojeda et al., 2013; Bellomo and Dogbé, 2008). A graph is defined by a set of nodes representing rooms or decision points, and edges representing doors, corridors, or other routes connecting the spaces represented by nodes (Yang and Worboys, 2015). Edges are associated with weights, which can be the distance between the connected nodes or the time required to travel between the connected nodes. A time-expanded graph (or time-aggregated graph) includes a graph and states of nodes and edges at different time steps (George and Shekhar, 2008; García-Ojeda et al., 2013; Wang, Zhao, and Winter, 2015). Optimization of route choices has been studied either by optimizing the flow of pedestrians (or vehicles) based on evacuation graph, or by finding evacuation routes with minimum cost algorithms such as Dijkstra’s, A*, Ant Colony Optimization, D*, or D* Lite.

For route planning, evacuees may either have the global knowledge of the graph or only have a limited view of the graph. All the knowledge is time stamped and may have become out of date due to the evolution of the disaster, thus introducing uncertainty to the knowledge. A research that considers the impact of the dynamics of disasters on the evacuation process was conducted by Tan, Hu, and Lin (2015). They considered both the stationary environment during a normal situation and the predictable spatial change caused by the activated fire safety facilities during emergency situations, such as a fire rolling shutter that would be shut off during emergency situations.

Alamdar, Kalantari, and Rajabifard (2015) suggest a framework integrating in situ multi-sourced sensors for disaster management. Ahn and Han (2011) develops an indoor augmented reality system which runs on the users’ smart phones. The system assumes the smartphones have external wireless connection such as 3G/4G, used to communicate with a cloud based central server. (Wang et al., 2014) propose a centralized evacuation service capable of providing updated shortest evacuation routes based on real-time monitored data. However such centralized services share a common shortcoming that they rely on a central infrastructure, which are likely to be affected
in a disaster (congested or damaged), or are simply non-existing (Gelemenbe and Bi, 2014).

Wu and Chen (2012) introduced a 3D geometric network model based on NRS to represent an indoor environment, before an ant colony optimization algorithm is applied to find the shortest route during evacuation. Pre-simulations deploying the Fire Dynamic Simulation (FDS) provided feedback of smoke spread in the system.

Han et al. (2013) have proposed an integrated real-time evacuation route planning method for high-rise building fires. The sensor data acquisition is also pre-simulated in FDS, and the data transmission is based on a wireless network. An interpolation method is applied to quantitatively assess a casual risk for each evacuee. Casual risk is based on the distance to the nearest exits.

Nguyen, Ho, and Zucker (2013a) proposed a fire evacuation model under the assumption that evacuees follow the boundaries of obstacles or walls to find the exits when their visibility is limited by smoke. In their agent-based model, they do not discuss the method to generate an evacuation route on account of smoke.

Zhang et al. (2012) proposed a multi-node hierarchical data model to extract route graphs by topological relationships among indoor units of a building. A hierarchical route planning algorithm dynamically schedules evacuation routes considering distance, risk level and waiting time for evacuees. In their approach route planning is risk aware, but no environmental features are involved.

Nauman et al. (2011) introduced a WSN-based safe route identification algorithm which depends on a dense sensor network and wireless communication technologies, and which routes along the sensor network. A location-based routing protocol is applied to dynamically generate an evacuation route in which the building structure and risk prediction are ignored.

Stahl and Schwartz (2010a) developed YAMAMOTO (Yet Another Map Modelling Toolkit) to model multi-level buildings using floor plans and to generate route graphs automatically by adding route vertices at key points on the basis of the outlines of spatial regions (Stahl and Schwartz, 2010a; Munzer and Stahl, 2011; Stahl, 2008; Stahl, 2010). The toolkit provides an approach for finding navigable routes that also allows for modeling environmental monitoring devices, such as sensors or actuators. In this thesis, the simulated evacuation experiments are built on top of YAMAMOTO.

There are indoor evacuation systems integrating egress time (Ahn and Han, 2012; Chen and Feng, 2009). Ahn and Han (2012) develop the RescueMe system to recommend an efficient exit route to mobile phone users in emergency situations. This system helps users to avoid crowded hallways in a building by detecting changes of speed in real-time. If the user’s walking speed is slowed down significantly the system will recalculate the shortest route and recommend it to the user. In this system there is no sensor data from building monitoring systems while the current status of the emergency is tracked by photos captured by users. Chen and Feng (2009) propose a fast flow control algorithm for real-time emergency evacuation in a large in-
door environment. Their algorithm includes the calculation of egress time based on dynamic capacity, and it separates single door and multiple doors, wide door and narrow door problems. They focus on flow control while no real environment information is included in the system.

In contrast to evacuation models aiming for realistic simulation of crowd dynamics, evacuation optimization aims to investigate efficient evacuation strategies, which is to be addressed in this thesis. This thesis prioritizes the number of successful evacuees over minimizing evacuation times, since not all the evacuees are guaranteed to be successfully evacuated.

## 2.3 Indoor Navigation

A review for techniques used in indoor human navigation systems can be found in Fallah et al. (2013), where technologies for indoor navigations are compared in four groups: locating the user, planning a route, representing the environment and interacting with the user. Spatial models for context-aware indoor navigation systems are reviewed by Afyouni, Ray, and Claramunt (2012).

Evacuees can be localized via QR code, radio frequency identification (RFID) (Rueppel and Stuebbe, 2008), landmark detection (Serrão et al., 2012), WiFi or other indoor localization techniques (Lee, 2007). In this regard, indoor space is more complex than outdoor space. Furthermore, indoor space is more constrained by the built structure, is multi-level and is (mostly) private, with the corresponding access regulations. Effective representations of complex buildings are well researched. For example, Richter and Winter (2011) conceptualize indoor space into three hierarchical dimensions. Liu et al. (2010) present a semi-automated method for identifying elements, such as hallways, elevators and stairways from 2D CAD files and constructing 3D building networks. A review of localization technology for smartphones has been reviewed by Maghdid et al. (2016).

Route planning is the task to find an optimal route navigating a person from a current location to a destination while minimizing the travel time (Ahn and Han, 2011), travel distance or hazard (Kulyukin et al., 2006; Wu, Lee, and Chung, 2007). Route planning in indoor space uses graphs (Becker, Nagel, and Kolbe, 2009) or grids (Afyouni, Ray, and Claramunt, 2012) to represent the environment. Most of current navigation systems use Dijkstra (Park et al., 2009; Wu and Chen, 2012) or A* algorithms (Wang, Zhao, and Winter, 2015). The data for route planning can be stored and treated both in a local database (Fischer et al., 2008) or a central database (Amemiya et al., 2004; Gelenbe and Bi, 2014), which then requires a wireless connection to communicate the routes to evacuees.

While more complex buildings have been constructed to accommodate rapidly-growing population, development of emergency evacuation technology is relatively stagnant. Current evacuation support facilities are mainly limited to stationary exit signs and emergency
maps, which are permanent without provision for ad hoc changes (Merkel, 2014). In recent years, the pervasive use of mobile devices, such as smart phones or tablet PCs, exhibits largely unexplored potential for more efficient evacuation. Since current emergency management and evacuation systems do not adapt information to each person, Aedo et al. (2012) provide personalized alerts and evacuation routes to each evacuee. Smart phones are used as a support for escaping, instead of static signals on walls and doors. Smart phones will interact with the system, sending their current location and receiving multimodal messages personalized according to the emergency situation. In order to achieve a context-aware situation and provide personalized evacuation routes, Wang et al. (2014) propose a framework for centralized evacuation, which combines a sensor system monitoring the whole environment with the route graph representing all of the possible routes. Evacuation routes are computed based on the original connectivity of indoor space and the data sensed in real time. Mobile devices are used for self-localization and visualizing the evacuation routes. This framework, although reflecting the best current knowledge, does not take into account that the evacuation routes may later be affected by the dynamics of the event. Even so, simulation suggests significantly better results than blind exploration. The framework has been improved by Wang, Zhao, and Winter (2015) through integrating also the temporal dimension and taking into account the influence that the dynamics of an event may have on the evacuation routes. A similar integrated real-time evacuation route planning method for high-rise building fires has been proposed by Han et al. (2013). Ahn and Han (2011) have developed an indoor augmented reality system called RescueMe that runs on the users’ smart phones to guide people to evacuate from buildings in emergency situations. The system requires a communication between a smart phone and a cloud server via mobile social networking infrastructure. However, such centralized systems share a common shortcoming: a lack or a breakdown of the central infrastructure will lead to a failure of the whole system (Winter et al., 2011).

Serrão et al. (2012) develop a system integrating GIS information of a building with landmarks detected from a hand-held camera for navigating blind or visually impaired persons in complex buildings. Routes are generated based on the neighborhood relations of room spaces and are updated in real-time in case that the person fails to follow the assumed-to-walk route. Nguyen, Ho, and Zucker (2013a) emphasize the fact that evacuees should follow the boundaries of walls and obstacles in condition of limited visibility because of smoke. They try to develop a more realistic simulation of emergency situation by taking into account the smoke diffusion and its effect on the evacuation. Cheng et al. (2014) propose an integrated navigation system by combining Global Positioning System (GPS) with Inertial Navigation System (INS) for outdoor navigation and combining WIFI positioning with INS for indoor positioning, where Extended Kalman Filter (EKF) has also been employed to reduce the growth of the INS error.
Reliable shortest route planning in a dynamic environment is to a limited extend possible with a centralized, real-time sensing system that creates situation aware pictures for each agent. However, such a centralized service will in most cases not exist due to lack (or damage) of sensing and communication infrastructure. In this situation traditionally robots fall back to autonomous and exploratory wayfinding operations.

Not much research can be found addressing the reliable shortest route problem from the perspective of a representation of the dynamics in the environment. From an economic perspective, looking at the economic value of data, Krek (2002) has studied the impact of out-of-date data to decision making. In other research the impact of prediction of future states on decision making has been studied; results demonstrated a high sensitivity for the validity of the extrapolation (Wang et al., 2014).

Based on existing built-in sensors on a smartphone and cloud servers via mobile social networking infrastructure, Ahn and Han (2011) developed an indoor augmented reality system that runs on the user’s smartphones to guide people evacuate quickly from buildings in emergency situations. Their system does not need extensive infrastructure, but only an external wireless connection such as 3G/4G is required. Rather than selecting the route with the shortest distance, it recommends a route with the shortest time to evacuate, taking the crowded route and the delays of other users into consideration.

The environment for evacuation is time-varying in terms of its passability and risk level of different subspace. In case of a fire emergency, the intensity of smoke in one location may be changing very fast such that a possible corridor may be blocked instantly. Thus, for evacuation real-time risk assessment is important and different methods have been proposed (Camillo et al., 2013; Nguyen, Ho, and Zucker, 2013a; Hadjisophocleous and Fu, 2004b).

**2.4 DECENTRALIZED EVACUATION**

Advances in technology such as sensors and smartphones make decentralized spatial computing possible. Existing sensors can detect acoustic, chemical, electromagnetic, optical, thermal, or mechanical stimuli, and convert such environmental stimuli into digital signals to be processed by a computer (Duckham, 2013). Such sensors can measure environmental data such as humidity, CO$_2$ concentration, temperature, or even location (Alamdar, Kalantari, and Rajabifard, 2016). A number of these sensors can be found on-board of smartphones, and thus, smartphones can be considered a node in a mobile sensor network. A sensor node has a microcontroller for computing, a wireless radio for communication, and one or more sensors for capturing data about its environment. Mobile sensor networks are examples of decentralized systems. A decentralized system is a special case of a distributed system where no single component knows the entire system state and each node in a decentralized system acts indepen-
dently and autonomously. In general, decentralized spatial computing is advantageous over centralized spatial computing in six aspects: energy constraints, information overload, scalability, sensor/actuator networks, latency, and information privacy (Duckham, 2013).

Centralized evacuation systems share a common shortcoming that they rely on a central infrastructure, which is likely to be affected in a disaster. It can be congested if a large number of evacuees need real-time information on evacuation routes concurrently with other legitimate users such as emergency personnel. It can also be blocked by authorities, if happens often in terrorist attacks. And it can be damaged by the event itself. In many cases, however, it is non-existing or is non-accessible by the particular devices of the evacuees. Failure of the central infrastructure directly incurs the failure of the evacuation system. Decentralized evacuation systems are scalable and robust against the failure of central infrastructures, but due to a lack of central infrastructure, the real-time information of the environment is unavailable, and evacuees rely on self-exploration and local communication, so the knowledge of the environment can be incomplete and delayed.

Richter et al. (2013) proposed a decentralized system for collaborative evacuation. This system utilizes smartphones with their sensors and their capacity for peer-to-peer communication where computation is performed directly on the devices held by evacuees and guidance is provided by a mobile service. The advantage of peer-communication and -collaboration correlates positively with the density of evacuees in the environment: the more evacuees exist in a certain environment, the more opportunity exists for exchanging knowledge. However, a larger number of evacuees also implies an increased risk of congestions (Merkel, 2014). Similar work has been done by Fujihara and Miwa (2014). They considered the opportunistic communication of mobile nodes in Mobile Opportunistic Networks (MONs), and assumed also a navigation service. Evacuees share disaster information by opportunistic encounter and short-range wireless communication. In their scenario the disaster information is finally gathered by a database server in the refuge and forwarded out of the disaster area by delay tolerant network technologies such as satellite-based communications. Komatsu, Sasabe, and Kasahara (2016) also introduced cooperation between evacuees with mobile sensor nodes. Each mobile node senses the environment and tries to navigate its evacuee by presenting an evacuation route. The mobile node estimates a road segment as blocked when it detects the difference between a recommended route and actual evacuation behavior. Then it recalculates an alternative evacuation route, which does not include the blocked road segments discovered. They focus specifically on reducing the network load. Iizuka, Yoshida, and Iizuka (2011) presented a method for decentralized evacuation, which considers evacuation as a distributed constraint optimization problem and estimates the location of evacuees so as to relieve congestion.

Due to the fundamental property of opportunistic communication, all the wireless mobile sensor networks share a shortcoming that
the effects of opportunistic communication become weaker when the number of users in the network is smaller. None of the previous work has addressed this issue. Thus, improving decentralized evacuation management for less occupied buildings is the an object to be addressed in this thesis.

So far, the task of decentralized evacuation route planning considering the uncertainty of information caused by the dynamics of events has received little attention from researchers. Recent research by Tan, Hu, and Lin (2015) is distinguished from other works by considering not only the stationary environment during a normal situation, but also the event knowledge of predictable change in the spatial accessibility. However, the potentially changed spatial accessibility they refer to is caused by the activation of fire safety facilities, such as the fire rolling shutters during emergency scenarios. The validity of knowledge for other spatial connectivity due to time elapsed has not been addressed. To our knowledge the only literature that raises the question of uncertain information regarding evacuation in decentralized frameworks is by Merkel (2014). However, the uncertainty they refer to is caused by occasional disconnection of ad hoc networks caused by the movement through the building and the delay of communication incurred.

In an attempt to address the possibly out-of-date knowledge caused by the dynamics of expanding events in decentralized evacuation, this thesis proposes a fading memory model, which represents not only the evacuees’ prior knowledge of the floor layout, but also the perceivable information about dynamic environment changes. System behavior when introducing fading memory concepts will be tested via simulations.

While static sensor networks can detect the extent of phenomena such as fires or concentrations of pollutants, and can delineate the boundaries of such regions, low-density in-situ sensor networks may not suffice to estimate the boundaries, especially in evacuation situations where the sensor nodes are outside of these hazardous regions. Brink (2015) suggest adding mobile sensors with an intelligent and adaptive sampling strategy to collect the missing information for monitoring the boundaries of highly dynamic phenomena such as plumes. In contrast, this thesis suggests static depositories at strategic locations that collect the knowledge acquired by the smartphones of evacuees passing by, merging data over time.

2.5 TIME AWARENESS

A comprehensive review of time-aware recommendation performance systems has been provided by Campos, Díez, and Cantador (2014). Time-aware decision support system has been studied by Milea, Frasincar, and Kaymak (2013) and Daneshmand et al. (2014).

Only recently, time-awareness starts drawing attention from researchers (Campos, Díez, and Cantador, 2014; Cheng and Liu, 2015; Daneshmand et al., 2014; De Maio et al., 2016; Milea, Frasincar, and Kay-
mak, 2013; Tagarelli and Interdonato, 2015; Westerlund, 2007; Zhao and Winter, 2016), among which the only one addressing evacuation challenges is carried out by Zhao and Winter (2016). In view of the unreliability of knowledge during evacuation in dynamic environments, Zhao and Winter (2016) propose a fading memory model that enables time-awareness for evacuation route planning. A fading memory model critiques the validity of knowledge from the temporal perspective, trusting less the older knowledge for decision making in dynamically changing environments. Results showed increased numbers of successful evacuees after applying fading memory. However, they applied the assumption that each person is familiar with the environment or has a complete map of the environment by the time of evacuation, which is idealistic. People can be required to evacuate an environment they are not familiar with, and then a complete map may either not exists or the access will rely on external infrastructure. To address this problem, this thesis also investigates time-aware decentralized evacuation while relieving the constraint of complete prior knowledge. Relieving such constraint will enable the decentralized model being applied to an arbitrary environment without extra support.
INTEGRATING SENSING AND ROUTING FOR INDOOR EVACUATION

This chapter is composed based on the following paper, with some extensions:

to which my contribution is about 25% and comprises the following aspects:

- Designing the experiment and analyzing the experiment results, verifying that context-awareness achieved from applying a sensor tracking and risk aware framework will significantly benefit evacuations.

Indoor evacuation systems are needed for rescue and safety management. A particular challenge is real-time evacuation route planning for the trapped people. In this chapter, an integrated model is proposed for indoor evacuation used on mobile phones. With the purpose of employing real-time sensor data as references for evacuation route calculation, this chapter makes an attempt to convert sensor systems to sensor graphs and associate these sensor graphs with route graph. Based on the integration of sensing and routing, sensor tracking and risk aware evacuation routes are generated dynamically for evacuees. Experiments suggest that such a sensor tracking and risk aware framework is capable of saving more evacuees and reducing evacuation time.

3.1 INTRODUCTION

Applying geographic information systems (GIS) for indoor environments has gained attention in way-finding contexts and in building facility management. The challenges for indoor GIS include the representation of indoor space for routing tasks and the integration of relevant building facilities. There is no standard representation for routing networks in indoor space until now because indoor space has multiple functional purposes that lead to different proper representations for the same indoor environment. Furthermore, people move more freely in indoor space than vehicles move in outdoor space (Richter, Winter, and Rüetschi, 2009). Many data structures realize in a unique way the representation of the navigable space in an indoor environment, with varying advantages and disadvantages (OGC, 2013; Lee

Liu and Zlatanova (2015) propose a method to compute indoor navigation paths. This method considers the impact that the boundaries of obstacles and the size of users have on the accessibility of indoor spaces of the users. The method is particularly advantageous in specific cases where there are many indoor obstacles and the pedestrian-related dimension is important. For example, a facility maintenance staffs in a factory operating a large vehicle or a wheeled cart want to find a navigation path passing through narrow spaces formed by goods and facilities. In evacuation circumstances, this method can be well applied by people with wheelchairs when some gaps in indoor space are too narrow for them to pass though.

The prior research on indoor space representation especially focused on utilization of the routing capabilities of GIS in response to indoor disasters, such as fire, gas leakage or terror attacks. This research was also used for simulation of navigation in evacuation scenarios considering building structure and emergency propagation characters (Wu and Chen, 2012; Liu et al., 2010; Kraus et al., 2011; Han et al., 2013; Jiyeong, 2007; Zhang et al., 2012; Tang and Ren, 2011). Generally, evacuation routes in these systems are built on route graphs which are originally derived from building floor plans and then dynamically updated in references to the predicted result of emergency simulation models or risk assessment.

However, in modern buildings different kinds of sensors obtain environmental parameters continuously, such that real-time sensing becomes possible. Some other evacuation applications take already advantage of wired or wireless building sensor systems to monitor a current environmental state for dynamic evacuation (Lei and Gaofeng, 2009; Nauman et al., 2011; Sha, Shi, and Watkins, 2006). In contrast to open (outdoor) environments the detecting area of a sensor inside a building is limited by the building structure. For example, near sensors can be independent because of a wall in between. Thus, linking sensor readings to routes requires complex analysis. Additionally, wireless building sensor systems (WSN) rely on the ad-hoc communication network of the sensor vertices, and special routing protocols (Al-Karaki and Kamal, 2004) are required to guarantee a near-real-time updating of evacuation routes.

The above review implies the need to identify an integrated data model that not only represents the routing properties of indoor environments, but also the observations of building sensor systems in their impact on routing. This data model should combine geospatial information such as route graphs and sensor graphs, and environmental information such as sensor readings to achieve real-time risk-aware evacuation planning in emergency situations. This chapter introduces such a data model for indoor evacuation. The suggested data model, implemented in a personalized evacuation system, will allow generating an evacuation route dynamically for each evacuee, depending on current sensor readings, and taking risk assessments into account. The integrated model enables indoor evacuation appli-
cations valuable for both accurate emergency localization and reliable evacuation guidance. The potential benefits of the model can also extend to offer an approach to correlate route network to sensor network for a wide range of indoor applications.

The rest of this chapter is structured as follows. Section 3.2.1 introduces the method of formulating route graphs, and Section 3.2.2 propose an algorithm to create sensor graphs with completely coverage of all area in building floor plans. Section 3.2.3 explains the integration of route graphs and sensor graphs. Section 3.3 provides a sensor tracking and risk aware evacuation plan using this novel data model. Experiments of the model are discussed in Section 3.4. Section 3.5 summarizes the work in this chapter.

3.2 THE PROPOSED MODEL

The model consists of three main parts, presenting a route graph for the indoor environment, sensor graphs for sensors in this environment, and the integration of the route graph with all sensor graphs.

3.2.1 Route graph

The main purpose of route graph is to associate evacuation routes with the building structure to ensure the feasibility of the generated evacuation route. The following is specifically based on the route graph of YAMAMOTO (Stahl, 2010), which is specified formally here for the first time. For this formal specifications, some definitions are introduced before generating a route graph.

**Definition 1** A region $R$ is a planar and accessible area with a unique identifier in the model, denoted as $R_i$.

Thus a region in this chapter refers to a two-dimensional bounded area with at least one entrance that could provide access for pedestrians, such as a room, corridor, or lobby. Entrances form virtual parts of the boundary of a region. Every two regions $R_1$ and $R_2$ must not overlap, but may neighbor, in which case they share at least one boundary line. Overlapping areas $P$ and $Q$ are separated into regions, either by $(P, (P \cup Q) \cap \overline{P})$, or by $(Q, (P \cup Q) \cap \overline{Q})$.

Every region is represented by a polygon. If a part of the boundaries of a region is curved, this curved part is substituted by a polyline, for example, using the successive bisection algorithm of Chandra (2012) adapting to a chosen level of accuracy. For convex regions, each pair of vertices inside or on a boundary of the region can be linked together by a straight line edge without piercing any boundary. These edges are passable. However, for concave regions the links between some pairs of vertices are not passable. For those pairs of vertices there exists always a set of passable edges between them, including a sequence of concave boundary vertices.

There are three types of vertices in a route graph, called inner vertex, access vertex and connecting vertex.
Definition 2 An inner vertex is a shifted concave boundary vertex of concave regions.

Inner vertices are used to form a passable edge of route graphs. They are placed one meter away from walls, boundaries or corners in order to keep a natural distance for pedestrians.

Definition 3 Access vertices are placed pair-wise on both sides of the virtual boundary of an entrance.

The edge between a pair of access vertices represents the accessibility of two adjoining regions in a route graph. The two vertices belong to different regions respectively. Also access vertices are placed one meter away from the virtual boundary of the entrance in order to keep a natural distance for pedestrians.

Definition 4 Connecting vertices are placed at the beginning, end and turning points of staircases.

The edges between a sequence of connecting vertices are route graph elements connecting two different floors.

In Figure 2, there are three pairs of access vertices between R₁ and R₂ among which v₂, v₅ and v₇ belong to R₁. A straight link between v₂ to v₅ is not passable in the concave region R₁, but one of the passable routes is v₂ – v₃ – v₄ – v₅ with v₃ and v₄ being inner vertices. Figure 3 shows four connecting vertices; v₁₀ and v₁₁ are placed at turning points of a staircase. Elevators, while connecting floors as well, are not represented in the route graph because they cannot be used for evacuation.
**Definition 5** A route graph $G = (V, E)$ consists of a set $V$ of inner vertices, access vertices and connecting vertices, together with a set $E$ of edges. The set $E$ consists of the edges between each pair of access vertices, the edges between every pair of vertices in the same region if the edge is passable, and the edges between every two consecutive connecting vertices along the same staircase.

As an example, Figure 4 shows a floor plan of a building. The five regions are named as $R_1$ to $R_5$, and $R_5$ is a concave region. The corresponding route graph $G$ is shown in Figure 5.

![Figure 4: Sample floor plan.](image)

### 3.2.2 Sensor graphs

In contrast to route graphs, the objective of sensor graphs is to give timely feedback of environmental factors in order to predict the impact on evacuation plans, including a risk assessment. The definition of a sensor graph is also based on some concepts that need to be defined first.

**Definition 6** A sensor detecting area $S_i$ of sensor $s_i$ is the collection of all points where sensor data can be obtained by sensor $s_i$. $S_i$ is represented by a polygon with a clock-wise ordered set of corner vertices $S_i := \{p_1, \cdots, p_m\}$, $m \geq 3$. Each vertex $p_k$, $1 \leq k \leq m$, is denoted by its position $(x_k, y_k, z_k)$.

The typical detection range of most types of sensors is a circular area of radius $r_s$ of which the center is the point of installation of the sensor. However, there are significant exceptions. For example, walls shield the reception of sensors (National Fire Protection Association, 2007). Hence, the actual detection area of each sensor is the intersection between the uninhibited sensor detection area and
the boundary of the region in which the sensor is installed. For example, in Figure 6 $S_3$ is the sensor detecting area of $s_3$ in $R_1$, thus, $S_3 := \{p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8\}$.

**Definition 7** $S_i$ of sensor $s_i$ and $S_j$ of sensor $s_j$ is considered intersecting if (a) $s_i$ and $s_j$ are in the same region and $S_i \cap S_j \neq \emptyset$, or (b) $s_i$ and $s_j$ are in different regions and $S_i \cap S_j$ covers at least one entrance between the regions, or (c) $s_i$ and $s_j$ are at the opposite entrances of a staircase (i.e., on neighboring floors).

The sensors in this chapter are different concepts from the sensors in a wireless sensor network. In a wireless sensor network, a connection indicates that two sensors are within communication range. In this chapter, two sensors at the opposite entrances of a staircase may not be in communication range, but they are considered as connected in order to predict the emergency dynamics. For example, the fire may spread through the staircase from downstairs to upstairs. In this case, it is possible that the sensor at the downstairs entrance reports fire information, then consecutively the sensor at the upstairs entrance detects the fire.

**Definition 8** A sensor graph $G' = (V', E')$ consists of a set $V'$ of sensor vertices $s_i$ representing the location of the sensors, together with a set $E'$ of edges if two sensors' detection areas are intersecting.

When forming a sensor graph, there is a complete coverage problem of sensor vertices. According to the objective of sensor graphs, the sensor network should cover all areas of a floor plan, or otherwise events may be not detected, and also the event simulation becomes
incoherent. Therefore, a sensor graph according to Definition 8 is completed by adopting an algorithm suggested originally in Aziz, Aziz, and Ismail (2009).

All together, the following steps describe the sensor graph generation.

Step 1: A floor plan is partitioned by a grid $T$, with equally spaced tiles $t_{p,q}$ ($p$ is the row number and $q$ is the column number). For those tiles that are divided by borders between regions, each part of the tile will be treated as separated tiles in different regions.

Step 2: The sensor vertices $S$ are added to $G'$ for each actual sensor in the environment.

Step 3: For a region $R_i$, a matrix $A(R_i) = [a_{p,q}]_{n \times m}$ ($1 \leq p \leq n$, $1 \leq q \leq m$) is formed corresponding to the $n \times m$ tiles that just cover $R_i$ and initialized by $0$’s. If there are some tiles in this matrix that are not part of the region the corresponding entries are set to infinite.

Step 4: For each tile $t_{p,q}$, if $t_{p,q} \cap S_j \neq \emptyset$ ($1 \leq j \leq |V'|$) in $R_i$ the entry $a_{p,q}$ in $A(R_i)$ will be set to 1.

Step 5: If $A(R_i)$ contains one or more zero elements, i.e., tiles inside the region that are not observed by a sensor, a virtual sensor is placed at the center of the first zero tile encountered in row order, and added to $V'$. Then goto Step 4. Otherwise, go to Step 6.

Step 6: If all regions in the floor plan have been operated goto Step 7. Otherwise, goto Step 3.

Step 7: connecting floors: For each staircase connecting two adjacent floors, two virtual sensor vertices are added to $V'$, which are placed in the middle of the entrances of the same staircase.

Step 8: For all pairs $s_i, s_j$, if $S_i$ and $S_j$ are intersecting add an edge between them to $E'$.
Step 9: If all floor plans in the building have been observed, stop. Otherwise, goto Step 1.

In Figure 7, the floor plan is firstly partitioned into tiles with an equal spacing, here of \( r_s/2 \) \( (r_s = 6m) \). The origin of the grid is at the top left corner. There are originally seven smoke sensors \( s_1 \) to \( s_7 \) in the sensor system, denoted by red squares.

Figure 7: Sensor detection areas in \( R_5 \).

For \( R_1 \), the matrix \( A(R_1) \) is \( 4 \times 4 \) although some of the tiles in \( R_1 \) are only partly inside. Since \( s_3 \) is the only actual sensor in \( R_1 \) and all grids in \( R_1 \) intersect with \( S_3 \) (Figure 6), all entries in \( A(R_1) \) equal to 1 and no virtual sensor vertex need to be added in \( R_1 \). \( R_2 \), \( R_3 \), and \( R_4 \) are similar, and \( S_4 \), \( S_5 \) and \( S_6 \) are added to \( V' \).

Figure 8: Sensor graph.
For $R_5$, however, Figure 7 shows some gaps in the sensor coverage. There are three actual sensors $s_1$, $s_2$ and $s_7$ whose detection areas are denoted with lines of different colors. Corresponding $A(R_5)$ is

\[
A(R_5) = \begin{bmatrix}
1 & 1 & 1 & \infty & \infty & \infty & \infty & \infty \\
1 & 1 & 1 & \infty & \infty & \infty & \infty & \infty \\
1 & 1 & 1 & \infty & \infty & \infty & \infty & \infty \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
0 & 1 & 1 & \infty & \infty & \infty & \infty & \infty \\
0 & 0 & 0 & \infty & \infty & \infty & \infty & \infty \\
0 & 0 & 0 & \infty & \infty & \infty & \infty & \infty 
\end{bmatrix}
\]

containing some zero values. Since the first zero value (in row order) refers to $t_{5,1}$ a virtual sensor $s_8$ is placed at its center, denoted by a red triangle, and $S_8$ is added, denoted by a purple line. After another iteration,

\[
A(R_5) = \begin{bmatrix}
1 & 1 & 1 & \infty & \infty & \infty & \infty & \infty \\
1 & 1 & 1 & \infty & \infty & \infty & \infty & \infty \\
1 & 1 & 1 & \infty & \infty & \infty & \infty & \infty \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & \infty & \infty & \infty & \infty & \infty \\
1 & 1 & 0 & \infty & \infty & \infty & \infty & \infty \\
0 & 0 & 0 & \infty & \infty & \infty & \infty & \infty 
\end{bmatrix}
\]

still contain some zero values. $t_{7,3}$ is the first zero value in search order, and a virtual sensor $s_9$ is added to $V'$. In the next iteration, $A(R_5)$ does no longer contain a zero value. The algorithm proceeds to Step 8 to generate edges $E'$. The final result of $G'$ is shown in Figure 8.

This sensor graph generation algorithm is easy to program, but not optimal because the number of virtual sensors is not the minimum. For the purpose of this chapter the algorithm is sufficient. In the future, another algorithm can be plugged in covering the whole area with a minimal number of virtual sensors.

Generally, when a building has different types of sensors simultaneously, separate sensor graphs are formed in the model.

### 3.2.3 Integration of sensor graph and route graph

The integration of sensor graph and route graph is actually a mapping from sensor network observations to route network elements. The integration facilitates the representation of affectedness of route graph vertices and edges, for passive and active sensors as well as for sensors at risk according to some prediction model. The following
method integrates one sensor graph with a route graph. With other sensor graphs the same method can be applied.

If a vertex \( v_i \) in route graph \( G \) is inside \( S_k \) of some sensor \( s_k \), vertex \( v_i \) is one of the affected vertices of \( s_k \). Also, if an edge \( e_j \) in \( G \) intersects with \( S_k \), edge \( e_j \) is one of the affected edges of \( s_k \). The latter provides a mechanism to represent that an edge is blocked although the endpoints may not. The relationship between route graph vertices and sensors is \( n : m \) since route graph vertices can be inside none, one or multiple \( S_i \), and there may be zero, one or more route graph vertices in \( S_1 \). The same applies for relationships between route graph edges and sensors because a straight edge may go through more than one \( S_1 \) and the range of a sensor may intersect with more than one route graph edge.

The integration of the sample floor plan is shown in Table 1. There are no affected route graph vertices or edges in \( S_1 \) which suggests that \( S_1 \) will not be crossed during evacuation. However, when \( s_8 \) is activated in an event, two route graph edges will be blocked (but no vertices are affected).

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Affected vertices</th>
<th>Affected edges</th>
</tr>
</thead>
<tbody>
<tr>
<td>( s_1 )</td>
<td>( \emptyset )</td>
<td>( \emptyset )</td>
</tr>
<tr>
<td>( s_2 )</td>
<td>( v_3, v_4, v_6, v_9 )</td>
<td>all edges start or end on ( v_3, v_4, v_6, v_9 )</td>
</tr>
<tr>
<td>( s_3 )</td>
<td>( v_{10}, v_{13} )</td>
<td>all edges start or end on ( v_{10}, v_{13} )</td>
</tr>
<tr>
<td>( s_4 )</td>
<td>( v_{12}, v_{14}, v_{15} )</td>
<td>all edges start or end on ( v_{12}, v_{14}, v_{15} )</td>
</tr>
<tr>
<td>( s_5 )</td>
<td>( v_5 )</td>
<td>all edges start or end on ( v_5 )</td>
</tr>
<tr>
<td>( s_6 )</td>
<td>( v_7 )</td>
<td>all edges start or end on ( v_7 )</td>
</tr>
<tr>
<td>( s_7 )</td>
<td>( v_8, v_{11} )</td>
<td>all edges start or end on ( v_8, v_{11} )</td>
</tr>
<tr>
<td>( s_8 )</td>
<td>( \emptyset )</td>
<td>( v_2-v_4, v_2-v_3 )</td>
</tr>
<tr>
<td>( s_9 )</td>
<td>( v_2 )</td>
<td>all edges start or end on ( v_2 )</td>
</tr>
</tbody>
</table>

3.3 SENSOR TRACKING AND RISK AWARE EVACUATION PLANNING

This section introduces evacuation planning based on the integrated route and sensor graph data model. It considers sensor states of being activated by an event, or at risk according to some prediction model. In emergency, evacuees who are familiar with the building tend to choose their habitual routes for evacuation although it may lead them to blocked or risky areas. Other evacuees who are unacquainted with the building may follow the crowd or the signed evacuation routes. Also these strategies may be in conflict with the event itself. Evacuation based on outdated information is blind evacuation. Recently, mobile application systems have emerged able to provide assistance for evacuees. Some of these applications are also blind, based on by
the event outdated data. Their evacuation route planning is static, it
does not adapt dynamically to the situation. Even if these applica-
tions receive the initial location of the emergency (updating their data
initially) they can not generate dynamically escape routes.

Few indoor evacuation systems are tracking sensors and risk aware. A sensor tracking evacuation is obtaining timely the sensor data from
building sensor systems to generate real-time evacuation routes for evacuees. In addition, a risk aware evacuation also avoids or reduces
risks after adopting some strategies to predict near-future states of
the event.

The proposed model in this chapter can be applied to realize sensor
tracking and risk aware evacuation planning. There are two reasons.
Firstly, sensor data is continuously read out by a building sensor sys-
tem. When unusual situations are reported at a time (i.e., some sen-
sors get activated), the identifiers of these sensors localize the event.
If these identifiers are forwarded to an evacuation application, the
affected route graph vertices and edges are directly accessible in the
integrated model, and are marked as blocked when generating a real-
time evacuation routes for individuals. Consequently, this application
meets the requirements of sensor tracking evacuation planning. The
application is also capable of risk awareness. When building sensor
systems report an event (i.e., some sensors are activated), the connectiv-
ity in the sensor network can be used to predict the near-future
spread of the event. Reporting risky sensors to the evacuation applica-
tion allows to mark the affected route graph vertices and edges being
at risk, e.g., by a risk rank value, which may be considered by some
weighting in the computation of individual evacuation routes.

Both sensor tracking and risk awareness requires a standing com-
munication between building sensor systems and evacuation plan-
ing applications. However, even only occasional updates and itera-
tive evacuation planning must be superior to blind or static evacua-
tion planning. This is tested in the following section.

3.4 EXPERIMENTS

This section demonstrates a mobile evacuation system application,
implementing the proposed model, in an office building. The objec-
tive of the experiments is to compare sensor tracking and risk aware
evacuation plans with blind and static evacuation plans. In this exper-
iment, fire disasters are assumed.

3.4.1 System implementation

The system implementation is built on a framework shown in Fig-
ure 9. There are six separately modules in the system. The building
sensor system gathers continuously the environment data, and re-
ports an alarm when it detects some unusually situation. The sen-
sor graphs, the route graph, and their integration have been pre-
calculated and stored in a server. On the user side, four modules
cooperate with each other to generate a safe and short evacuation route for each evacuee. The location module gives the current position of each user. The risk assessment module evaluates the emergency situation and renews the risk rank value of affected vertices and edges in route graph. Route generation module sets an optimal evacuation route dynamically by considering both the distance and the risk value. The building model provides a platform to the user to follow the evacuation route and related instructions. The thick lines in Figure 9 denote the dynamic data and the filaments denote the pre-generated information.

The entire evacuation system is developed by expanding YAMAMOTO in C#. YAMAMOTO is a 2.5 dimensional modeling toolkit (for floors and connections between floors) to represent the navigable indoor space. YAMAMOTO takes as input 2D floor plans imported from CAD systems through an XML format. The output is a navigable graph suited for representing human movement behavior in indoor space. It automatically generates a graph by adding points at doors, openings and turning corners where two walls include an angle greater than 180 degrees. Nodes are placed at a certain distance away from walls, boundaries or corners in order to keep a natural distance for human movement. It also applies an A* search algorithm to find the shortest path between a start and end point in this graph. In addition, YAMAMOTO allows to model the sensors in the environment in form of sensor graphs. In particular, it links the sensors, or their detection ranges, with the navigable graph.

In this thesis YAMAMOTO is applied as geometric basis to demonstrate the proposed models. Sensor graphs, route graphs, and their integration are all generated by this toolkit and are exported for the agent-based simulations as XML files.

The current location of each evacuee is obtained by QR-code scanning which obviously can be substituted by any other positioning mechanism. The risk assessment module is accomplished by a series of risk assessment strategies synthesized from Dow’s Fire and Explosion Index (American Institute of Chemical Engineers, 1994) and Fire
Safety Evaluation System (National Fire Protection Association, 2013). In particular, the risk assessment mechanism is an independent part of the entire application, and could also be easily replaced by any other risk assessment method. The route generation module is that of YAMAMOTO, but now using dynamic route graph of the proposed model. The user interface is built by Open Graphics Library for Embedded System. Figure 10 shows section of the office building model together with sensor detection areas, and Figure 11 gives the interface of the system.

![Figure 10: Section of building model with sensor layers.](image)

![Figure 11: System implementation.](image)

### 3.4.2 Simulation and result analysis

The model has been simulated in Repast Simphony. Repast Simphony is an agent-based modeling and simulation toolkit, which allows users to define their own agents. Each agent has attributes and actions that need to be defined by the users. The users also need to set the rules for the interaction between the agents and their environments. Repast Simphony also provides visualization of the spatial structure and the simulation process. In this thesis, agents consist of evacuees, route graph nodes, route graph edges, sensor graph nodes and sensor graph edges. Evacuees have attributes such as their current locations, their walking speeds and their knowledge of the environment. Sensor nodes have attributes such as their locations, sensor types, radius of
detecting area, sensor status, their connected neighbor sensors, their affected route graph nodes and affected route graph edges. The sensor graph and the route graph have been created in Repast Simphony by transferring the XML files exported from YAMAMOTO.

The office building used in this experiment has five floors and three blocks including office rooms, lecture theaters and laboratories. Each block is connected to an adjacent block by a staircase. Simulated fire emergencies spread via a sensor graph. The simulation assumes that one sensor detects the fire from the beginning. Then, because of the continuity of the fire spreading, the next sensor that detects the fire should be one of its neighbored sensors. Thus, an extended process can be simulated through simulating the state transfer of the sensors. The simulation assumes that fire can only spread from the detection area of a sensor to the detection area of its adjacent sensors. Fires that spread through air tunnel where no sensors are installed are different scenarios that have not been covered by the fire simulation in this chapter.

Blind, static and sensor tracking and risk aware evacuation plans are simulated in Repast Simphony for the same twenty fire emergencies to keep the results comparable. The speed of user movement is assumed to be 1.5 m per second. The initial position of 100 evacuees are randomly given and recorded into an XML file which will be imported at the beginning of each emergency simulation to ensure all evacuees escape from the same initial position.

Figure 12 shows a sensor tracking and risk aware evacuation emergency with a part of the route graph. The blue cube indicates the evacuee, the red circles the blocked, and the yellow circles the risky vertices in the route graph. For readability the sensor graph is not shown. Only sensor vertices are indicated (red cube: blocked, yellow: risky, gray: normal, dark: extinguished). The fire source is on the fourth floor, and most of the evacuees are near the staircase except E1. The evacuation system generates evacuation routes, so most evacuees are escaping toward the staircase, and E1 escapes to the other block as the only pathway to the staircase in this block is blocked.

![Figure 12: Evacuation simulation.](image-url)
The potential advantages of this conceptual model have been simulated via agent-based simulation. In the simulation, route nodes, sensors and evacuees were conceptualized as agents. The route graph was exemplified by the architecture of the office building of the Department of Infrastructure Engineering. 100 mobile agents were assumed. Their start locations were randomly picked up from the route graph nodes and saved in files for repeated simulations. The simulations were repeated under 20 different random emergencies.

Table 2 shows the results which were produced after the publication by Wang et al., 2014. Three parameters, namely, the number of successful evacuees, the average evacuation time and the maximum evacuation time, were compared and plotted in Figure 13, Figure 14 and Figure 15, respectively. Blind evacuation plan, static evacuation plan, sensor tracking and risk aware evacuation plan have been denoted by BLIND, STATIC and ST&RA, respectively. In Table 2, Suc represents the number of successful evacuees, AvT represents the average time required for successful evacuees, and MxT represents the time consumed by the last successful evacuee.

As can be observed from the experiment results, in eight emergency cases (i.e., Event 1, Event 2, Event 3, Event 6, Event 7, Event 9, Event 15 and Event 18), sensor tracking and risk aware evacuation plan has demonstrated significant advantage, saving more people than blind evacuation plan. For example, 98 people were saved in Event 1 compared with only 90 people saved by blind evacuation plan. Another experiment that demonstrates the substantial advantage of ST&RA is Event 2. For Event 2, eleven more people have been saved by sensor tracking and risk aware evacuation plan, who would otherwise fail to evacuate if blind evacuation plans were adopted.

In a few cases (Event 1, Event 2 and Event 15), the static evacuation plan has also saved more people than blind evacuation plan, which indicates that even very limited improvement of risk aware-
Table 2: Experiment results for evacuating twenty independent fire emergencies using three different evacuation plans: blind evacuation plan (BLIND), static evacuation plan (STATIC), sensor tracking and risk aware evacuation plan (ST&RA). In this table, Suc represents the number of successful evacuees, AvT represents the average time required for successful evacuees, and MxT represents the time consumed by the last successful evacuee.

<table>
<thead>
<tr>
<th>Event</th>
<th>ST&amp;RA</th>
<th>STATIC</th>
<th>BLIND</th>
</tr>
</thead>
<tbody>
<tr>
<td>ID</td>
<td>Suc</td>
<td>AvT</td>
<td>MxT</td>
</tr>
<tr>
<td>1</td>
<td>98</td>
<td>73.07</td>
<td>150</td>
</tr>
<tr>
<td>2</td>
<td>98</td>
<td>95.86</td>
<td>194</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
<td>70.77</td>
<td>149</td>
</tr>
<tr>
<td>4</td>
<td>91</td>
<td>71.48</td>
<td>169</td>
</tr>
<tr>
<td>5</td>
<td>99</td>
<td>69.57</td>
<td>149</td>
</tr>
<tr>
<td>6</td>
<td>99</td>
<td>73.83</td>
<td>149</td>
</tr>
<tr>
<td>7</td>
<td>100</td>
<td>72.85</td>
<td>149</td>
</tr>
<tr>
<td>8</td>
<td>98</td>
<td>71.32</td>
<td>149</td>
</tr>
<tr>
<td>9</td>
<td>90</td>
<td>66.30</td>
<td>120</td>
</tr>
<tr>
<td>10</td>
<td>100</td>
<td>70.56</td>
<td>149</td>
</tr>
<tr>
<td>11</td>
<td>100</td>
<td>69.49</td>
<td>149</td>
</tr>
<tr>
<td>12</td>
<td>98</td>
<td>68.80</td>
<td>149</td>
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<td>13</td>
<td>90</td>
<td>64.74</td>
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<td>14</td>
<td>100</td>
<td>69.77</td>
<td>149</td>
</tr>
<tr>
<td>15</td>
<td>100</td>
<td>72.55</td>
<td>150</td>
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<td>16</td>
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<td>17</td>
<td>97</td>
<td>68.58</td>
<td>149</td>
</tr>
<tr>
<td>18</td>
<td>100</td>
<td>71.03</td>
<td>162</td>
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<tr>
<td>19</td>
<td>98</td>
<td>68.94</td>
<td>149</td>
</tr>
<tr>
<td>20</td>
<td>92</td>
<td>64.77</td>
<td>120</td>
</tr>
<tr>
<td>Avg</td>
<td>97.20</td>
<td>71.14</td>
<td>148.65</td>
</tr>
</tbody>
</table>

ness (e.g., knowing the initial location of emergency) will benefit the evacuations. But there is no case that static evacuation plan has saved more people than sensor tracking and risk aware evacuation plan, which may due to the very limited risk awareness acquired by static evacuation plan in comparison with sensor tracking and risk aware evacuation plan.

Noticeably, there are more than half of the emergency cases, where the three different evacuation plans saved the same number of evacuees. The reasons for this observation are two-fold:

1. Each fire emergency started at a certain location and has initially covered a certain area. Evacuees in this area have failed the evacuation at the start of an emergency, thus after that different evacuation plans makes no difference for these evacuees.
At the same time, other evacuees have been located at such locations that their evacuation route have not been affected by the fire spread.

2. The sample building has limited number of exits, and each node in the route graph has limited connections to reach the exits. For some nodes, there can be only one way towards the exits. Once this way has been blocked by the fire emergency, this node becomes a dead end node, and any evacuee located at this node will definitely fail the evacuation regardless of which evacuation plan this evacuee has adopted.
These two reasons also indicate that although sensor tracking and risk aware evacuation plan is advantageous, it does not guarantee to save all the evacuees.

When examining the average evacuation time for each emergency case, it can be observed that ST&RA strategy generally saving evacuation time for each evacuees compared with BLIND evacuation strategy. But there are exceptions. For Event 6, the average time for ST&RA is 73.83 seconds which is greater than that of BLIND plan. To explain this, we need to combine the number of successful evacuees and the average time consumed by those successful evacuees. There are two possible reasons:

- The average evacuation time is the quotient of the sum of evacuation time and the number of success evacuees. People who fail to evacuate in STATIC or BLIND evacuation plans are not included in the calculation, but those people may need a little more time to evacuate with ST&RA plans, which leads to the special case.

- Another reason is a blocked sensor vertex at time $T_1$ may change to extinguished at time $T_2$. The sensor tracking and risk aware planning will generate a longer but safer evacuation route at time $T_1$. When evacuees follow this route it will take more time to escape. In blind evacuation, since no feedback from sensor and risk assessment evacuees may follow the shortest route at time $T_1$ and at time $T_2$ they are so lucky to pass the extinguished area which were blocked at time $T_1$.

Similar examples can be found in the maximum of evacuation time in Figure 15. The maximum evacuation time refers to the escape time of the last successful person. In one case (Event 18), the evacuation for ST&RA finished later than BLIND plan. Noticeably, the ST&RA plan saved one more evacuation than BLIND plan. This evacuee has been saved by ST&RA plan, but consumed 162 seconds, which is longer than the time consumed by the last evacuee in BLIND plan. There is no case that ST&RA saved the same number of evacuees as BLIND plan but has a larger maximum evacuation time which is possible though. Regardless of the unsuccessful evacuees, the maximum evacuation time for ST&RA plan is generally the least.

Overall, the results of the simulation demonstrate that sensor tracking and risk aware evacuation plan is safer and more reliable than the other two evacuation plans.

3.5 Summary and Discussion

This chapter proposes an integrated data model for indoor evacuation on the basis of building sensor systems and building structure. With the purpose of employing real-time sensor data as references for evacuation route calculation, this chapter converts monitoring sensors to sensor graphs, and integrates these sensor graphs to a route
graph. With this integration, sensor tracking and risk aware evacuation routes may be generated dynamically for evacuees, which have been shown to be superior to static or blind evacuation plans. Fundamentally, this model lays foundations for refined integration of modern building facilities and indoor GIS applications.

Real-time risk awareness of the environment has been proved beneficial for evacuation; however, it is not without deficiencies. If the evacuation process is considered as a complex system involving multiple factors, then whether an evacuee can successfully evacuate is the output of this complex system. If we look at the sensor tracking and risk awareness evacuation plan from the temporal perspective, in each step, it calculates a route based on the current state of the environment without consider the future change of the environment. In this case, such a route will in effect only guarantee to be safe and shortest at the current moment, but the route may be blocked by the expanding fire disaster in the short future. Then the evacuee will have to go back, or take a detour. Such alternation between planned evacuation routes leads to a waste of time, and in the worst case, causes failing in the evacuation.

Examining the space-time route of a successful evacuee, a successful route does not need to be always passable during the whole evacuation process, rather, the route need to guarantee that any segment of that route is passable at the particular moment when this evacuee is passing by that segment of route. To avoid detour, an optimal evacuation route should guarantee the passability not only at the current moment but also the moments after. In the next chapter, the future state of environment will also be considered when planning an evacuation route at each moment.
This chapter is based on the following paper, with some extensions:

to which my contribution is about 33% and comprises the following aspects:

- To implement context-aware and time-aware evacuation system via simulation.
- To verify via experiments that accurate prediction improves the evacuation results, saving more people than sensor tracking and risk aware evacuation plan.

This chapter presents an integration of building sensor information with indoor route graphs for the purpose of real-time evacuation planning. This integration allows dynamic risk assessment by prediction, for both the sensor graph and the route graph, and thus enables evacuation route planning aware of predicted risks. The model assumes a dynamic sensor graph according to building monitoring systems and varying sensor states over time. Sensor states are then propagated to a dynamic route graph through the building with regard to passability of edges at time $t$, using a risk model that quantifies risks of an impact on evacuation. The chapter proves the concept in an agent-based simulation, and tests whether foresight computed from the risk-aware model improves the evacuation.

4.1 INTRODUCTION

An integration of sensor graphs and route graphs in Chapter 3 allows a situation- and risk-aware indoor evacuation planning. In this prior work, evacuation risk had been considered statically in the evacuation planning: In the iterative route planning through the evacuation, at each iteration step the current situation as reported by the sensors had been taken into account. This strategy, although reflecting best current knowledge, does not yet take into account the dynamic behavior of most emergency events. For example, if at the time of evacuation planning a particular sensor is active (sending an alarm) and vertex $v_i$ in the route graph is in the coverage area of this sensor, then $v_i$ will be considered to be blocked for evacuation, despite a chance that its state may change in the future, and despite the likelihood that the state of other sensors may change in the future as well. Thus, it can be expected that an integration of event spread models for the prediction of sensor states will improve the evacuation planning.
A dynamic risk assessment mechanism will evaluate the risks as the event is predicted to progress. In this chapter, this prediction is linked to a time expanded sensor graph. The risk states or risk values of sensors at particular times are propagated to the vertices and edges of an equally time expanded route graph, and thus considered in evacuation route planning. Evacuation routes can now be generated for the minimal total or local risk along the route, rather than for distance. For example, a strictly risk-adverse evacuation planning strategy would only consider the vertices and edges in the route graph that are not intersecting with the area covered by sensors at risk.

Thus, this chapter expands the prior integration of sensor graphs and route graphs by looking ahead and integrating an event propagation model. A dynamic sensor graph is represented by a static sensor graph and a time-stamped sensor state table, while a dynamic route graph is represented by a static route graph and a time-based vertex risk table, as well as a time-based edge risk table. The time-stamped sensor risk state table is produced according to a set of rules, and then quantifies risks to a sensor risk table over time by appended to an event propagation model. From the integration of sensor graphs and route graphs, the vertices in route graphs inherit the maximum event risk values from their related sensors. Real-time congestion risk for each vertex in route graph is also considered when creating a vertex risk table. The dynamic edge risk table is produced on the dynamic vertex risk table. The escape route for evacuees then is calculated on both distance and risk values. The hypothesis of this chapter is that integration of time in evacuation facilitates risk-aware evacuation planning, which improves both evacuation times and the number of saved lives significantly.

Such a hypothesis can be investigated by simulation in which a risk-aware model is implemented to provide foresight for evacuees. A simulated event needs a behavior of its own, a prediction model of its behavior, and a variety of seeded scenarios to evaluate the impact of the added model in a general and robust manner. For the purpose of this chapter three simple event prediction models are implemented. One of them—and this is the advantage of using simulations—is predicting exactly the event behavior. Thus the experiment design allows also to assess the tendencies of simulated evacuations using coarser or finer event prediction models. In the implementation, the prediction model is defined by a set of rules. These rules can be easily exchanged with any smarter, more context-aware and event type specific model for practical applications. However, the experiment is sufficient to verify the hypothesis. In order to do so, the simulation compares the number of successful evacuees and the average and maximum evacuation time without, with conservative, and with exact foresighted risk assessment. The results show that only the exact foresight is superior to the other two, emphasizing the need for good event behavior prediction models.

The hypothesis is focusing only on the value of the provided information, and thus the experiment is not influenced by individual human behavior. In order to test the hypothesis it is sufficient to as-
sume in the simulation that people will follow their provided route directions. Whether people in real environments and evacuations will follow route directions is a question of factors such as access to this information, form of presentation (cognitive load, trust), and stress. Each of them is independent from the hypothesis and outside of scope of this work.

The chapter is structured as follows. Section 4.2 introduces the definition and representation of dynamic sensor graphs, dynamic route graphs, and their integration for dynamic route planning. Section 4.3 presents the implementation in a simulation, and the observations coming out of the simulation. Section 4.4 assesses the sensitivity of the accuracy of foresight evacuation. Section 4.5 summarizes the work of this chapter.

4.2 AN INTEGRATED DYNAMIC ROUTE AND SENSOR GRAPH

This section defines the dynamic route graph and dynamic sensor graph, describes how they are generated, and presents their integration in a dynamic evacuation process.

4.2.1 Dynamic route graph

Based on the definitions of a static route graph $G$ in Chapter 3 and Wang et al. (2014), a dynamic route graph over a set of predetermined time periods $t = 0, 1, 2, \ldots T$ is defined as below.

**Definition 9** A dynamic route graph $G_T = (V_T, E_T)$ consists of a set $V_T$ of vertices $v_i(t)$, representing the vertices $v_i$ of a static route graph $G$ and their properties with regard to passability at time $t$, together with a set $E_T$ of edges of $G$ and their properties with regard to passability at time $t$, denoted as unordered pair $(v_i(t), v_j(t))$.

Thus, the dynamic route graph $G_T$ is a time expanded version of route graph $G$, providing for vertices and edges in $G$ that may be blocked or at risk at times when sensors report an abnormal situation. The two sets $V_T$ and $E_T$ vary along with the changing states of vertices and edges at time $t$. $G_T$ can be represented by the static route graph $G$ and a dynamic vertex risk table storing the state of each vertex at time $t$, as well as a dynamic edge risk table storing the state of each edge at time $t$.

4.2.2 Dynamic sensor graph

Based on the definitions of a static sensor graph $G'$, which is constructed from sensors $s_i$ as vertices, and the connectivity provided by intersecting sensor detecting areas $S_i$ and $S_j$ of sensors $s_i$ and $s_j$ as edges, a dynamic sensor graph over a set of predetermined time periods $t = 0, 1, 2, \ldots T$ is defined as below.

**Definition 10** A dynamic sensor graph $G'_T = (V'_T, E'_T)$ consists of a set $V'_T$ of vertices $s_i(t)$ representing the sensors $s_i$ with their state at time $t$, and a
constant set $E'$ of edges denoted as unordered pair $\{s_i, s_j\}$ if $S_i$ and $S_j$ are intersecting.

Thus, the dynamic sensor graph $G'_T$ is a time expanded version of sensor graph $G'$ as the state of each sensor is changing with time. $G'_T$ can be represented by $G'$ and a dynamic sensor state table. Such a dynamic sensor state table is organized as a two-dimensional table of all sensors over time, where $N$ indicates sensors reporting normal states, $R$ indicates sensors considered or reporting to be at risk and $A$ indicates active sensors, i.e., reporting abnormal states. Table 3 shows an example.

<table>
<thead>
<tr>
<th></th>
<th>$t_0$</th>
<th>$t_1$</th>
<th>$t_2$</th>
<th>$\cdots$</th>
<th>$t_T$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_1$</td>
<td>$N$</td>
<td>$N$</td>
<td>$R$</td>
<td>$\cdots$</td>
<td>$N$</td>
</tr>
<tr>
<td>$s_2$</td>
<td>$A$</td>
<td>$A$</td>
<td>$A$</td>
<td>$\cdots$</td>
<td>$A$</td>
</tr>
<tr>
<td>$s_3$</td>
<td>$N$</td>
<td>$R$</td>
<td>$R$</td>
<td>$\cdots$</td>
<td>$N$</td>
</tr>
<tr>
<td>$\cdots$</td>
<td>$\cdots$</td>
<td>$\cdots$</td>
<td>$\cdots$</td>
<td>$\cdots$</td>
<td>$\cdots$</td>
</tr>
<tr>
<td>$s_m$</td>
<td>$N$</td>
<td>$N$</td>
<td>$N$</td>
<td>$N$</td>
<td>$N$</td>
</tr>
</tbody>
</table>

In emergency situations evacuees have to escape the indoor environment in the shortest time. At the same time the emergency event will propagate, which may have severe impact on individual evacuation routes or chances to escape. This chapter assumes a reasonable threshold maximum time value $t_T$ at which all evacuation opportunities should be exhausted, in order to cap the time expansion and reduce the calculation complexity. The value of $t_T$ should be considered with the number of evacuees, the size of the building, and the emergency event (Li and Ozbay, 2014). Furthermore, the time when the first sensor switches to active, i.e., reports an abnormal state, is set to $t_0$. The time interval is typically defined by the sensor monitoring system.

The states of sensor $s_i(t)$ are either known from sensor readings (i.e., $t \leq t_{cur}$, where $t_{cur}$ is the current time), or could be predicted by reasoning rules if $t > t_{cur}$ from any event spread model. Such rules specify current cellular automata models (Gardner, 1970); here they are applied on a (sensor) graph. A set of simple rules is sufficient for illustration, such as:

$$\text{state}_i(t) = \begin{cases} 
\text{set to } A & \text{if its current state is active} \\
\text{set to } R & \text{if at } t_{pre} \text{ one or more of its neighbors are } A \text{ or } R \\
\text{set to } N & \text{if state}_i(t_{pre}) \text{ is } N \text{ and it is not been set to } R 
\end{cases}$$

(1)

where $t_{pre}$ is one time interval prior to $t_{cur}$.

The simple prediction model of Equation 1 implies that when a sensor’s state at $t$ is active all the future states of $s_i$ will keep being active in the dynamic sensor state table, and all connected sensors,
if not active themselves, will change to at risk at the next time. After two time intervals all connected normal sensors of sensors at risk will also change to at risk, thus the emergency event will spread with time along the graph of the sensor graph. The dynamic sensor state table can be completely filled starting from the moment when at least one sensor reports an abnormal situation \( t_0 \) until a set time \( t_T \), and is updated after each time interval (in real time) with the readings from the sensor monitoring system and revised predictions. However, other, more informed event prediction models can be used instead of Equation 1 without loss of generality.

Let us illustrate Equation 1 for the indoor environment of Figure 7 and its extracted sensor graph (Figure 8). Table 4 shows the dynamic sensor state table of this environment at time \( t_0 \). At \( t_0 \) the sensor \( s_3 \) reports an emergency event. Thus, at this time \( (t_{\text{cur}} = t_0) \), according to Equation 1, the state of \( s_3 \) is set to A while all others are N. For a prediction at \( t_1 \), the state of \( s_3 \) keeps being A, but the sensors connected to \( s_3 \), i.e., \( s_2 \) and \( s_4 \) (Figure 8), change to R. Predicting states at \( t_2 \), also the states of \( s_1, s_5, s_7, s_8 \) and \( s_9 \) change to R because of their connection to \( s_2 \) and \( s_4 \). For \( t_3 \) the state of \( s_6 \) changes to R. From then on, until \( t_T \) there are no further changes of the prediction of all sensor states, and the dynamic sensor state table created at \( t_0 \) is complete. When \( t_{\text{cur}} \) changes to \( t_1 \), the actual sensor readings at \( t_1 \) will replace the predicted states at \( t_1 \), and predictions from \( t_2 \) to \( t_T \) will be re-computed based on this new information.

<table>
<thead>
<tr>
<th></th>
<th>( t_0 )</th>
<th>( t_1 )</th>
<th>( t_2 )</th>
<th>( t_3 )</th>
<th>( \cdots )</th>
<th>( t_T )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( s_1 )</td>
<td>N</td>
<td>N</td>
<td>R</td>
<td>R</td>
<td>( \cdots )</td>
<td>R</td>
</tr>
<tr>
<td>( s_2 )</td>
<td>N</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>( \cdots )</td>
<td>R</td>
</tr>
<tr>
<td>( s_3 )</td>
<td>A</td>
<td>A</td>
<td>A</td>
<td>A</td>
<td>( \cdots )</td>
<td>A</td>
</tr>
<tr>
<td>( s_4 )</td>
<td>N</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>( \cdots )</td>
<td>R</td>
</tr>
<tr>
<td>( s_5 )</td>
<td>N</td>
<td>N</td>
<td>R</td>
<td>R</td>
<td>( \cdots )</td>
<td>R</td>
</tr>
<tr>
<td>( s_6 )</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>R</td>
<td>( \cdots )</td>
<td>R</td>
</tr>
<tr>
<td>( s_7 )</td>
<td>N</td>
<td>N</td>
<td>R</td>
<td>R</td>
<td>( \cdots )</td>
<td>R</td>
</tr>
<tr>
<td>( s_8 )</td>
<td>N</td>
<td>N</td>
<td>R</td>
<td>R</td>
<td>( \cdots )</td>
<td>R</td>
</tr>
<tr>
<td>( s_9 )</td>
<td>N</td>
<td>N</td>
<td>R</td>
<td>R</td>
<td>( \cdots )</td>
<td>R</td>
</tr>
</tbody>
</table>

4.2.3 Dynamic risk model

The dynamic sensor state table can already be used to propagate sensor states into the route graph and evacuation route planning. However, the table can also be refined by quantifying the risk of an impact on evacuations, and many event spreading models will provide such quantitative risk measures. For fire events, for example, such models exist (e.g., Taylor et al. (1997)), and are used in evacuation modelling elsewhere (e.g., Nguyen, Ho, and Zucker (2013b)). Typi-
cally such models describe the risks by a number of separate risk components of an event (e.g., Hamacher and Tjandra (2002) and Hadjisophocleous and Fu (2004a)), here represented by a vector $P_i$ for each sensor $s_i$:

$$P_i(t) = \begin{pmatrix} \text{risk}_{i,0}(t) \\ \text{risk}_{i,1}(t) \\ \vdots \\ \text{risk}_{i,n}(t) \end{pmatrix}$$

For example, in the event of a fire the $\text{risk}_{i,0}(t)$ may be the temperature level of $s_i$, the $\text{risk}_{i,1}(t)$ may be smoke level, and the $\text{risk}_{i,2}(t)$ may be the toxicity level, each observed at time $t$. Once these risk components have been assessed, the overall risk $r_{s_i}$ of sensor $s_i$ is the maximum risk observed:

$$r_{s_i}(t) = \max(P_i(t)) = \max(\text{risk}_{i,j}(t))$$

Quantified risks can replace sensor states by a dynamic sensor risk table. For example, Table 5 is the corresponding dynamic sensor risk table of Table 4; shown are only the first three rows for illustration.

**Table 5: Sample dynamic sensor risk table at $t_0$.**

<table>
<thead>
<tr>
<th></th>
<th>$t_0$</th>
<th>$t_1$</th>
<th>$t_2$</th>
<th>$t_3$</th>
<th>$t_4$</th>
<th>$t_5$</th>
<th>$\cdots$</th>
<th>$t_T$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_1$</td>
<td>0</td>
<td>0</td>
<td>0.3</td>
<td>0.4</td>
<td>0.6</td>
<td>0.8</td>
<td>$\cdots$</td>
<td>1.0</td>
</tr>
<tr>
<td>$s_2$</td>
<td>0</td>
<td>0.6</td>
<td>0.6</td>
<td>0.7</td>
<td>0.9</td>
<td>1.0</td>
<td>$\cdots$</td>
<td>1.0</td>
</tr>
<tr>
<td>$s_3$</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>$\cdots$</td>
<td>1.0</td>
</tr>
</tbody>
</table>

A risk of 0 implies an unaffected area, or with all probability a free passage. A risk of 1 implies an actively impacted area, or with all probability a blocked passage. Risks between 0 and 1 are probabilities between. Any practical discretization will set thresholds such that a risk $r_s$ between 0 and a low threshold $p_N$ is classified N (say, ‘normal’), a risk between a higher threshold $p_A$ and 1 is classified as A (say, ‘activated’), and the interval in-between is classified R (say, ‘risky’). These thresholds are context-dependent and should be set by an expert. Generic (default) values might be, for example, $p_N = 0.25$ and $p_A = 0.75$.

**INTEGRATING DYNAMIC RISK IN ROUTE GRAPHS** Generally, the passability of routes is affected by two phenomena, the impact of the event and the behavior of people. Forward-looking evacuation route planning will consider the prior, impact of the event, by a dynamic sensor risk model, and the latter by congestion risk.

Each vertex in a time expanded route graph will inherit the (maximum) event risk value from those $j$ sensors covering the route vertex with their detection area, $\max_j(r_{s_j}(t))$.

The congestion risk $r_{c_i}(t)$ for a route vertex $v_i$ is depending on capacity and load. Capacity is constant and can be computed from
the minimum width required per person and the actual width of an entrance (if \(v_i\) is an access vertex in the typology of Wang et al. (2014)), a staircase (if \(v_i\) is a connecting vertex), or a corridor (if \(v_i\) is an inner vertex). Thus, the congestion risk \(rc_i(t)\) can be represented as:

\[
rc_i(t) = \min \left( 1, \frac{\text{evacuee}N_i(t)}{\text{capacity}_i} \right)
\]

where \(\text{evacuee}N_i(t)\) is the total number of evacuees at vertex \(v_i\) at time \(t\), and \(\text{capacity}_i\) is the capacity of vertex \(v_i\). Since \(\text{evacuee}N_i(t)\) is unknown (if not managed through a route allocation optimization) it can also be replaced by (static) betweenness centrality as an approximation (Freeman, 1977; Kazerani and Winter, 2009).

Accordingly, the synthetical risk value of each route vertex is formulated by Equation 4:

\[
rv_i(t) = \max(\max_j(r_{sj}(t)), rc_i(t))
\]

Route vertices with high risk values should be avoided in evacuation route planning, for any of the risks of encountering affected areas by the event (blocked routes) or of congestion.

A dynamic route vertex risk table can be established similar to a dynamic sensor risk table. For example, Figure 5 shows the route graph \(G\) of the indoor environment of Figure 7. Table 6 provides the synthesized risk for each route vertex at \(t_3\) using the equations above, except for \(v_1\) and \(v_{16}\), which are the safe vertices outside of the environment.

<table>
<thead>
<tr>
<th>(v_1)</th>
<th>(v_2)</th>
<th>(v_3)</th>
<th>(v_4)</th>
<th>(v_5)</th>
<th>(v_6)</th>
<th>(v_7)</th>
<th>(v_8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(rc_i(t_3))</td>
<td>0.5</td>
<td>0.3</td>
<td>0.2</td>
<td>0.2</td>
<td>0.5</td>
<td>0.6</td>
<td>0.8</td>
</tr>
<tr>
<td>(rv_i(t_3))</td>
<td>0.3</td>
<td>0.7</td>
<td>0.7</td>
<td>0.5</td>
<td>0.7</td>
<td>0.8</td>
<td>0.8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(v_9)</th>
<th>(v_{10})</th>
<th>(v_{11})</th>
<th>(v_{12})</th>
<th>(v_{13})</th>
<th>(v_{14})</th>
<th>(v_{15})</th>
<th>(v_{16})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(rc_i(t_3))</td>
<td>0.2</td>
<td>0.2</td>
<td>0.5</td>
<td>0.5</td>
<td>0.1</td>
<td>0.4</td>
<td>0.2</td>
</tr>
<tr>
<td>(rv_i(t_3))</td>
<td>0.7</td>
<td>1.0</td>
<td>0.5</td>
<td>0.5</td>
<td>1.0</td>
<td>0.4</td>
<td>0.4</td>
</tr>
</tbody>
</table>

The risk value of each edge in the route graph is the maximum risk value of its two endpoints. Equation 5 defines the risk value of an edge \(\{v_i(t), v_j(t)\}\):

\[
re_{ij}(t) = \max(rv_i(t), rv_j(t))
\]

A dynamic edge risk table could also be organized. For example, the risk value of an edge \(\{v_2(t_3), v_3(t_3)\}\) at \(t_3\) is the maximum risk value of its two endpoints \(v_2\) and \(v_3\). In Table 6, \(rv_2(t_3)\) is 0.3 while \(rv_3(t_3)\) is 0.7, so \(re_{2,3}(t_3)\) is equal to 0.7.

4.2.4 Dynamic evacuation

Now it is possible to discuss dynamic indoor evacuation that uses the integration of sensor graphs and route graphs of (Wang et al., 2014),
and in addition is able to introduce foresight by assessing the future risks of an event impacting on the evacuation routes available.

Under normal conditions the sensor graph just monitors. At this stage the integration of the static sensor graph and route graph have been pre-computed and stored. As soon as at least one sensor gets activated and reports an event, a dynamic evacuation process is initialized. The dynamic (time expanded) sensor graph $G'_T$ and route graph $G_T$ are set up for a period $T$ appropriate for the event, and tables of sensor states (or sensor risks), route graph vertex risks and route graph edge risks are initialized with observations at $t_0$. These tables are updated every cycle.

For computing evacuation routes for each evacuee, instead of computing shortest routes, this additional information is taken into account. Thus, the length of an evacuation route matters less than the risks to be encountered along the route. In principle, an evacuation route should have the following property: It should be shortest provided that it does not pass route vertices considered $A$ (blocked), and minimizes the exposure to risks of level $R$. The evacuation progress starts at $t_0$ and ends when all evacuees escape successfully or when there is no further chance to escape.

Since all risk tables are updated every time interval, one critical problem for an implementation of the model is scalability. A central server may be overloaded with frequent updating of the risk tables and the subsequent re-computation of the shortest routes for each agent in the environment. In order to lower the computational load at the server side, one solution is to put the responsibility of the computation of shortest routes to the mobile devices at the client side (the agents). In this case the server only maintains the tables with real-time data and broadcasts these tables periodically to clients. Each client updates their risk tables locally and calculates an appropriate escape route.

Since routes are computed iteratively, it is possible that during an evacuation one or more evacuees will be sent back, being advised to take an alternative route because their original one has been blocked. With a continuously changing or moving event such as a fire, blocked edges in the route graph develop also continually. Thus when an evacuee turns back towards an alternative route, typically their alternative route is passable. It is unlikely, but not impossible, that when they turn and follow the alternative route, the event (e.g., a fire) is jumping and then blocking also the alternative route. In the worst case, evacuees can become trapped, finding themselves on a component of the route graph that has become disconnected to all exits.

In the simulation in Section 4.3.2, some evacuees are indeed observed turning back, and sometimes even turning forth again. However, it is worth mentioning that turning around for an alternative route happens in particular in no foresight scenarios because the other strategies try to anticipate, while the no foresight strategy only guarantees a passable route at the current time. For exact foresight, a turning around for an alternative route will never happen to be necessary.
4.3 SIMULATION AND RESULTS

The model has been implemented in an agent-based simulation of dynamic indoor navigation with Repast Simphony\(^1\). The system behavior of integrating timing and looking ahead in evacuation planning has been assessed through comparison of different scenarios.

4.3.1 Emergency event simulation

Sensors continuously monitor the indoor environment and report the real-time conditions reflected by what is called states in this chapter. The sensor graph implemented in this simulation is covering all levels of a (real) building floor plan. The sensor graph together with the real-time states of each sensor reflect all the impacts of an emergency event that can be detected and utilized for evacuation planning. Thus an emergency event can be represented by a dynamic sensor graph (i.e., a static sensor graph and a sensor state table) assuming that the states of sensors at any time are reflecting current sensor readings. Thus the propagation of the emergency event itself can be simulated through the way how sensors switch their states as time goes by. Similarly the (actual) impact the emergency event has on evacuation process can be simulated by propagating the (actual) dynamic sensor states into the route graph used for evacuation route planning.

For generic tests, the risks are discretized into the three states N, R, and A. Sensors are initialized with N—monitoring with no abnormal observations—and an event is seeded by initializing one sensor with A (‘activated’). This is the moment when an evacuation alarm is triggered ($t_0$). The simulations are running for $T = 600$ seconds. During the simulations, in each time interval of 10 seconds the risk states of sensors are reconsidered by a propagation model. For the nine seconds in between, the sensor states are extrapolated by its previous sensor state, so that the sensor states have values at each second for simulation purpose.

Instead of the sample rules in Equation 1, which are perfectly predictable, this simulation implements a similar simple, but randomized one, with a certain probability of sensor state transfer between 0% and 100% (e.g., here 50% is applied):

- A sensor state is set active (A) if its state at $t_{pre}$ is active. It is also set active, but only with a probability of 50%, if at time $t_{pre}$ it is at risk (R) and one or more of its neighbors are already active; otherwise it is left R.

- A sensor state is set at risk (R), but only with a probability of 50%, if at time $t_{pre}$ it is normal (N) and one or more of its neighbors are already at risk or active. Otherwise it is left N.

- A sensor state is left N if at time $t_{pre}$ it is normal (N) and all its neighbors are N.

\(^1\) http://repast.sourceforge.net/
In this model risk states of sensors are monotonously increasing, describing intuitively the spread of a fire. In this model, a sensor with a state of N may either stay N or switch to R, and a sensor with a state of R may either stay R or switch to A. A sensor of state A stays A. Because of the randomness in this simulation, event simulations are recorded and recalled when comparing different evacuation scenarios, in order to ensure the comparisons are referring to the same event.

The sensor state table used for event simulation differs to that used for a foresight in the way how the sensor states are obtained. For the former, all the sensor states are supposed to be the real states recorded from sensor reading of an event, while for the latter, only the sensor states at and before current time $t_{cur}$ are from sensor readings and coincide with the corresponding parts of the former, the sensor states after current time $t_{cur}$ are predicted ones and can be coincident with the former only when the prediction is completely accurate. In this sense, the sensor state table for an event simulation can also be used as an exact foresight for evacuation route planning, and the sample rules in Equation 1 can be regarded as a reasonable and inaccurate prediction, so that the impact of both foresight and its accuracy on the system behavior of indoor evacuations can be assessed.

4.3.2 Evacuation scenarios

Working with a set of pre-computed events, the system behavior can be compared with different scenarios: an evacuation with no foresight (NF), an evacuation with conservative foresight (CF), and an evacuation with exact foresight (EF).

- For scenario NF, evacuation routes will be calculated on the basis of the states of the route graph elements at the current time instance; this strategy may not guarantee the routes remain passable as time goes by.

- For scenario CF, a safe assumption is an increase of the sensor risk states in each time interval. Thus, conservatively the states of N sensors that are neighbored to at least one R sensor will change from N to R with a probability of 100%, and similarly those with at least one A neighbor from R to A with a probability of 100%. Apparently, by these conservative propagation rules (which are comparable to Equation 1), the predicted emergency event propagates faster than the simulated emergency event, which guarantees that routes computed with this conservative foresight (if they exist) are always safe until the evacuee successfully escapes. One would expect longer evacuation times though.

- For scenario EF, the saved simulated emergency event itself can be regarded as exact foresight. An agent with perfect knowledge of future states will be able to find passable evacuation
routes that will never be changed in the iterative revisions during the evacuation process, just because the predicted portions of the dynamic sensor state table will be iteratively replaced by the same simulated values. One would expect optimal evacuation times.

The simulation process can be illustrated with the flow chart in Figure 16. A subprocess for updating sensor state table at current time instance is illustrated in Figure 17. Another subprocess for calculating a safe route according to the dynamic sensor graph and dynamic route graph is presented in Figure 18.

Sensor state tables are here used serving two purposes in simulations. Sensor state tables represent the simulated emergency events—the reality. In foresight scenarios, sensor state tables are also used to represent what the evacuees (or their guidance systems) guess about the emergency event when adopting predictions. Only in scenario EF, the guessed event coincides with the reality.

The differences among these scenarios are mainly reflected by how the evacuation routes are computed. A route will firstly be computed on the basis of the route graph and the risk information propagated from the current sensor reading. For scenario NF, this is the route the evacuee should follow to move forward. But for scenarios with foresight this route will be checked for its safety in the future according to the predicted sensor states. This is done through iteratively propagating the predicted sensor states in chronological order to the route graph and check whether any segments of this route will be blocked when the evacuee passes by in the future. If the route is assessed to be safe, then the evacuee will follow this route; otherwise the route segments which are predicted to be blocked when the evacuee passes by in the future will be added to a tabu list, then route will be recalculated and its safety will be reassessed.

For foresight scenarios, when $t_{cur}$ shifts to the next time instance, the dynamic sensor state tables will be updated. Sensor states at $t_{cur}$ will be replaced by states from new sensor reading, and based on the current sensor reading, the predicted sensor states after $t_{cur}$ will be recomputed. Evacuation routes are computed and assessed based on the propagation of sensor states from this new sensor state table. Scenario EF is special in that all the predicted sensor states are accurate, thus no sensor state will be changed during the updating. Thus, a route computed from scenario EF, if exists, will be an unchanged one and will be safe until the evacuee successfully reach an exit.

In terms of evacuation route calculation, scenario NF is equivalent to a special circumstance of foresight scenarios when the sensor states after $t_{cur}$ are predicted to be always equal to that at $t_{cur}$ (i.e., in all predictions the probability of sensor state transfers is regarded constantly as 0%). Since scenario CF is a foresight scenario where in all predictions the probability of sensor state transfers is regarded as 100%. To differentiate EF with CF and NF, the probability of sensor state transfer applied in the emergency event simulation can be any value between 0% (not included) and 100% (not included).
Build the static route graph $G$
Build the static sensor graph $G'$
Simulate an event and save the sensor state table to a file

Static route graph $G$
Static sensor graph $G'$
Dynamic sensor state table

Dynamic route graph $G_T$ and dynamic sensor graph $G'_T$ at $t_{cur}=t_0$, wait=0

Update static route graph with sensor states at $t=t_{cur}$
Calculate the shortest path weighted by risks

With foresight?

Update the dynamic sensor state table by replacing the states at $t_{cur}$ from sensor readings and recomputing the predictions after $t_{cur}$

Check whether it is a safe path with all segments not blocked when the evacuee passes by, according to the dynamic sensor graph and the dynamic route graph; otherwise try to find one

A safe path is found?

Move for 1 second following the path

Escaped?

Succeed

wait=wait+1

wait>100?

Failed

wait>600?

Figure 16: Simulation process for the evacuation of an evacuee with and without foresight. This process figure describes how the evacuation with and without foresight works for an evacuee in the simulation. For dynamic evacuation, two subprocesses are included.

4.3.3 Experiments and results

The experiments adopt a five floor office building as the evacuation environment. 20 sample emergency events starting at varying locations are simulated and saved in the form of sensor graphs and dynamic sensor state tables. Experiments simulate the evacuation pro-
cess of 100 evacuees in the event of the pre-computed 20 emergencies. The number of successful evacuees and the time they consumed under different evacuation scenarios are collected and compared. In Table 7, each row summarizes the results of the three scenarios for one emergency event. The item ‘Emergency’ denotes the ID of each independent emergency event. Table 8 compares the time consumed by the last successful evacuee in each scenario. Figures 19–21 show the detailed results of these experiments. Specifically, Figure 19 shows the number of successful evacuees for the three scenarios over the 20 simulated events. Figure 20 shows the average time that all the successful evacuees have consumed. Finally, Figure 21 shows the maximum evacuation time, i.e., the egress time of the last successful evacuee. Having chosen $T = 600$ seconds, and observing maximal evacuation times of about 150 seconds, indicates that the few evacuees who do not find out in the simulation are no longer searching but stuck.

Table 7: Successful evacuations (out of 100) and average evacuation times of successful evacuations for each evacuation scenario.

<table>
<thead>
<tr>
<th>Emergency</th>
<th>SucNF</th>
<th>AveTimeNF</th>
<th>SucEF</th>
<th>AveTimeEF</th>
<th>SucCF</th>
<th>AveTimeCF</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>98</td>
<td>64.15</td>
<td>98</td>
<td>64.15</td>
<td>98</td>
<td>64.15</td>
</tr>
<tr>
<td>2</td>
<td>96</td>
<td>61.24</td>
<td>96</td>
<td>61.24</td>
<td>96</td>
<td>61.24</td>
</tr>
<tr>
<td>3</td>
<td>99</td>
<td>80.31</td>
<td>99</td>
<td>80.26</td>
<td>99</td>
<td>80.46</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
Integrating sensing, routing and timing for indoor evacuation

Figure 18: Subprocess of route finding for foresight scenarios. This is a subprocess of Figure 16, illustrating how an evacuation route is found for dynamic evacuation.

Table 8: Maximum evacuation time for each evacuation scenario.

<table>
<thead>
<tr>
<th>Emergency</th>
<th>MaxTimeNF</th>
<th>MaxTimeEF</th>
<th>MaxTimeCF</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>149</td>
<td>149</td>
<td>149</td>
</tr>
<tr>
<td>2</td>
<td>149</td>
<td>149</td>
<td>149</td>
</tr>
<tr>
<td>3</td>
<td>149</td>
<td>149</td>
<td>149</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

4.3.4 Observations

From the results, the following observations can be made:

1. The numbers of successful evacuees in scenario EF under different emergency events are never lower and in a few cases higher than that in scenario NF.

2. The numbers of successful evacuees in scenario CF are in some cases lower and in some cases higher than that in scenario NF, but never higher than that in scenario EF.

3. The average evacuation time for all successful evacuees in scenario EF are not always lower than that in scenario NF, but with-
Figure 19: Number of successful evacuees (out of 100) for the three scenarios over the 20 simulated events. The numbers of successful evacuees in scenario $EF$ are never lower and in a few cases higher than that in scenario $NF$, and always higher than that in scenario $CF$.

Figure 20: Average evacuation time of the successful evacuees. The average evacuation time for all successful evacuees in scenario $EF$ are not always lower than that in scenario $NF$ and $CF$, but without exception this happens only when the successful number of the former is larger than that of the latter two.

4. The average evacuation time for all successful evacuees in scenario $CF$ in some cases has the lowest value among the three, but without exception this happens only when the successful number of scenario $CF$ is lower than that of scenario $EF$.

5. In most events, the evacuation time consumed by the last successful evacuee, which is also the time when the evacuation is deemed as finished, has no difference across different scenarios. For the cases that the time differs, the evacuation time for scenario $NF$ is higher than that for scenario $EF$. 
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Figure 21: Maximum evacuation time of the successful evacuees. The maximum evacuation time of scenario NF and EF are almost equal, and for the different ones the maximum evacuation time of scenario NF is higher than that for scenario EF. The maximum evacuation time for scenario CF is in some cases higher and in some cases lower than that for scenario EF. For the lower cases, it is because of the lower numbers of successful evacuees in scenario CF.

6. The maximum evacuation time for scenario CF is in some cases higher and in some cases lower than that for scenario EF. For the cases that the maximum evacuation time for scenario CF is lower than that for scenario EF, with no exception scenario CF has lower numbers of successful evacuees.

Observations 1, 3 and 5 indicate that introducing exact foresight leads to better evacuation system behavior, saving more people and reducing the evacuation time. Although in some cases the scenario EF has a larger average time than NF, EF saved more people than NF. These additional successful evacuees have relatively longer evacuation routes, thus take longer time to evacuate, but the scenario NF fails to find these longer evacuation routes to rescue them. Similarly, although in some cases the maximum time for scenario NF is shorter than that for EF, they are at the expense of more failing evacuees, while scenario EF finds passable evacuation routes for these evacuees albeit taking longer evacuation time.

Observations 2, 4 and 6 indicate that with foresight, even the accuracy of prediction cannot be guaranteed, in a few cases evacuation behavior can still be improved. In some other cases, CF is inferior to NF because CF may overestimate the condition so that no evacuation route can be generated for a few evacuees, causing these evacuees to fail in the evacuation.

From the comparison of scenario EF and scenario CF, it can be inferred how much the system behavior can benefit from introducing timing for route planning is sensitive to the accuracy of foresight. It is expected that as the accuracy of the foresight improves, a more significant advantage of including foresight will be observed. The following experiment is to test this expectation.
In Section 4.3, $EF$ represents an ideal circumstance in which the prediction is absolutely accurate; the simulation results reflect how an accurate foresight can improve the evacuation process. $CF$ represents a sample foresight scenario where the accuracy of prediction cannot be guaranteed. In Section 4.3.1, when simulating the emergency event, the propagation of sensor states is assigned with a probability of 50%. Since this probability is a parameter that reflects the propagation speed of an emergency event, varying this parameter leads to emergency events with diverse severity. Since $CF$ assume a constant probability (100%) in sensor state prediction, varying this probability in the simulated event also means a varying accuracy of the prediction for $CF$. In this section, the probability of sensor state transfers in event simulation will be modified so as to investigate the system behavior with emergency events of different severity and prediction of relatively different accuracy.

![Figure 22: Average successful evacuees over different probability values in event simulations. This figure shows how the average of successful evacuees changes in three evacuation scenarios when applying different probability values in event simulations. Each point in the figure represents the average of successful evacuees in 20 evacuations.](image)

The experiments in Section 4.3.3 will be repeated, but with different probability of sensor state transfers in event simulations. Figure 22 illustrates how the average successful evacuees vary when adopting different probability values in event simulations. A larger value corresponds to a faster spreading event. Each point in Figure 22 represents the average successful evacuees of evacuations with 20 simulated events where events start at different locations but propagate with a same sensor state transfer probability. Figure 23 shows the trend of how scenarios with foresight outperform the no-foresight scenario when the probability parameter differs. Each point for $CF-NF$ represents the difference in the number of average successful evacuees between $EF$ and $CF$. $EF-NF$ represents the difference of average successful evacuees between $EF$ and $NF$. 
From Figure 22 and 23 and original data of simulation results, the following observations have been made:

1. When the probability in event simulation is set as 0%, scenario EF is equivalent to scenario NF, saving the same summation of evacuees and consuming the same amount of time in all simulations. When the probability is 100%, scenario EF is equivalent to scenario CF. The reason has been presented in Section 4.3.2.

2. For comparison between CF and NF, when the probability is below 40%, NF is always better than CF; when the probability is above 70%, CF is always better than NF. When the probability increases from 40% to 70%, CF transfers from being disadvantageous to being advantageous compared with scenario NF. Since CF applies a probability of 100% in prediction, when the probability in event simulations increases and approaches 100%, the accuracy of prediction for CF increases. The transfer of CF from being disadvantageous to being advantageous indicates that when the prediction in practical application becomes more accurate, foresight scenarios will outperform no foresight scenarios. The retaining advantage after 70% indicates when the prediction is accurate enough, applying foresight is guaranteed to be always better than without foresight. Observation here not only gives the reason why foresight scenarios are not always advantageous, but also suggests the solutions for a beneficial dynamic evacuation, i.e., improving the accuracy of prediction.

3. In particular, when the probability is between 40% and 60%, for any specific simulation out of the 20, whether CF is better or not than NF is highly unstable, and also from which more generic
Table 9: Sensitivity test with varying probability of sensor states transfer in event simulation.

<table>
<thead>
<tr>
<th>Probability</th>
<th>AveSucEF</th>
<th>AveSucCF</th>
<th>AveSucNF</th>
<th>Diff(EF-NF)</th>
<th>Diff(CF-NF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>98</td>
<td>96.8</td>
<td>98</td>
<td>0</td>
<td>-1.2</td>
</tr>
<tr>
<td>10</td>
<td>97.8</td>
<td>96.95</td>
<td>97.8</td>
<td>0</td>
<td>-0.85</td>
</tr>
<tr>
<td>20</td>
<td>97.95</td>
<td>97.15</td>
<td>97.95</td>
<td>0</td>
<td>-0.8</td>
</tr>
<tr>
<td>30</td>
<td>97.55</td>
<td>97.05</td>
<td>97.35</td>
<td>0.2</td>
<td>-0.3</td>
</tr>
<tr>
<td>40</td>
<td>97.65</td>
<td>97.3</td>
<td>97.4</td>
<td>0.25</td>
<td>-0.1</td>
</tr>
<tr>
<td>50</td>
<td>97.45</td>
<td>97.1</td>
<td>97.25</td>
<td>0.2</td>
<td>-0.15</td>
</tr>
<tr>
<td>60</td>
<td>97.25</td>
<td>97</td>
<td>97.25</td>
<td>0</td>
<td>-0.25</td>
</tr>
<tr>
<td>70</td>
<td>97.2</td>
<td>97.15</td>
<td>97</td>
<td>0.2</td>
<td>0.15</td>
</tr>
<tr>
<td>80</td>
<td>97.1</td>
<td>97.1</td>
<td>96.75</td>
<td>0.35</td>
<td>0.35</td>
</tr>
<tr>
<td>90</td>
<td>96.9</td>
<td>96.8</td>
<td>96.6</td>
<td>0.3</td>
<td>0.2</td>
</tr>
<tr>
<td>100</td>
<td>96.75</td>
<td>96.75</td>
<td>96.45</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>Average</td>
<td>97.42</td>
<td>97.01</td>
<td>97.25</td>
<td>0.16</td>
<td>-0.24</td>
</tr>
</tbody>
</table>

Observations can be obtained. E.g., when the probability is 40%, in 5 cases NF is better, saving a total of 7 people more, but in 1 case CF is better, saving 5 people more, the average successful number of evacuees for CF is low than NF though.

4. Figure 22 shows a clear downward trend in the average successful evacuees for both EF and NF, which is understandable in that as the probability value gets larger, the event gets fiercer so that the indoor space gets blocked faster. What can also be observed is that EF always save the largest number of evacuees, which coincides with the results in Section 4.3.4.

5. Figure 23 shows that when the event is moderate, the advantages that scenario EF has over scenario NF is not significant; however, as the event propagation becomes fiercer, EF shows an increasing advantage in saving more evacuees. Similarly, as the probability value gets larger, the prediction in scenario CF becomes more accurate, and when the prediction is accurate enough (after 70% in the figure), it outperforms NF. A clear rising trend for CF-NF in Figure 23 also indicates that as the accuracy of prediction improves, the performance of foresight scenarios improves.

Overall, experiments test the generic model and evacuation framework developed in this chapter. Results indicate that exact foresight always leads to better system behavior, saving more people and reducing the evacuation time. Foresight is proved to be an approach to improving existing evacuation scenario. The significance of improvement is sensitive to the accuracy of event prediction. As the accuracy of prediction increases, adopting prediction leads to increasingly better results. Thus in practical applications, accurate and problem specific prediction modules should be developed and plugged in.
4.5 Summary and Discussion

This chapter has deployed time expanded versions of the sensor graph and the route graph, and demonstrated that all principles of the integration process are applicable straight away. In addition, this chapter has investigated whether the time expanded versions, allowing route planning with foresight, are advantageous. Overall, the experiment supported the hypothesis in this chapter that risk-aware evacuation planning improves evacuation times and the number of saved lives. It has also shown, though, that the impact of the model is sensitive to the accuracy of the foresight in the risk-awareness, and hence, good event spreading models are required. They may exist for events such as fire spreading or gas leaking, but other types of events (say, a sniper roving around) are harder to predict.

The event simulation is designed for the purpose of testing the conceptual model proposed in this chapter. The reason to use such a simple contiguous event spreading simulation for this purpose is the advantage of being able to control the experiment. The more realism is brought into a simulation, e.g., through random models or noise, the less the individual parameters can be controlled. Since the current simulation is providing the experimental evidence to accept or reject the hypothesis. More sophisticated and realistic event spread models are safe to be applied within the simulation, or in real applications, without limiting the generality of the findings.

The simulation presented used a simple, randomized model of event spread. However, the generic formulation of allowance of foresight presented in Section 4.2.3 is only based on probabilities of risk factors in space and time. This treatment of risk can directly be connected to any smarter event spreading model, for example anyone that uses information about the building structure and materials. Domain experts such as fire experts or smoke experts can directly plug in their predictive tools producing local probabilities.

The presented generic framework for indoor evacuation with foresight can be expanded in several ways. One is the addition of further sensor states. For example, in addition to working normal, activated, or risky sensors there could also sensors be destroyed by an event. If a sensor is destroyed any communication with a central server fails, and the central server has to treat this location with a status unknown. A conservative evacuation strategy, for example, would exclude route edges and vertices labeled by sensors with status unknown. Another possible extension can allow for mobile sensors. For example, people moving in the environment could be tracked, indicating free evacuation routes, or their mobile communication devices could sense environmental parameters such as smoke, and report back to a central service. Such mobile sensors need to be integrated in real-time with the route graph.

The centralized evacuation systems developed in this chapter and Chapter 3 are efficient for evacuation in that:
• Decision making is conducted on top of a full awareness of the current spatial connectivity and the current risk benefited from the real-time monitored data.

• The accurate predictions in Chapter 4 enable a full awareness of the spatial connectivity and risk across the whole process of the evacuation. Based on this full awareness, the evacuation routes are ideally the fastest and the safest ones.

Such centralized services share a common shortcoming that they rely on a central infrastructure, which are likely to be affected in a disaster (congested or damaged), or is simply non-existing. Failure of the central infrastructure directly incurs the failure of the whole system. Then evacuees may fall back to decentralized evacuation (Richter et al., 2013). Decentralized evacuation systems are scalable and robust against the failure of central infrastructures, but due to a lack of central infrastructure, the real-time information of the environment is unavailable, and thus accurate prediction will also become impossible. The only information available for decentralized evacuation system is the out-of-date information in the past, which can easily be changed by the dynamically expanding event. Time awareness of the out-of-date information with uncertain reliability is important for decentralized evacuation. In the next chapter, a fading spatial model will be developed, which particularly considers the time awareness of the unreliable knowledge in dynamic environment.
This chapter is based on the following paper with some extensions:


My contribution is 90%; the second author had only a supervisory role.

Knowledge of dynamic environments expires over time. Thus, using static maps of the environment for decision making is problematic, especially in emergency situations, such as evacuations. This chapter develops a fading memory model for mapping dynamic environments: a mechanism to put less trust on older knowledge in decision making. The model has been assessed by simulating indoor evacuations, adopting and comparing various strategies in decision making. Results suggest that fading memory generally improves this decision making.

5.1 INTRODUCTION

The decision making of agents traveling in search of target destinations in a dynamic environment is a common research topic. The agents may be evacuees trying to find their way out of a building in the event of an emergency, or service robots moving towards a destination in an indoor environment with roaming kids and movable furniture, or vehicles traveling on road networks with crossing pedestrians. The challenge for decision making is that such environments change all of the time. While learned and accumulated spatial knowledge may be trustworthy for decision making in (sufficiently) static environments, in dynamic environments, the past experience of the environment may form out-of-date knowledge. How to fulfill the wayfinding tasks of agents with potentially outdated knowledge is the research question addressed in this chapter.

To date, the predominant evacuation strategies still rely on static signs, e.g., stationary exit signs (Kraus et al., 2011) or you-are-here maps, which are of low efficiency (Montello, 2010) and are often perceived as confusing and unclear, especially when people are stressed or panicked (Merkel, 2014). Reliable shortest route planning in a dynamic environment is possible with a centralized, real-time sensing system that creates situation-aware pictures for each agent. However, such a centralized service will in most cases not exist due to the lack (or damage) of the required sensing and communication infrastructure. In this situation, robots traditionally fall back to autonomous and exploratory wayfinding operations. For humans, only recently decentralized collaborative wayfinding has been suggested (Richter et al., 2013). Other research addressed this question mainly from the
agents’ perspective. They deem the task as a Markov decision process or variations of it (Zhang and Silva, 2014) and facilitate mission fulfillment by adapting and reacting to the uncertainty with strategies like multi-agent reinforcement learning, distributed learning algorithms (Nguyen et al., 2014).

Not much research can be found addressing the reliable shortest route problem from the perspective of a representation of the dynamics in the environment. Only from an economic perspective, Krek (2002) has studied the impact of out-of-date data on decision making. In other research, the impact of the prediction of future states on decision making has been studied; results demonstrated a high sensitivity for the validity of the extrapolation (Wang et al., 2014; Wang, Zhao, and Winter, 2015). To address the time variance of spatial networks, George and Shekhar (2008) proposed a storage-efficient spatio-temporal network model called a time-aggregated graph. Instead of replicating the network over time, a time-aggregated graph model tracks the attributes of nodes and edges such as the presence and the time dependent weights of edges by attaching a time series to each node and edge. However, in evacuation circumstance, attributes are available only for time series in the past, and such attributes are prone to change shortly over time. The current chapter, in contrast, suggests a novel approach: a map with fading memory by adding the temporal dimension to the acquired spatial knowledge. The chapter presents an experiment to test the performance of shortest route planning considering the age of information in memory, putting less trust in older spatial knowledge and reports the results.

Fading memory devalues spatial knowledge with time, trusting recent explorations more than older ones. The hypothesis of this chapter is that fading memory is beneficial for agents’ decision making in a dynamic environment. If this hypothesis is true, it has implications for all kinds of spatial analysis, but it also brings up questions of ethics: a service deliberately devaluing information that may in particular cases actually still be true is a service that accepts to produce in these cases suboptimal decisions in favor of on average better decisions.

The remainder of this chapter is organized as follows. In Section 5.2, a conceptual model for fading memory is described. Section 5.3 outlines the implementation of the simulation experiment, and in Section 5.4, results are presented and discussed. Finally, Section 5.5 summarizes the work in this chapter.

### 5.2 System Model Formulation

This section introduces the definition of fading memory and describes how it can be applied in spatial decision making. The running examples are evacuation processes.
5.2.1 Fading memory

Route planning for indoor evacuation can be accomplished by calculating the shortest route on the basis of a route graph $G = (V, E)$, which consists of a set $V = \{v_1, v_2, \ldots, v_K\}$ of vertices and a set $E = \{e_1, e_2, \ldots, e_N\}$ of edges, where $K$ is the total number of vertices and $N$ is the total number of edges. The route graph embedded in $\mathbb{R}^3$ draws a map of the walkable connectivity of all subspaces of the indoor environment. Different ways of deriving these route graphs for indoor environments have been proposed (Lorenz, Ohlbach, and Stoffel, 2006; Song et al., 2009; Dudas, Ghafourian, and Karimi, 2006; Goetz and Zipf, 2011; Stahl and Schwartz, 2010b; Kim, Yoo, and Li, 2014).

For centralized evacuation, the conditions of the environment can be sensed in real time by infrastructure; all of the evacuees share the same up-to-date knowledge maintained by a central server (Wang et al., 2014). When sensing and communication infrastructure becomes unavailable, evacuees acquire knowledge of the environment through self-exploration, on the one hand, and communication with others, on the other hand (Richter et al., 2013). In this case, the knowledge depends heavily on personal experience and may vary from person to person, such that each person computes their individual evacuation route based on their personal knowledge of the environment.

The critical information for route planning is whether a computed route is still passable or not. For example, an event may block a particular exit door or may have made a certain corridor unsafe. Independent from the type of event and related safety thresholds, e.g., for temperature, smoke or oxygen fraction, the passability of an edge in a route graph can be represented by a generic attribute called $state$. This attribute shall have two values: $blocked$ and $unblocked$, where $blocked$ means the space is unsafe and not passable.

Before an event, all of the edges of the route graph should be $unblocked$, and this state will be valid until the event start, which is when the states of some edges switch to being $blocked$, while others may follow later. During the evacuation, the state of the edges can be observed in various ways. In centralized systems, sensors will track passability, while decentralized systems encountering a blocked passage update the knowledge. Even an encounter with other evacuees can help: an evacuee can share with the encountering evacuee their individual knowledge of the environment, for example via short range radio communication on their smartphones (e.g., Bluetooth). A node in the route graph, representing a sub-space, can also be blocked by an event, but this case can be represented by setting all of the edges ending in this node as $blocked$.

5.2.1.1 Definition

In this chapter, the knowledge possessed by an evacuee for route planning is called the route status map, which consists of a set of triples called memory segments:
**Definition 11** A memory segment is an edge attached with an attribute describing its state and an attribute \( t \) describing the specific time when this memory segment has been acquired or has been last updated:

\[
\text{memseg} = (e, \text{state}, t)
\]

where \( e \) denotes an edge of the route graph, \( \text{state} \) denotes the value of the state associated with that edge and \( t \) denotes the last time this memory segment was updated.

Let \( E_m = \{\text{memseg}_i\} \); then, the route graph in memory is \( G_m = (V, E_m) \). Let also \( t_{\text{cur}} \) denote the current time. Then, \( t_{\text{cur}} - t \) indicates the risk that the state of an edge in memory might be out-of-date. With this, fading memory can be defined as:

**Definition 12** A fading memory \( G_{fad} = (V, E_m)_{t_{\text{cur}}} = (V, \{(e, \text{state}, t_{\text{cur}} - t)_i\}, \) where \( i \in \{1, 2, \ldots, N\} \).

Thus, the fading memory \( G_{fad} \) is an extended version of a route graph \( G \) representing the state of each edge and the age of the information about the state.

A memory collection can be represented by an attribute table for edges storing the attributes of each edge at time \( t_{\text{cur}} \). Table 10 shows an example of an attribute table for edges.

Table 10: Fading memory attribute table for edges, at an arbitrary time \( t_{\text{cur}} \).

<table>
<thead>
<tr>
<th>Edge</th>
<th>State</th>
<th>Last Updated</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>( e_1 )</td>
<td>( \text{state}_1 )</td>
<td>( t_1 )</td>
<td>( t_{\text{cur}} - t_1 )</td>
</tr>
<tr>
<td>( e_2 )</td>
<td>( \text{state}_2 )</td>
<td>( t_2 )</td>
<td>( t_{\text{cur}} - t_2 )</td>
</tr>
<tr>
<td>( \ldots )</td>
<td>( \ldots )</td>
<td>( \ldots )</td>
<td>( \ldots )</td>
</tr>
<tr>
<td>( e_n )</td>
<td>( \text{state}_n )</td>
<td>( t_n )</td>
<td>( t_{\text{cur}} - t_n )</td>
</tr>
</tbody>
</table>

For simplicity, this chapter assumes that before the event, people have a complete map of the environment, *i.e.*, a complete route graph. The fading memory attribute table will therefore cover all of the edges in the route graph.

During the event, the knowledge of an evacuee can be represented by a fading memory. From the components of the memory collection, fading memory \( G_{fad} \) can be regarded as a map of the dynamic environment with three components. The edges compose the spatial components, describing the original topology of the spaces (before the event) for evacuation route planning. The states compose the dynamics of the environment, representing the update of the topology of the spaces during the event. The time composes the temporal components, describing how much the knowledge has been out of date. Thus, fading memory represents the spatial and temporal features of the updated knowledge of the dynamic environment.
In particular, if for all of the edges \( t = t_{\text{cur}} \), this fading memory is a real-time memory, which reflects the real-time conditions of the environment.

**Definition 13** A real-time memory consists of fading memory segments that are valid (sensed) at the current time, denoted by \( M_{\text{real}} \).

\[
G_{\text{real}} = (V, \{(e, \text{state}, 0)_i\})
\]

where \( i \in \{1, 2, \ldots, N\} \).

For decentralized evacuation, real-time memory is never available.

### 5.2.1.2 Updating Fading Memory

The dynamic environment can be represented by a global route graph with all of the edge states sensed in real time (i.e., a real-time memory). The knowledge of any evacuee can be represented by different local route graphs (or fading memory) possessed by each evacuee. The edge states of local route graphs coincide with the global route graph before the event. After the event, people share and update their knowledge in the form of memory segments. The fading memory can be updated in two ways:

- People acquire updated knowledge of the environment on a physical encounter with a changed environment. The memory segments acquired before the event or a longer while ago will be replaced by the memory segments that reflect the new observation of the encountered edges.

- People acquire updated knowledge of the environment on an encounter with fellow evacuees by exchanging their mutual time-stamped knowledge. Any memory segment that has a more recent counterpart in the encountered evacuee’s memory will be replaced by this more recent memory segment.

Evacuees update their local route graphs from their own trajectories when exploring the environment and from communication with fellow evacuees. These local route graphs are used by evacuees to plan evacuation routes.

### 5.2.2 Routing with fading memory

Fading memory is represented by an attributed graph highlighting not only the connectivity of the space, but also representing the elapsing time after acquiring that knowledge. Thus, routing can be a standard k-shortest route problem, labeling edges known to be blocked by infinite costs. The k alternative routes are then assessed by trusting more the recently acquired knowledge and less the knowledge that has been explored a longer time ago. Spatial factors, such as the location of the blocked edges, can also be taken into consideration,
for example, by preferring routes that do not not come near blocked edges.

Threshold-based assessment methods have been used in a number of studies (e.g., to detect human faces from color images (Jenila and Iyda, 2012)). To demonstrate how a time-aware routing map can be achieved with fading memory, an evolving threshold-based method is deployed here exemplarily. This method can be replaced by any other reasonable method. For demonstration, a sample route graph with six nodes is illustrated in Figure 24. The original connectivity can be represented by Table 11, where \( \text{connected}\{v_i, v_j\} = 1 \) if there is an edge linking \( v_i \) and \( v_j \), else \( \text{connected}\{v_i, v_j\} = 0 \); \( i, j \in \{1, 2, \ldots, 6\} \).

![Figure 24: A sample route graph.](image)

Table 11: The connectivity of the sample route graph.

<table>
<thead>
<tr>
<th>( G )</th>
<th>( v_1 )</th>
<th>( v_2 )</th>
<th>( v_3 )</th>
<th>( v_4 )</th>
<th>( v_5 )</th>
<th>( v_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( v_1 )</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>( v_2 )</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>( v_3 )</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>( v_4 )</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>( v_5 )</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>( v_6 )</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

The states of the edges in the route graph can be represented by Table 12, where the \( \text{connected}\{v_i, v_j\} \) contains the state for edge \( \{v_i, v_j\} \). Before the event, all edges have status \( u \), denoting an unblocked state.

Table 12: The original states of the sample route graph.

<table>
<thead>
<tr>
<th>( v_1 )</th>
<th>( v_2 )</th>
<th>( v_3 )</th>
<th>( v_4 )</th>
<th>( v_5 )</th>
<th>( v_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( v_1 )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
</tr>
<tr>
<td>( v_2 )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
</tr>
<tr>
<td>( v_3 )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
</tr>
<tr>
<td>( v_4 )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
</tr>
<tr>
<td>( v_5 )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
</tr>
<tr>
<td>( v_6 )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
<td>( u )</td>
</tr>
</tbody>
</table>
Suppose the event starts at $t_{\text{event}}$. Since then, an evacuee $P_1$ acquires some additional knowledge, be it through self-exploration or peer-to-peer knowledge exchange, and updates the corresponding four segments in his or her memory as in Table 13 (assume $t_{\text{event}} < (t_1, t_2, t_3, t_4) < t_{\text{cur}}$). The corresponding updated route graph is shown in Table 14 (b denotes a blocked state).

### Table 13: The attribute table for the fading memory at a time $t_{\text{cur}}$, with four updated memory segments.

<table>
<thead>
<tr>
<th>Edge</th>
<th>State</th>
<th>Last Updated</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>${v_1, v_2}$ &amp; ${v_2, v_1}$</td>
<td>blocked</td>
<td>$t_1$</td>
<td>$t_{\text{cur}} - t_1$</td>
</tr>
<tr>
<td>${v_1, v_3}$ &amp; ${v_3, v_1}$</td>
<td>unblocked</td>
<td>$t_2$</td>
<td>$t_{\text{cur}} - t_2$</td>
</tr>
<tr>
<td>${v_3, v_4}$ &amp; ${v_4, v_3}$</td>
<td>unblocked</td>
<td>$t_3$</td>
<td>$t_{\text{cur}} - t_3$</td>
</tr>
<tr>
<td>${v_1, v_4}$ &amp; ${v_4, v_1}$</td>
<td>unblocked</td>
<td>$t_4$</td>
<td>$t_{\text{cur}} - t_4$</td>
</tr>
<tr>
<td>${v_1, v_6}$ &amp; ${v_6, v_1}$</td>
<td>unblocked</td>
<td>$t_{\text{event}}$</td>
<td>$t_{\text{cur}} - t_{\text{event}}$</td>
</tr>
<tr>
<td>${v_2, v_3}$ &amp; ${v_3, v_2}$</td>
<td>unblocked</td>
<td>$t_{\text{event}}$</td>
<td>$t_{\text{cur}} - t_{\text{event}}$</td>
</tr>
<tr>
<td>${v_2, v_4}$ &amp; ${v_4, v_2}$</td>
<td>unblocked</td>
<td>$t_{\text{event}}$</td>
<td>$t_{\text{cur}} - t_{\text{event}}$</td>
</tr>
<tr>
<td>${v_2, v_5}$ &amp; ${v_5, v_2}$</td>
<td>unblocked</td>
<td>$t_{\text{event}}$</td>
<td>$t_{\text{cur}} - t_{\text{event}}$</td>
</tr>
<tr>
<td>${v_3, v_5}$ &amp; ${v_5, v_3}$</td>
<td>unblocked</td>
<td>$t_{\text{event}}$</td>
<td>$t_{\text{cur}} - t_{\text{event}}$</td>
</tr>
<tr>
<td>${v_3, v_6}$ &amp; ${v_6, v_3}$</td>
<td>unblocked</td>
<td>$t_{\text{event}}$</td>
<td>$t_{\text{cur}} - t_{\text{event}}$</td>
</tr>
<tr>
<td>${v_4, v_5}$ &amp; ${v_5, v_4}$</td>
<td>unblocked</td>
<td>$t_{\text{event}}$</td>
<td>$t_{\text{cur}} - t_{\text{event}}$</td>
</tr>
<tr>
<td>${v_4, v_6}$ &amp; ${v_6, v_4}$</td>
<td>unblocked</td>
<td>$t_{\text{event}}$</td>
<td>$t_{\text{cur}} - t_{\text{event}}$</td>
</tr>
<tr>
<td>${v_5, v_6}$ &amp; ${v_6, v_5}$</td>
<td>unblocked</td>
<td>$t_{\text{event}}$</td>
<td>$t_{\text{cur}} - t_{\text{event}}$</td>
</tr>
</tbody>
</table>

### Table 14: The states of the route graph after state propagation from the fading memory.

<table>
<thead>
<tr>
<th></th>
<th>$v_1$</th>
<th>$v_2$</th>
<th>$v_3$</th>
<th>$v_4$</th>
<th>$v_5$</th>
<th>$v_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$v_1$</td>
<td>b</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td></td>
</tr>
<tr>
<td>$v_2$</td>
<td>b</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td></td>
</tr>
<tr>
<td>$v_3$</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td></td>
</tr>
<tr>
<td>$v_4$</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td></td>
</tr>
<tr>
<td>$v_5$</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$v_6$</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This updated fading memory can be used for route planning. The following steps describe the process applying an evolving threshold-based route assessment approach:

1. **Step 1**: Initialize the route graph. Propagate the current states in the fading memory to the route graph (Table 14).

The next step (2a,b) is optional and introduces a mechanism to avoid edges known to be unblocked if they are near blocked edges.
and the knowledge of being unblocked is quite old, \textit{i.e.}, the risk that they are no longer unblocked is high.

2 Step 2a: Considering the spatial features, label the states of some edges as \( c \) (for further checking): these are the edges that are currently marked as \( u \) for \textit{unblocked}, but are directly connected with one or more \textit{blocked} edges.

Table 15 shows the updated state table for the running example: the edge that has a state of \textit{blocked} in fading memory is \( \{v_1, v_2\} \); thus, all of the edges that end either in \( v_1 \) or \( v_2 \) and are currently \textit{unblocked} are labeled \( c \).

Step 2b: Considering the temporal features, revise the states of some edges with a threshold. For all edges that are labeled \( c \), check the age of the knowledge of their states: if the age exceeds a threshold (initialed with a predefined threshold denoted by \( T_h \)), then their states will be revised to \textit{blocked}, otherwise their state will be reverted to \textit{unblocked}.

In the running example, suppose \( t_{\text{event}} = 0 \), \( t_{\text{cur}} = 40 \), \( T_h = 20 \), and \( t_1, t_2, t_3 \) and \( t_4 \) have some value between \( t_{\text{event}} \) and \( t_{\text{cur}} \). Then, the attribute table will look like Table 16. Note how the states of edges \( \{v_1, v_4\}, \{v_4, v_1\}, \{v_1, v_6\}, \{v_6, v_1\}, \{v_2, v_3\}, \{v_3, v_2\}, \{v_2, v_4\}, \{v_4, v_2\}, \{v_2, v_5\} \) and \( \{v_5, v_2\} \) have been revised to \textit{blocked} and \( \{v_1, v_3\}, \{v_3, v_1\} \) have been reverted to \textit{unblocked} (Table 17).

3 Step 3: Update the route graph and compute the evacuation route. Set the weight for the edges labeled \( b \) as infinity. Set the weight for the edges labeled \( u \) by any cost function, for example one (for routes of the fewest legs) or their actual length (for routes of the shortest distance). Calculate the shortest route based on the weights of the edges in the route graph.

4 Step 4: Adapt the threshold in case no evacuation route is available due to the potential overestimation of the severity of the event. If the shortest route calculated from Step 3 contains blocked edges or edges that have been checked as blocked, adapt the threshold by setting the threshold with a larger value, and go to Step 2b. If the adaptive threshold exceeds a limitation and still no passable route can be found, the evacuee is considered as failing in evacuation.

The evolving routing method with fading memory considers the spatial and temporal factors of the knowledge acquired, considering the age of the spatial knowledge. The out-of-date knowledge can only be tolerable when no evacuation route is available due to conservatism. Even with the threshold being adapted in each step, the initial threshold can still affect the route planning by biasing to choose a route that is a detour, but is deemed to be safer if more than one route is available. The simulation process can be illustrated with the flow chart in Figure 25.
Table 15: The states of the route graph after marking the states that need further checking.

<table>
<thead>
<tr>
<th></th>
<th>( v_1 )</th>
<th>( v_2 )</th>
<th>( v_3 )</th>
<th>( v_4 )</th>
<th>( v_5 )</th>
<th>( v_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( v_1 )</td>
<td>c</td>
<td>c</td>
<td>c</td>
<td>c</td>
<td>c</td>
<td>c</td>
</tr>
<tr>
<td>( v_2 )</td>
<td>b</td>
<td>c</td>
<td>c</td>
<td>c</td>
<td>c</td>
<td>c</td>
</tr>
<tr>
<td>( v_3 )</td>
<td>c</td>
<td>c</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
</tr>
<tr>
<td>( v_4 )</td>
<td>c</td>
<td>c</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
</tr>
<tr>
<td>( v_5 )</td>
<td>c</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>c</td>
</tr>
<tr>
<td>( v_6 )</td>
<td>c</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td>u</td>
</tr>
</tbody>
</table>

Table 16: The attribute table with sample value when \( t_{\text{cur}} = 40 \).

<table>
<thead>
<tr>
<th>Edge</th>
<th>State</th>
<th>Last Updated</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>{v_1, v_2} &amp; {v_2, v_1}</td>
<td>blocked</td>
<td>10</td>
<td>30</td>
</tr>
<tr>
<td>{v_1, v_3} &amp; {v_3, v_1}</td>
<td>unblocked</td>
<td>25</td>
<td>15</td>
</tr>
<tr>
<td>{v_3, v_4} &amp; {v_4, v_3}</td>
<td>unblocked</td>
<td>30</td>
<td>10</td>
</tr>
<tr>
<td>{v_1, v_4} &amp; {v_4, v_1}</td>
<td>unblocked</td>
<td>15</td>
<td>25</td>
</tr>
<tr>
<td>{v_1, v_6} &amp; {v_6, v_1}</td>
<td>unblocked</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>{v_2, v_3} &amp; {v_3, v_2}</td>
<td>unblocked</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>{v_2, v_4} &amp; {v_4, v_2}</td>
<td>unblocked</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>{v_2, v_5} &amp; {v_5, v_2}</td>
<td>unblocked</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>{v_3, v_5} &amp; {v_5, v_3}</td>
<td>unblocked</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>{v_3, v_6} &amp; {v_6, v_3}</td>
<td>unblocked</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>{v_4, v_5} &amp; {v_5, v_4}</td>
<td>unblocked</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>{v_4, v_6} &amp; {v_6, v_4}</td>
<td>unblocked</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>{v_5, v_6} &amp; {v_6, v_5}</td>
<td>unblocked</td>
<td>0</td>
<td>40</td>
</tr>
</tbody>
</table>

5.2.3 A generic method

The threshold-based approach above is relatively crude in its consideration of the age of acquired information. A more generic method to apply fading memory in evacuation management is to use a two-step method for routing.

In the first step, the states and the age of the acquired knowledge in fading memory will not be considered. Instead, a standard k-shortest route algorithm is applied, on the static route graph, calculating a list of shortest routes. Such k-shortest route algorithms have been studied by many scholars (Yen, 1971; Yang and Chen, 2005; Nielsen, Andersen, and Pretolani, 2005; Aljazzar and Leue, 2011; Liu et al., 2015; Singh and Singh, 2015). A classical loopless k-shortest route algorithm is described by Yen (1971) and used here.

Only in the second step the fading memory exhibits its influence. The second step assesses the alternative k shortest routes for their likelihood to be unblocked, trusting more the recently-acquired knowl-
Table 17: The states of the route graph after further checking.

<table>
<thead>
<tr>
<th></th>
<th>v1</th>
<th>v2</th>
<th>v3</th>
<th>v4</th>
<th>v5</th>
<th>v6</th>
</tr>
</thead>
<tbody>
<tr>
<td>v1</td>
<td>b</td>
<td>u</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td></td>
</tr>
<tr>
<td>v2</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td></td>
<td></td>
</tr>
<tr>
<td>v3</td>
<td>u</td>
<td>b</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td></td>
</tr>
<tr>
<td>v4</td>
<td>b</td>
<td>b</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td></td>
</tr>
<tr>
<td>v5</td>
<td>b</td>
<td>u</td>
<td>u</td>
<td>u</td>
<td></td>
<td></td>
</tr>
<tr>
<td>v6</td>
<td>b</td>
<td>u</td>
<td>u</td>
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edge. The assessment of a route can be represented by any suited evaluation function \(\text{fade}()\), such that \(\text{fade}(\text{Path}^i) \geq 0\), where \(\text{Path}^i\) is the \(i\)-th shortest route \((i \leq k)\). \(\text{fade}(\text{Path}^i)\) denotes the trust that route \(\text{Path}^i\) is unblocked according to the fading memory and, thus, can be recursively defined:

\[
\text{fade}(\text{Path}^i) = \min\{\text{fade}(e_{ij})\} \tag{8}
\]

The selection of a route (e.g., by an evacuee) can then be based on balancing the length of the route and the trustworthiness of the route. For example, in life-threatening scenarios, one will accept any detour and choose the route of lowest risk. This consideration also suggests that the evaluation function itself has to be chosen carefully for particular applications. It may depend on the type of event (how fast it spreads) or, more generally, on the dynamicity of the environment. The evolving threshold-based approach above is one example for an evaluation function:

\[
\text{fade}(e_{ij}) = \text{Th} - (t_{\text{cur}} - t)_j \tag{9}
\]

where \(\text{Th}\) is the threshold, and a value of \(\text{fade} < 0\) is considered blocked. The threshold \(\text{Th}\) is first set with an initial value and then is adaptive to avoid potential overestimation of the severity of the event.

### 5.3 Experiments

The concept of fading memory has been implemented in an agent-based simulation of an emergency event and consecutive evacuation. The experiment has been designed to test and compare the success rates of evacuations with and without fading memory.

The simulation is designed to test the system behavior when introducing the concept of fading memory. Thus it suffices to assume that evacuees follow the aforementioned evacuation strategies during the evacuation, \(i.e.,\), follow route instructions of their mobile devices that maintain the fading memory and compute optimal routes. Thus, the simulation does not aim to predict human behaviour, which also has been considered almost impossible elsewhere (Joo et al., 2013). It does also not aim to simulate a particular event-spreading process, such as a fire in a building (Elms, Buchanan, and Dusing, 1984; Cheng and
Hadjisophocleous, 2011), but could be fed with particular spreading models.

Events at different levels of speed have been simulated. For each level of speed, 60 different events are simulated, recorded and recalled when comparing evacuation scenarios, such that each comparison refers to the same event.

5.3.1 Event simulation

For the experiment, a spatially-extended and temporally-varying event has been assumed, for example a fire breaking out in a building, starting from a single location and continuing to expand. Events of other characteristics, such as earthquakes that impact at multiple locations at the same time or bomb explosions that do not expand after going off, will not be covered by this particular experiment, but could be tested in the same way in differently-designed simulations. At the beginning of an event, some edges in the route graph will be affected and become blocked. Then, the event expands, affecting more edges
and causing them to be blocked. Because of the continuity of the event spreading, the effected subspaces in the indoor environment are adjacent and connected (i.e., not separated by walls).

In order to simulate the event, this chapter adopts the concept of sensor graphs described by Wang et al. (2014). The real-time situation of the environment is assumed to be monitored by a virtual sensor network that covers the whole area of the indoor environment. The sensor network is generated by adding an edge between two sensor nodes if their detecting areas are adjacent and connected. Two sensor nodes are neighboring each other if they are connected with an edge. One sensor is set to be active from the beginning. Then, because of the continuity of the event spreading, the next active sensor should be a neighbored sensor of the already active one. Thus, an extended process can be simulated through simulating the state transfer of the sensors. The advantage of modeling the event independently from the route graph is obvious: the sensors can be distributed equidistantly and can cover also spaces that are not directly covered by the route graph.

In this chapter, a sensor shall have two possible states, normal (denoted by N) and active (denoted by A). A sensor stays in the normal state when its detecting area is safe and passable and may shift to active when its detecting area becomes unsound because of the event. Before the event, all sensors should be in the normal state, then one sensor that covers the area where the event starts shifts to active. As the event expands, for any neighbored sensor of an active sensor, a state transfer from normal to active may happen not definitely, but with a certain probability (denoted by p), which depends on the speed of the event expansion. A larger value of the probability p means a faster expanding event. In the implemented simulation, every 10 s, the event is updated by selecting the neighbored sensors of a randomly-picked active sensor and will be set active with a certain probability. This way, 60 events have been recorded, such that different memory strategies can be applied to the same events.

5.3.2 Evacuation strategies

For simplicity, this experiment assumes that all people are acquainted with the environment before the event: they have complete knowledge of the (static) route graph. In addition, this experiment assumes that during an event, people acquire knowledge and update their memory applying the two mechanisms mentioned above:

• People acquire updated knowledge of the environment upon a physical encounter with a changed environment.

• People acquire updated knowledge of the environment upon an encounter with fellow evacuees by exchanging their mutual time-stamped knowledge.

Each evacuee computes their own evacuation routes based on their own memory of the environment. The routes will be adjusted each
time when their memory of the environment is updated. Routes will be computed applying the steps described in Section 5.2.2. Since the communication channel may be blocked, considering whether peer-to-peer communication is allowed and whether dynamic routing with fading memory is applied, strategies that can be applied by evacuees are classified into four categories:

- **FS**: apply fading memory for dynamic route planning; communication is allowed so that evacuees share knowledge.
- **CS**: not applying fading memory, but communication is allowed.
- **FN**: the same as FS, except that communication is not allowed, so that knowledge cannot be shared.
- **CN**: The same as CS, except that communication is not allowed, so that knowledge cannot be shared.

Although the movement velocity of elderly people, young children or those with some form of impairment varies, in this experiment, this chapter assume a constant speed of 1.5 m/s. When the fire alarm is set off, all occupants start to evacuate. If no evacuation route is available for an evacuee, this evacuee is declared as failing. Depending on the circumstances, such evacuees may survive, e.g., if the fire is extinguished before it reaches them; however, in the context of this experiment, only the successfully evacuating agents are counted.

Both the models of event spreading and the evacuation of agents with fading memory have been implemented and tested in Repast Simphony (North et al., 2013). The experiment adopts a five-floor office building with four main exits as a sample evacuation environment. The building is about 126 meters long and 23 meters wide. The route graph of this building consists of 1739 edges and 1120 nodes. The graph is 1-connected: Most of the rooms correspond to an end vertex of the graph. The maximum and the average shortest path lengths from all the nodes to the exits is 271.1 meters and 94.7 meters respectively. One hundred evacuees are placed at predefined locations when the events start and then walk following the route generated from the route graph during evacuation. For comparability, these evacuees always start at the same locations; only the seed location and (random) spread of the event varies from simulation to simulation.

5.4 RESULTS

5.4.1 Experiment 1: Communication allowed

Experiments test the evacuation performance of the 100 evacuees with FS and CS under 60 emergency events with the initial threshold selected from a list of values: 1, 5, 10, 20, 40, 80, 160, 320. When all of the evacuees reach an exit or have no route left to evacuate, the evacuation process is considered as completed.
Figure 26 shows 60 paired comparisons of FS and CS in their evacuation success when the initial threshold for FS is set as one. Each circle in the scatter plot corresponds to a simulated emergency event. The coordinates of each circle shows the evacuation success of the two compared evacuation strategies simulated under that emergency event. Circles on the red line indicate that the two evacuation strategies have saved equal number of evacuees in those emergency events. A circle above the red line corresponds to an emergency event where FS has saved more evacuees than CS, while a circle below the red line corresponds to an emergency event where FS has saved less evacuees than CS.

![Scatter plot comparing FS and CS evacuation success](image)

**Figure 26:** Comparison between FS and CS when the initial threshold is one.

When the initial threshold for FS is one, in most cases (49 cases), the effect of applying fading memory leads to neither an increase nor a decrease in the quantity of successful evacuees. However, for the rest of the cases, fading memory outperforms CS in 10 cases, saving 3.2 people more on average per case. CS is better only in one case (Event 9), saving two people more. When examining the details of Event 9, both of the two people fail because of a sudden change of the environment. As described in Section 5.3.1, the event expands in the simulation every 10 s, which is not a smoothly-changing environment. The two people have first selected a longer route due to a rigid initial threshold of one, then suddenly failed because the event expanded and blocked the edges in which the two people were standing. In contrast, for the corresponding CS strategy, the two people have first chosen a shorter route and just avoided standing in a blocked edge when that event suddenly expanded.

Figure 27 compares the evacuation success of CS and the evacuation success of FS when applying varying initial thresholds. Small circles correspond to FS with smaller initial thresholds, while larger
circles correspond to FS with larger initial thresholds. For readability, Figure 27 only shows the 12 event cases where the quantity of people saved by different evacuation strategies exhibits differences.

Figure 27: Comparison between FS and CS for the event cases where the quantity of people saved by different evacuation strategies exhibits differences.

Generally, FS strategies are saving more evacuees than CS strategy, and FS applying smaller initial thresholds are saving more evacuees than FS applying larger initial thresholds. For Event 55, compared with CS, which has saved 84 evacuees, FS has saved 90 evacuees when applying smaller initial threshold such as 1, 5 and 10. FS also saved more evacuees than CS when applying a threshold of 20 (saving 87 evacuees) and 40 (saving 86 evacuees), but applying an even larger threshold such as 80, 160 and 320, would only allow FS to save the same number of evacuees as CS. For Event 40, FS has saved 100 evacuees when applying an initial threshold of one, while all other evacuation strategies have saved the same number of evacuees which is 98. There are also cases when applying smaller thresholds has saved less evacuees than applying larger thresholds, or FS applying some thresholds has saved less evacuees than CS.

Figure 28 shows the average success drawn from the 60 events when applying different evacuation strategies. Applying fading memory always saves a larger average number of evacuees. When the initial threshold gets larger, the effect of fading memory decreases.
5.4.2 Experiment 2: Communication not allowed

Peer-to-peer communication can be achieved by using mobile devices (Richter et al., 2013). However, even short-range communication channels may not exist (e.g., on smartphones with no Bluetooth). In order to investigate whether applying fading memory is still beneficial independent of any communication channel, experiments have also tested the performance of FN with varying initial thresholds applied when peer-to-peer communication is not allowed. Results show a similar pattern in the average number of successful evacuees (Figure 29). On average, fading memory exhibits an advantage. This advantage diminishes as the initial threshold increases until approaching a limit at which the performance of the threshold-based method equals that without applying fading memory. This is reasonable, because when the initial threshold gets larger, more out-of-date knowledge will be trusted, and in particular, when the initial threshold exceeds the evacuation time of all evacuees, fading memory degrades not applying fading memory. Figure 30 compares the event cases where the quantity of people saved by different evacuation strategies exhibits differences. Fading memory shows better performance than CN in 11 events, while only in three cases, a varying initial threshold fails to guarantee saving more people than CN.

5.4.3 Experiment 3: Sensitivity test for event speed

The probability p of sensor state transfer adopted in the event simulation reflects the speed of the expansion of an event. In Experiments 1 and 2, a transfer probability of 100% has been adopted, but this probability p is an arbitrary choice. In order to test whether the simulation result is sensitive to the selection of this parameter, the previous experiment has been repeated, but the sensors update their states with
5.4 Results

Figure 29: The average number of successful evacuees for CN and FN with varying initial thresholds.

Figure 30: Comparison between FN and CN for the event cases where the quantity of people saved by different evacuation strategies exhibits differences.

probabilities selected from a series of values: 20%, 40%, 60%, 100% and 0%.

Figures 31–34 show that independent of the expansion speed of an event, the quantity of average success shows a similar pattern. Applying fading memory saves on average more people than without applying fading memory. With growing thresholds, this advantage diminishes until the success rates reach the same outcomes as without applying fading memory. Since a high probability $p$ means a faster
expanding event and, thus, less opportunity for evacuating, it is rea-
sonable that when the probability $p$ in the event simulation is lower
(for example 20%), more people have been safely evacuated than with
higher probabilities, whether applying fading memory or not.

![Figure 31](image1.png)

Figure 31: The average number of successful evacuees when the probability
value of the sensor state transfer adopted in the event simulation
is 20%.

In particular, when the probability value decreases to zero, the
event becomes a static event, an event that affects some edges in the
route graph and does not expand. When the dynamic event degrades
to a static event, the topology and states of the route graph will re-
main constant. Thus, all of the knowledge acquired by evacuees will
always be valid, represents the real-time circumstance of the envi-
ronment and should be completely trusted. For this particular event,
applying fading memory is expected to make no improvements in
Figure 33: The average number of successful evacuees when the probability value of the sensor state transfer adopted in the event simulation is 60%.

Figure 34: The average number of successful evacuees when the probability value of the sensor state transfer adopted in the event simulation is 100%.

the number of successful evacuees, but whether it deteriorates the result needs to be tested. Experiment results for a static event show that exactly the same number of evacuees will be saved no matter whether fading memory has been applied and no matter what initial threshold has been applied for the route planning with fading memory (Figure 35).

The sensitivity test for different speeds of events indicates that the advantages of fading memory are maintained across events of all speeds and, in particular, is reliable even for static events. The dynamic routing method with fading memory is capable of guaranteeing a higher average of successful evacuees.
Figure 35: The average number of successful evacuees when the probability value of the sensor state transfer adopted in the event simulation is 0%.

5.4.4 Experiment 4: Comparison with real-time knowledge

Evacuees acquire and update knowledge through exploration and communication with fellow evacuees. The knowledge of an evacuee has been represented by a fading memory so far, which is a local route graph with time-stamped states. Fading memory draws a map of the dynamic environment and can be applied to achieve an evolving dynamic route planning with spatial and temporal factors taken into consideration. The fading memory for different evacuees may differ due to their varying trajectories. As mentioned in Section 5.2.1.2, the real-time conditions of the environment can be represented by a real-time memory, which is a global route graph with all states sensed in real time. In the decentralized evacuation process, the global route graph is always unique and is not accessible for evacuees. However, in centralized evacuation, the real-time knowledge can be sensed and computed in a central infrastructure (Wang et al., 2014). Based on the real-time information of the environment, personalized evacuation routes can be computed and sent to each evacuee via mobile devices.

The evacuation results of centralized evacuation planning with real-time knowledge are a benchmark for decentralized evacuation with fading memory. In order to investigate the gap between fading memory and a centralized evacuation, this last experiment compares the centralized evacuation implemented by Wang et al. (2014) and evacuations with fading memory. Figure 36 compares the performance of centralized evacuation and decentralized evacuation with fading memory, both when knowledge is shared and not shared.

As can be observed from Figure 36, although fading memory is capable of improving evacuation success in decentralized evacuation, it is not likely to be better than the evacuation performance of centralized evacuation. From the experiment results, centralized evacuation
5.5 Summary and Discussion

Spatial knowledge of dynamic environments fades in its value for decision making because of the growing risk that it has become invalid...
over time. This chapter proposes a fading memory model to represent the knowledge of a dynamic environment and applies it to route planning. Results show that this fading memory model can improve the evacuation success rates for expanding events or in general improve the decisions made in a dynamic environment.

To implement fading memory, this chapter develops a threshold-based method. The threshold starts with an initial value which is normally very small, so that only the very recently knowledge is trusted. If in this case no route is available, then the threshold doubles its value, so that knowledge which is older but still quite recent will also be trusted. In each step, if a route exists, the threshold method can always find a route by exponentially increasing the threshold value. When the threshold value is larger than the maximum evacuation time, threshold-based method degrades to a normal process that does not apply fading memory.

This chapter is the first approach to fading memory and a beginning to the full exploration of the properties and promises of fading memory on decision making in dynamic environments. The prior knowledge of evacuees has so far been assumed to be complete; however, this is most likely not the case in real-world situations in complex indoor environments. Thus, evacuation from an environment with limited (or no) prior knowledge and fading memory is also need to be studied. The experiments in this chapter are completed based on a sample building with limited alternatives. More generic graphs that represent different dynamic environments should also be tested. The density of evacuees in the experiment is limited, and a higher density of evacuees means that more opportunity for communication and that more space can be covered by the trajectories of evacuees in a short time; thus, this may lead to higher efficiency of evacuation. To address the above-mentioned concerns, the next chapter (Chapter 6) will investigate whether fading spatial memory model is also working well in decentralized evacuation with incomplete prior knowledge.
This chapter is based on the following paper with some extensions:


My contribution is 90%; the second author had only a supervisory role.

When people have to evacuate, their prior knowledge of the environment is in most cases incomplete. In addition, this environment has already been changed by an event, and is continuously changing with dynamic events, making the existing knowledge of the environment unreliable. This makes evacuating challenging. Prior, decentralized evacuation with ad-hoc short-range communication has already been proven effective in the absence of external infrastructure support to address incomplete knowledge (Richter et al., 2013). A recently developed model – fading memory, has also been proven effective for decentralized evacuation when complete prior knowledge is available. This chapter combines fading memory with decentralized evacuation with incomplete prior knowledge, suggesting a decentralized paradigm that facilitates time-aware and risk adverse evacuation. The experiment suggests that fading memory improves the evacuation performance in decentralized evacuation services when complete knowledge of the environment is unavailable.

6.1 INTRODUCTION

Evacuating an area affected by dynamic events such as building fires, bush fires, floods, damaged nuclear power plants or chemical industrial parks has received extensive attention from researchers. Most of the suggested evacuation methods rely on given information and communication infrastructures. Only Richter et al. (2013) suggest a decentralized evacuation paradigm that exploits smartphones as independent sensing platforms capable of ad-hoc near-range communication, and thus not relying on any infrastructure; they prove that sensing and then locally sharing knowledge, although incomplete, leads to evacuation times close to a centralized global evacuation management with full situational awareness. So far knowledge has been indiscriminately trusted, ignoring the possibility that the dynamic event has changed and continues to change the environment. This chapter goes a step further by adopting the decentralized evacuation paradigm and asking the question whether evacuees are better off if they are also considering the age of their collected knowledge, given that they are encountering (typically) a dynamic event.

In order to add time-awareness to the evacuation route planning, this chapter combines the decentralized evacuation paradigm with
the ‘fading memory’ model, a mechanism that trusts less the older knowledge for decision making in a dynamically changing environment. Fading memory has been suggested for centralized evacuation and has been proven beneficial particularly in indoor environments and when evacuees have complete prior knowledge of the environment (Zhao and Winter, 2016). However, in practice people may be required to evacuate an area which they are not familiar with, or equivalently, by the time of evacuation, evacuees may not always have a complete map that elaborates the full connectivity of that environment. A full knowledge of the environment may either be unavailable, or depends on certain service infrastructures which may either be unavailable or can easily get damaged in the disaster. Relieving the constraint of complete prior knowledge is of significant value because in this case no infrastructure of a particular environment is required so that an evacuation system can be transferable for different environments and is thus more robust.

Evacuating unfamiliar environments with dynamically expanding events is challenging in at least two aspects: the incompleteness of the knowledge of the environment and the unreliability of the acquired knowledge due to the dynamics of the events. Evacuating unfamiliar environments involves the exploitation of existing knowledge and the exploration of the unknown knowledge. Way-finding involves a combination and an iteration of the two, which induces a significant amount of uncertainty. Questions that need to be addressed include: what will be the paradigm for decentralized evacuation incorporating fading memory model, and what will be the shortest route in this case? What will be the heuristics for exploring unknown environment in case that from the existing knowledge no evacuation route can be derived? How to balance the exploitation of existing knowledge and the exploration of unknown environment?

This chapter proposes a decentralized evacuation paradigm embedded with a fading memory model, in order to verify the effectiveness of fading memory in circumstances when prior knowledge is incomplete. The hypothesis of this chapter is that fading memory improves the evacuation performance in decentralized evacuation services. If the hypothesis is true, fading memory can benefit evacuation in a much broader spectrum, and the proposed paradigm with fading memory will be a more effective and robust method independent from any external infrastructures.

In general, following contributions have been made in this chapter:

- A modified fading memory model has been proposed, which is a time-aware route graph for decentralized evacuation with incomplete prior knowledge.

- A decentralized evacuation paradigm has been proposed, which does not require any external central service and communication infrastructures.
• This chapter has verified that fading memory is advantageous for decentralized evacuation when complete prior knowledge is not available.

The remainder of this chapter is organized as follows. Section 6.2 describes general concepts of the model. Section 6.3 outlines the logic and implementation of the simulation. Section 6.4 depicts the experiment setting and briefly describes the main results of the experiments. Section 6.5 summarizes the findings of this chapter and provides suggestions for future research.

6.2 TIME-AWARE DECENTRALIZED EVACUATION WITH INCOMPLETE MAP

This section introduces the fading memory model for unfamiliar environments and develops a time-aware decentralized evacuation paradigm with fading memory.

6.2.1 Fading memory of unfamiliar environment

Networks (or graphs), in their semantic richness and well-defined format, are preferred for route computation and navigation (Yang and Worboys, 2015; Vanclooster, Weghe, and Maeyer, 2016). In this chapter, a graph \(G(V,E)\) has been used as a representation of an arbitrary environment, where \(V\) is a set of vertices \(v_i\) with a total count of \(\|V\| = m\), and \(E\) is a set of edges \(e_j\) with a total count of \(\|E\| = n\). Some of vertices are assigned as exits.

Fading memory is a time-aware graph representing the knowledge of evacuees (Zhao and Winter, 2016). It consists of a collection of triplets named memory segments, which store in mobile devices not only the edge and state of the edge, but also the time stamp when that knowledge has been acquired or lastly updated. For evacuation with incomplete prior knowledge, a complete map which elaborates the connectivity of spaces for that environment is unavailable. This chapter modifies the fading memory proposed by Zhao and Winter (2016) with an additional fourth dimension known to the triples, indicating whether the edge or vertex is known to the evacuee.

**Definition 14** A time-aware vertex is a vertex attached with an attribute known describing its availability to an evacuee, an attribute describing its state, and an attribute \(t\) describing the specific time when this vertex has been visited:

\[
v_{TA} = (v, \text{known}_v, \text{state}_v, t_v)
\]

where \(v\) denotes a vertex of the route graph, \(\text{known}_v\) denotes whether the vertex is known by an evacuee (by value 1) or unaware by an evacuee (by value 0), \(\text{state}_v\) denotes the value of the state associated with that vertex, \(t_v\) denotes the time when that vertex has been visited or has been last updated. \(t_v\) depends on the evacuee who visits the corresponding vertex and the time when the evacuee visits that vertex, thus \(t_v\) is randomly determined.
Definition 15 A time-aware edge is an edge attached with an attribute known describing its availability to an evacuee, an attribute describing its state, and an attribute \( t \) describing the specific time when this edge has been visited:

\[
e_{TA} = (e, known_e, state_e, t_e)
\]  

(11)

where \( e \) denotes an edge of the route graph, \( known_e \) denotes whether the edge is known by an evacuee, \( state_e \) denotes the value of the state associated with that edge, and \( t_e \) denotes the time when that edge has been visited.

In this chapter, this chapter assume each edge has two possible states: unblocked and blocked, where unblocked means that the connection is passable, while blocked indicates the space is untenable due to, for example, smoke, toxicity, or temperature (Kobes et al., 2010). Each vertex (or node by Zhao and Winter (2016)) of the route graph has three possible states: unblocked, blocked and risky. A blocked vertex indicates a vertex with all its adjacent edges being blocked. A risky vertex refers to a vertex connecting blocked edges and unblocked edges.

Let \( t_{cur} \) denote the current time. Then \( t_{cur} - t \) indicates the risk that the state of an edge in memory might be out-of-date. With this, fading memory in decentralized evacuation with incomplete map can be defined as a set of time-aware vertices and a set of time-aware edges considered at current time.

Definition 16 Fading memory in decentralized evacuation with an incomplete map is a set of time-aware vertex together with a set of time-aware edges considered at current time:

\[
G_{TA} = (V_{TA}, E_{TA})
\]  

(12)

\[
= \{(v, known_v, state_v, t_{cur} - t_v)_{i}, (e, known_e, state_e, t_{cur} - t_e)_{j}\}
\]

where \( i \in \{1, 2, \ldots, m\}\), \( j \in \{1, 2, \ldots, n\}\).

Thus, a fading memory graph \( G_{TA} \) is an extended version of a route graph \( G \) that covers the principle information needed for route planning. The paradigm applies fading memory as the knowledge of evacuees, and in particular takes the temporal component into consideration for route planning. In contrast, conventional methods ignore the time component.

Definition 17 The real-time memory of the condition of an environment can be represented as a special case of fading memory, where all \( known_v \) and \( known_e \) have a value of 1, and all \( t_v \) and \( t_e \) have a value of \( t_{cur} \):

\[
G_{RealTime} = \{(v, 1, state_v, 0)_{i}, (e, 1, state_e, 0)_{j}\}
\]  

(13)

where \( i \in \{1, 2, \ldots, m\}\), \( j \in \{1, 2, \ldots, n\}\).

For evacuating in an unfamiliar environment, evacuees have no access to the real-time condition of the environment; the vertices and edges to which they have access for computing evacuation routes is a subset of the whole graph, thus it only has some of the \( known_v \) and \( known_e \) set to 1, and also, since their knowledge is not always real time, only some of the \( t_v \) and \( t_e \) in their graphs equal to \( t_{cur} \).
6.2.2 Prior knowledge

Prior knowledge here refers to people’s awareness of the spatial connectivity of the environment before the event. Complete prior knowledge is either acquired or depends on a particular infrastructure (e.g., in a most simple case, evacuees are greeted with a map of a building at the moment of entering a building). Both may vary from one environment to another. This chapter assumes such infrastructure does not exist or is not accessible after the event.

In order to cater for acquired knowledge, people are assumed to have no prior knowledge of an environment before their (first) entry. Then they start roaming around. Each person carries a mobile device which reacts for decentralized evacuation in case of an emergency. Once a person enters the environment, the mobile device starts to record the trajectory of that person. The trajectory draws a partial map of the environment and composes the prior knowledge of a person before the event. Thus, people typically have an incomplete map before an event, and thus are to some degree unfamiliar with the environment.

6.2.3 Device for decentralized sensing and computation

A mobile device is assumed to be carried by each evacuee that can complete four tasks for decentralized evacuation:

- record the trajectories of each evacuee;
- sense the safety information of the environment (e.g., whether a corridor has been blocked by the event or is still safe for free access);
- support short-range communication and data exchange between two devices;
- calculate an evacuation route based on the knowledge collected by this mobile device.

The paradigm in this chapter assumes that before the disaster this device only records the trajectories of evacuees when they enter and start roaming an environment. Sensing is not triggered, in order to save power. Short-range communication and data exchange between devices have not started for privacy reasons. Route calculations before the event are not necessary. Only upon occurrence of a disaster, the mobile device mobilizes all its functions: continuing with trajectory recording, it turns also on environment sensing, peer-to-peer communication, and route calculation.

6.2.4 Knowledge acquisition

Evacuees shall be able to acquire and update knowledge of the environment with the carried devices in four ways:
1. Trajectory recording before the event. At the moment an occupant enters an environment, the mobile device attached with this person starts mapping the environment via trajectory recording. The collected trajectories form the knowledge of the persons they can draw on in the case of an evacuation, and thus this knowledge differs among all evacuees.

2. Ad-hoc communicating during the event. When two evacuees are in communication range, their mobile devices share the data they have collected (in such a situation privacy concerns are lifted). This stream of additional knowledge depends on how frequently people meet with each other.

3. Exploring the unknown environment during the event. Prior knowledge acquired before the event and the exchanged knowledge from peer evacuees add to the chance of finding an evacuation route but do not guarantee a feasible solution especially when the known route to exit is found blocked by the event. In this situation the evacuee falls back to the exploration of an unknown environment, recording new trajectories and sensing the safety information of the new trajectories.

4. Revisiting edges and vertices in existing knowledge. When evacuees follow an evacuation route calculated from existing knowledge or when exploring unknown parts of the environment, evacuees may revisit the edges and vertices of their existing knowledge. In this case, the temporal component of the corresponding edges and vertices will be updated with the current time.

6.2.5 Ad-hoc short-range communication

Ad-hoc short-range communication is a way to collaboratively map the environment in decentralized manner. Richter et al. (2013) indicated that for evacuation in decentralized manner, collaboration is always beneficial. In this chapter, ad-hoc communication is assumed to be available, i.e., while any two evacuees are in communication range (e.g., within one hop distance for ad-hoc communication), their mobile devices share the data saved on each of the two mobile devices.

A large communication range will certainly lead to more opportunity for data exchange and higher efficiency in mapping the environment. Messages are also possible to be forwarded or flooded across parts of a sensor network via designed portals (Jeong et al., 2015). To simplify, this chapter adopts one-hop communication with no message forwarding or message flooding.

6.2.6 Routing

Routing in this paradigm includes two parts.
1. Exploitation of existing knowledge: The routing will always try to compute a shortest route based on existing knowledge, while trusting less the older knowledge.

2. Exploration by way-finding heuristics: If no evacuation route is available in the existing knowledge, then the routing will explore the unknown part of the environment using certain way-finding heuristics.

Evacuees are assumed to firstly calculate a route based on existing knowledge. However, the resulting route may be found out to have been blocked by the event, so routing involves an iteration of the two principles above: exploitation of existing knowledge and an exploration of unknown environment.

6.2.7 Exploitation of existing knowledge

For route calculation, rather than indiscriminately applying the raw data acquired from previous experience, fading memory trusts more the recently explored knowledge than that explored a long while ago; and additionally it considers the knowledge close to the event (if known) as less reliable. An exemplified way to implement this is to simply set a threshold (denoted by $T_h$) for the temporal component of the knowledge. If the age of knowledge has not exceeded the threshold, routing will trust the knowledge; otherwise, routing considers the state of edges or vertices has changed to be blocked now. Existing knowledge will be examined before being utilized for route calculation in such a manner:

1. Consider all the blocked edges in fading memory as being blocked and all the unblocked edges as unblocked. This chapter considers only such disasters that once it affects a part of the environment, that part of environment will be destroyed and cannot be recovered within the period of an evacuation process. E.g., if corridors are blocked by fire disaster, or transportation lanes are damaged by floods, nuclear leaks or tornadoes, they cannot be recovered within the evacuation period.

2. Considering all the unblocked edges in memory, if they are directly connected with one or more blocked edges in the knowledge base, mark these edges as need checking.

3. Considering the temporal feature for each edge that has been marked as needs checking, if the age (i.e., the difference between the time stamp of last visit and the current time) of this edge exceeds the threshold $T_h$, then do not trust the knowledge of this edge and consider it as being blocked; otherwise trust this knowledge and consider this edge as being unblocked.

Step 1 just trusts the knowledge as it is; however, Step 2 and Step 3 is where fading memory in this chapter affects the route planning
in an evacuation process, devaluing the aged knowledge to avoid perceived risks. After these three steps, the original knowledge has been critiqued and adjusted.

For the rest of this chapter, scenarios that implement all these three steps will be called as applying fading memory and denoted by FD, while for scenarios that implement only Step 1 as not applying fading memory denoted by NFD. To contrast, this chapter will compare scenarios that only implement Step 1 as a benchmark and evaluate whether applying fading memory improve evacuation performance. The process can be explained with the flow chart in Figure 37.

Fading memory is a way for risk aversion from the spatial and temporal perspective of acquired knowledge.

6.2.8 Exploration and way-finding heuristics

Based on acquired knowledge, an evacuation route may not always be available. For example, due to the expansion of the event, the only way to the known exits may consist of one or more edges that are experienced to be blocked. Another possibility is that, in the risk-averting strategy of fading memory, some edges have been labeled as being blocked although they would still be passable. This happens particularly when the threshold is assigned a too small value, i.e., when fading out knowledge that is still relatively young. In either of these two cases, evacuees then fall back to exploring unfamiliar parts of the environment where heuristics apply. Two sample heuristics – a random-search and a least-angle strategy – have been applied by Richter et al. (2013), which can be replaced also by any other reasonable heuristic. The two strategies are modified in accordance with the experiment in this chapter.

6.2.8.1 Random-search strategy

Based on existing knowledge, when no route can be derived by the mobile device, the device examines all the adjacent edges with three criteria:

1. Criteria 1: Whether the edge is not blocked.

2. Criteria 2: Whether the vertex on the other side of the edge is not risky.

3. Criteria 3: Whether the edge is unknown to the device of this evacuee.

Adjacent edges which satisfy all the three criteria are not always available, in which case the device gives priority to Criteria 1, then Criteria 2 and finally Criteria 3. Firstly the device randomly picks up one of the adjacent edges that satisfy all the three criteria. If no such edge is available, the device tries picking up one of the adjacent edges that satisfy both Criteria 1 and Criteria 2. If no such edge is available, the device tries picking up one of the adjacent edges that satisfy both Criteria 1 and Criteria 3. If again no such edge exists, the device tries
picking up one of the adjacent edges that satisfy only Criteria 1; failing to find an available edge in this case means all the adjacent edges have been blocked and thus this evacuee fails to evacuate. The process can be explained with the flow chart in Figure 38.

Criteria 3 suggests exploring unknown parts of the environment when a safe path is not available based on the current knowledge of an evacuee. Fading memory devalues knowledge which used to be safe at a time instance exceeding the threshold, in order to avoid potential risk, because such knowledge is prone to expire in a dynamically changing environment. The nodes which used be safe may have been blocked or will shortly get blocked. Therefore, taking the
node which used be safe at a time instance exceeding the threshold may navigate evacuees to somewhere blocked and add to their exposure to potential risk, conflicting with the purpose of applying fading memory method. Instead, exploring unknown parts of the environment provides a way that enables evacuees to acquire new knowledge while not eliminating the effect of fading memory.

For the capacity of nodes, each node in this chapter represents a point and evacuees can be at anywhere along the edges, therefore it is not likely that many evacuees are located at the same node. People only pass through nodes, and they do not wait or choke nodes. Candidate routes that are already visited by other evacuees can also be safe routes. For example, other evacuees just passed those routes and confirmed with their most recent knowledge that those routes are safe.

![Random-search strategy for exploring unknown environment.](image-url)
6.2.8.2 Least-angle strategy

The least-angle strategy will also apply the three criteria with the same order of priority, but it differs from the original random-search strategy in that it always prefers alternatives that are in a direction that creates a least angle to the closest known exit.

6.3 EXPERIMENTS

In this section, simulation experiments compare scenarios applying fading memory with scenarios without applying fading memory. The simulation is conducted in the agent-based simulation tool – Repast Simphony.

6.3.1 Route graph

In the experiments, a homogeneous graph is adopted to represent the space. Two vertices are labelled as the exits of this environment (Figure 39).

![Figure 39: A sample route graph.](image)

6.3.2 Event simulation

An event is simulated through propagating blocked states of vertices and edges to the route graph. Before the event, all the vertices and edges in the route graph should be unblocked, then starting from one initial vertex of the graph, all its adjacent edges are set blocked. All the ending vertices of these blocked edges are set risky and added to a risky vertex list. After a time interval (denoted by delay), all the risky vertices as well as all their adjacent edges are set as blocked, then the vertices connecting blocked and unblocked edges are labeled as risky and added to the risky vertex list. The number of blocked vertices and
edges grow in such a way until all the vertices and edges in the graph are blocked.

For a specific graph, the expansion of the event is determined by the first vertex which has been initially set blocked. Events initialize at a specific location and expand towards varying directions. The time interval delay measures how fast an event expands. A small value of delay indicates a fast spreading event, while a large value of delay corresponds to a slowly extending process. An infinitely large value of delay becomes a static event (e.g., a bomb explosion, which afterwards is quite static).

To ensure each comparison refers to identical events, all the events are simulated and saved to files, which then are recalled in various evacuation simulations.

6.3.3 Human action simulation

Eighty indiscriminate (future) evacuees are assumed to consecutively enter the experimental environment through one of the two designated exits. After entering the environment, evacuees start walking around randomly, and at the same time their mobile devices start mapping the space by recording their trajectories – at this stage all traveled edges are labeled unblocked. For each step in the simulation, evacuees walk from one vertex to one of its neighboring vertices. The trajectory of each evacuee before the event is also saved to files for retrieval in comparison simulations.

After a certain period (or number of steps; forty steps in the presented simulations), an alarm is assumed to be triggered and a few initial vertices and edges has been blocked by an event. All the evacuees immediately switch from randomly walking mode to evacuation mode. Each device attempts to calculate an evacuation route based on the acquired data and the current location of the evacuee:

- If a route can be successfully retrieved, the evacuees are assumed to follow the evacuation route calculated by the device until they find the edge in front has been blocked. Then the evacuee considers exploring an alternative edge, such that the device, detecting this action, updates that edge as blocked and retrieves an alternative route according to its updated knowledge if available.

- If no evacuation route can be successfully retrieved, the device will guide the evacuee in exploring the environment along a heuristic strategy.

- If all the adjacent edges are found to be blocked, the evacuee is failing to evacuate.

In this regard, the mobile device has three modes: random walking mode, evacuation mode, and exploration mode. The mobile device is in:

- random walking mode before the event;
• *evacuation mode*, if, after the event, a route is available from existing knowledge;

• *exploration mode*, if, after the event, a route is not available from existing knowledge, and the device is using heuristics to guide the evacuee.

In terms of whether the knowledge has been critiqued before used for route planning, the device has two options: applying fading memory (FD) and not applying fading memory (NFD).

### 6.3.4 Evacuation scenarios

The experiments will particularly compare evacuation performance when applying the fading memory strategy (FD) with no fading memory strategy (NFD). The time threshold (Th) determines which data is considered out-of-date, and affects the performance of evacuation. Experiments test a number of Th values: 2, 4, 8, 16, 32, 64 time instances. For heuristics, experiments test both the random-search and the least-angle strategy.

It is expected that applying fading memory will not guarantee always to save more evacuees. Quite to the contrary, due to its conservative decision making, it can even behave sometimes worse, losing lives. The success will depend on a choice of Th appropriate for a particular event: Setting a small threshold value for a slowly expanding event would be particularly harmful. Thus, the only questions is whether fading memory will on average exhibit advantages.

### 6.4 RESULTS

#### 6.4.1 Result for least-angle strategy

Experiments test the evacuation performance of the eighty evacuees applying fading memory (FD) and without applying fading memory (NFD) under sixty emergency events with thresholds (Th) of 1, 2, 4, 8, 16, 32, and 64 time instances.

Figure 40 compares the difference between the number of successful evacuees derived from FD scenarios with various thresholds (Th) and NFD scenarios. Each point in the scatter plot corresponds to the evacuation success for a simulated emergency event. Each emergency event starts at a different location. Points on the red line indicate the two evacuation scenarios have saved equal number of evacuees in those emergency events. Figure 40 demonstrates a significant advantage of applying fading memory when the threshold adopts relative small values: 1, 2, 4, 8. Among the comparisons of evacuation results from 60 independent dynamic events, in a large number of cases, FD scenarios save more people than NFD scenario. Only in a few cases, FD scenarios save less people than NFD, and this only happens when the threshold is 1 or 2. When the threshold for FD is larger than 16, FD scenarios perform equally with NFD. This is because in most cases
evacuation finishes in a few steps, much less than 32 steps or 64 steps. When the threshold is large, in very few cases, if any, the knowledge is considered out of date before the evacuation is completed. The total number of evacuees in this experiment is 80 and the events spread at a relative high speed with a delay value of 2.

6.4.2 Robustness test

In order to investigate whether the advantage of FD over NFD is robust against the density of evacuees and the speed of the event, simu-
lation for events of varying speeds and varying numbers of evacuees are compared. Figure 41 and Figure 42 verify that, compared with NFD, FD has a robust advantage against various speeds of events and various numbers of evacuees.

Figure 41: The average number of successful evacuees among events of varying speeds for least angle strategy. The total number of evacuees in this experiment is 80.

Figure 41 depicts the average number of successful evacuees out of 80 total evacuees for 60 events of 5 different levels of speeds with delay value being 2 (fast event), 4, 6, 10 and 20 (slow event). Results show that independent from the speed of events, FD almost always exhibits an advantage over NFD. FD scenarios with any Th value always have a higher average number of successful evacuees when the event dynamics becomes slower. Compared with NFD scenario, for the event at any speed, FD scenarios generally maintain a higher success rate than NFD. With the value of delay increasing, the event speed get slower, and larger a threshold value affects more the simulation results in FD scenarios. For instance, in Figure 41, the fastest event has a delay of 2, and its larger thresholds (16, 32 and 64) have no effect in improving the success, but in comparison, when the delay is 20 FD scenarios with threshold 32 and 64 can also save averagely large number of evacuees. That is because for a slow event, even if some evacuees need more steps to evacuate a slow event gives them enough time to move around. In contrast, for a fast event these evacuees will quickly be embezzled by the event and thus may fail to evacuate.

Figure 41 also indicates that a small threshold is not always better than a large threshold. When the event expands slowly, the optimal threshold becomes larger. FD scenarios show significant advantage in
fast spreading events over slow events. For an extreme case, when the delay is infinite, the event becomes a static event. For a static event, FD and NFD should save the same number of evacuees; the ones who failed in the evacuation are those who have been trapped by the event.

Figure 42 shows the success rate among various total counts of evacuees for fast spreading events, where delay adopts a value of 2. The success rate is calculated by dividing the average number of successful evacuees by the total number of evacuees. Results show that the FD scenarios always have at least the same if not larger success rates than NFD scenarios. A higher density of evacuees with its increased opportunity of communication generally derives higher success rates. Exceptions have been found in the experiment result of the NFD scenario with 20 evacuees, which generates a slightly higher success rate than the NFD scenario with 40 evacuees. The possible reason is that when the density of evacuees gets lower, the initial locations where the evacuees start to evacuate have more impact on the simulation result. In this experiment, for the 40 evacuees scenarios, 20 evacuees are initially located at the same locations as the 20 evacuees scenarios, while the other 20 evacuees are initially randomly located and probably far from all exits.

6.4.3 Random-search strategy

While results indicate that fading memory benefits evacuation significantly when applying a heuristic of least-angle strategy, whether
this advantage is robust against any reasonable heuristics is to be discussed. This experiment also tests the random-search strategy with fast events ($delay = 2$), the results of which are presented in Figure 43 and Figure 44. FD scenarios are in principle still advantageous (Figure 44).

Compared with the least-angle strategy, which maintains almost consistently a larger number of successful evacuees in evacuating in any event, the random-search strategy involves more noise in the results (Figure 43), even for larger threshold values when fading memory has little impact on the evacuation process. The noise is supposed to be incurred by the randomness in random searches. During the ex-

Figure 43: The number of successful evacuees for scenarios applying fading memory and scenarios without applying fading memory for the random-search strategy with fast events ($delay = 2$).
ploration process, rather than selecting a least-angle edge, this strategy randomly picks up one alternative in each step. A simulation result for this strategy is just one observation of the many possibilities incurred by a combination of steps with random choices. Even for the same event, repeating the simulation may also result in varying number of success rates. In order to verify this, this chapter randomly picked up a specific event (Event 28) and run a number of repeated simulations.

Results show that among 500 repeated simulations, the number of successful evacuees varies for both the fading memory scenario and the non fading memory scenario (Figure 45 and Figure 46). Results show that the FD scenario significantly outperforms NFD. Although in one specific simulation FD not necessarily saves more evacuees...
than NFD, for a large number of repeated experiments the average number of successful evacuees converges and implies significant differences between the two strategies (Figure 45). As the count of repeat increases, the mean of both FD and NFD scenarios approaches constant values of 62.5 and 54.4. In the 500 repeats, the successful evacuees of fading memory ranges from 54 to 72 with a median value of 63, while for non-fading memory it ranges from 41 to 66 with a median value of 54.

The repeated simulation is based on Event 28 where fading memory outperforms non-fading memory (Figure 43). Whether the statistics in this experiment is robust against varying events has also been investigated.

Figure 47 and Figure 48 compare the results for repeated simulation with another event, Event 20, picked because fading memory saved less evacuees here (Figure 43).

In the 500 repeats, the successful evacuees of fading memory range from 58 to 71 with a median value of 65, while for non-fading memory it ranges from 59 to 69 with a median value of 64. As the count of repeat increases, the mean of both scenarios approaches 64.7 and 63.9. Statistics for this event indicate again that fading memory is advantageous over non-fading memory. The difference for Event 20 indicates a smaller advantage, though, of fading memory, compared to Event 28.

In order to test whether for a random-search strategy the advantage of FD is robust against varying the level of event speed and the density of evacuees, experiments simulate 40 evacuees evacuating from slower events (delay = 6). Results shows a similar noisy pattern in each specific simulation but on average more successful evacuees for FD scenarios than NFD scenarios (Figure 49).
Figure 47: Number of successful evacuees and the cumulated average for 500 repeated simulations for Event 20 with a random-search strategy.

Figure 48: Statistics for 500 repeated simulations for Event 20 with a random-search strategy.

6.4.4 Tests on a building graph

The model and experiment employs a general graph with enough alternatives and general heuristics for the experiment results to have implications on a broad spectrum of applications, but the heuristics should be carefully designed for specific problems. Comparing the average successful evacuees using a least-angle strategy in Figure 41 and a random-search strategy in Figure 44, the least-angle strategy yields better results than the random-search strategy for both FD sce-
Figure 49: The average number of successful evacuees when applying a random-search strategy as heuristics for a slower events (delay = 6) and 40 evacuees.

scenarios and NFD scenarios. One heuristic may work well for one specific application, but may not for another application. For instance, the least-angle strategy may not work well for evacuating a building in that stairs are typically spiral structures with continuously changing angles, while a random-search strategy can be applied for indoor environments but tends to be irrational in such typically sparse and regular graphs.

Experiments also test the evacuation of a building that was already employed by Zhao and Winter (2016) using a random-search strategy. Results suggest that the random-search strategy is not a preferable and rational heuristic for evacuating an indoor space (Figure 50). Other sophisticate heuristics should be developed specifically for indoor space evacuation.

Figure 50: The average number of successful evacuees when evacuating a building with a random-search strategy.

In combination of all the above experiment results, decentralized evacuation is supposed to benefit from trusting the more recently acquired or updated knowledge, and less the knowledge acquired a
long while ago, independent from the prior knowledge of the agents and robust against the density of evacuees, the speed of events, as well as the tested heuristics.

6.5 SUMMARY AND DISCUSSION

This chapter challenges the general validity assumption of spatial knowledge in evacuation routing, and improves the existing decentralized evacuation method by a fading memory concept. A decentralized evacuation paradigm has been developed. In this paradigm, each evacuee is equipped with one mobile device, which facilitates trajectory recording before the event and also communication and route calculation during the event. The evacuation process with this mobile device involves two iteration steps. The device firstly tries calculating a route based on existing knowledge, where time-awareness has been considered to avoid potential risks. Then if a route is not available, the device suggests exploration of the environment with heuristics. Experiments show that decentralized evacuation will benefit from trusting more recently updated knowledge and less so the knowledge acquired a long while ago, independent from the prior knowledge of the agents. Based on this conclusion, applying fading memory in decentralized evacuation is suggested. Such a concept, because of its independence from any central infrastructure, is transferable to any environment, e.g., being applied to any building, without revision of the system. Since the simple heuristics in this chapter are already providing evidence to the hypothesis, other more elaborate heuristics are expected to provide similar or better evidences.

Both this chapter and Chapter 5 investigate fading spatial memory model in decentralized evacuation; however, there are some differences. Compared with the research in Chapter 5, this chapter:

• relieves the constraint in prior knowledge before evacuations. Instead of assuming that people are familiar with the environment from which they are trying to evacuate, this chapter considers evacuees as first-time visitors of that environment. Relieving such constraint will allow the research outcome to be applicable to arbitrary environments.

• applies general graphs rather than the graph of any specific building. A general graph represents a broad spectrum of applications such as a street network. Research outcome in this chapter will have implications on a broad realm of applications.

• for the implementation of fading spatial memory, adopts a constant value for the threshold instead of applying an adaptive threshold in Chapter 5. Adopting small threshold values will certainly mean more selective for the most recent (and in general the most reliable) knowledge; however, a small threshold value may easily come up with no available evacuation route. In this case, for Chapter 5 when people have a full map of unaffected environment, an evacuation route can only be possible
if they keep trying a large threshold value. But for this chapter when people have incomplete knowledge of the environment, in order to find an available route, they may either choose to adopt a larger threshold value or to explore the unknown environment with certain heuristics. A trade-off of these two options refers to a balance of whether to give priority to the exploitation of existing knowledge or to the exploration of unknown environment. Adopting adaptive threshold will thus mix the effect incurred by the fading spatial memory model and the adopted heuristics. In this chapter, the threshold is not considered as adaptive, so that the simulation results reflect only the effect of fading spatial memory model.

For decentralized evacuations, people acquire risk information through self-exploration and peer-to-peer communication. Peer-to-peer communication highly relies on the chance that people meet, which can be very low in evacuation situations when people are heading similar directions to the closest exits. In order to meet, two evacuees must have at least one common point in their space-time routes. I.e., their trajectories need to have at least one intersection point, and they also need to arrive at this intersection point at the same time. The lack of efficient communication channel for evacuees in decentralized evacuation impedes evacuees from keeping updated with the risk information of their environment. Inspired by the ant phenomenon that ants communicate not only by point-based ant-to-ant encounter, but also field-based pheromone that keeps being updated by passers-by, the next chapter (Chapter 7) will develop a field information model to enhance the communications among people and thereafter produce better evacuation outcome.
This chapter is based on the following paper, with some extensions:


My contribution is 80%; the second author and the third author had only supervisory roles.

The lonelier evacuees find themselves, the riskier become their wayfinding decisions. This research supports single evacuees in a dynamically changing environment with risk-aware guidance. It deploys the concept of decentralized evacuation, where evacuees are guided by smartphones acquiring environmental knowledge and risk information via exploration and knowledge sharing by peer-to-peer communication. Peer-to-peer communication, however, relies on the chance that people come into communication range with each other. This chance can be low. To bridge between people being not at the same time at the same places, this chapter suggests information depositories at strategic locations to improve information sharing. Information depositories collect the knowledge acquired by the smartphones of evacuees passing by, maintain this information, and convey it to other passing-by evacuees. Multi-agent simulation implementing these depositories in an indoor environment shows that integrating depositories improves evacuation performance: It enhances the risk awareness and consequently increases the chance that people survive and reduces their evacuation time. For evacuating dynamic events, deploying depositories at staircases has been shown more effective than deploying them in corridors.

7.1 INTRODUCTION

When disasters strike, such as a fire, a gas leak, a chemical spill, an earthquake, a flooding, or a roaming sniper, the first and foremost action is to get people out of the disaster area. This chapter focuses on those evacuees who find themselves without organized help when the alarm goes off. For them, environmental knowledge, knowledge about the dynamically changing event, and thus some risk awareness in their decision making is essential (Wang et al., 2014). For these situations, decentralized evacuation has been embraced by recent research due to its robustness and scalability (Zhao and Winter, 2016; Richter et al., 2013).

In decentralized evacuations evacuees are guided by their smartphones that are acquiring environmental knowledge and risk information as the evacuees explore the environment. These smartphones
are sharing their collected knowledge by peer-to-peer communication with other smartphones within communication range. Decentralized evacuation has the advantage that no further infrastructure is required, i.e., it is applicable in any environment. In simulation, it has proven to work well where there are good chances that evacuees come into communication range with each other. In reality, however, the chance that evacuees encounter may be low due to the following facts.

- Encounters happen when two people walk in opposite directions; however, in evacuation situations people tend to move in similar directions, i.e., from their current positions to where they guess the closest exit is.

- Even when people move towards each other, for example, trying to get to the same staircase from opposite directions, they may still miss each other if one person reaches the staircase earlier than the other. More formally, even if their two trajectories have a joint point in space, they still can miss each other by time.

- High density of evacuees, although desirable in the context of exchanging knowledge, is also leading to congestions and panic situations (Helbing, Farkas, and Vicsek, 2000), and thus risk-aware evacuees might actively avoid crowded spaces.

The success of a single evacuee depends on up-to-date knowledge of the dynamics in the environment. A recently proposed ‘fading memory’ method, distrusting older knowledge, introduces some aspects of risk awareness, and generally improves evacuation success (Zhao and Winter, 2016). However, the fading memory method produces can even decrease evacuation success when older information is discarded that is still valid. The research question of this chapter is how to effectively maintain the spatial and temporal information of the dynamic environment within the environment, and how to robustly keep evacuees updated.

To bridge the spatial and temporal gaps in the communication of single evacuees in decentralized evacuations, and inspired by ants that communicate by pheromone traces that keep being updated by passers-by, this chapter suggests information depositories in the field for decentralized evacuation. Information depositories enable the environment to maintain information and interact with passing-by evacuees. They record and update the environmental and risk information deposited by passing-by evacuees, and provide this information to later passers-by. They are sharing points in the environment for evacuees passing the same location at different times, enabling asynchronous communication (Harvey and Macnab, 2000; Raubal, Miller, and Bridwell, 2004). Thus information depositories add to peer-to-peer communication, can address all three challenges listed above, and therefore are expected to produce better evacuation outcomes.

The hypothesis is that even a small number of information depositories will enhance risk awareness of evacuees and improve the evacuation results.
The hypothesis will be verified through agent-based simulation by adding information depositories to a decentralized evacuation of an indoor environment. Simulation results will be evaluated with the success rates of evacuees, the number of steps required to exits, and the amount of knowledge that has been updated. The contributions of this chapter are as follows.

- This chapter proposes information depositories for asynchronous communication in decentralized evacuation.
- This chapter verifies that integrating information depositories benefits decentralized evacuation.
- This chapter shows that already a small number of information depositories make a difference if these depositories are deployed at strategic locations such as staircases.
- This chapter compares the alternative approaches of fading memory and information depositories, showing that their mutual advantages can be combined.

The research scope of this chapter is to investigate a conceptual model of decentralized indoor evacuation with information depositories, while it leaves aside specific implementations of technologies. For example, a conceptual model may involve multiple modules such as simulation of the emergency event, localization and navigation, the sensing of the environment, risk assessment, and ad-hoc communication. This chapter does not limit the implementation of each module to specific technologies. Any existing or emerging technologies can be plugged in. In this chapter, sensing is assumed to happen on a mobile device in the background and is taken for granted. To explain and to investigate the conceptual model of evacuation with information depositories, this chapter assumes that each evacuee carries a mobile device such as a smartphone, and evacuation happens in a departmental building after a fire broke out. The fire is spatially extended and varying over time.

The rest of this chapter is organized as follows. Section 7.2 develops the concept of immobile information depositories for roving, self-localizing and mapping agents. Section 7.3 implements the information depositories in an agent-based simulation of decentralized evacuation from an indoor environment. Section 7.4 presents the results of simulations, which are discussed and summarized in Section 7.5.

### 7.2 Information Depositories

#### 7.2.1 Awareness of the Indoor Environment

The indoor space of a building can be represented by a navigable graph $G(V, E)$, where $V$ is a set of vertices $v_i$ with a total count of $\|V\| = m$, and $E$ is a set of edges $e_j$ with a total count of $\|E\| = n$. Nodes represent locations, and edges represent a possibility to move directly between two locations. Moving agents (evacuees) can
have partial or complete knowledge of this graph, depending on their individual familiarity with the environment. The partial or complete awareness of the indoor space during evacuation consists of at least three dimensions:

- The (partial or complete) original graph of the indoor environment. It represents the connectivity of the indoor environment before being affected by a disaster.

- The state of the original graph. States of nodes and edges track the changes caused by the disaster that evolves dynamically. This chapter assumes two possible states of each edge or node: unblocked and blocked. A blocked edge is not passable for evacuees, while an unblocked edge allows evacuees to pass through freely. A blocked node can be represented by setting all its adjacent edges as blocked. In decentralized evacuation different evacuees can have different knowledge of the states of the graph.

- The time stamp of the state. It labels when that state of an edge or node has been lastly updated. Since the only sensors in decentralized evacuation are the (smartphones of the) evacuees, edges and nodes are only updated when encountered and found in a different state by an evacuee. Thus, these times are transaction times of individual sensors, not valid times of changes in the environment. Furthermore, in decentralized evacuation different sensor nodes can obtain the same information at different times.

Awareness of the indoor environment can be represented by a set of triplets:

\[ \{(e, \text{state}_e, t_e)\}_{j \in \{1,2,\ldots,n\}} \]

where \(e\) denotes an edge of the graph, \(\text{state}_e\) denotes the state of that edge, and \(t_e\) denotes the time when that \(\text{state}_e\) has been obtained.

Such awareness of the indoor environment is an enhanced graph for computing shortest evacuation routes while avoiding the known-to-be-blocked edges.

7.2.2 Update of awareness

In decentralized evacuation, evacuees generally update their awareness in two ways:

- By exploration. Awareness of the indoor environment can be updated when an evacuee encounters new locations or passages, or new states of already known locations or passages.

- By peer-to-peer communication. Two evacuees exchange their awareness of the indoor environment when they get close (technically: into short-range radio communication range). Their awareness of the environment may differ in completeness and in currency. After the exchange, both evacuees will have the same
knowledge, where the merging operation ensures that among duplicates only the awareness with the more recent time stamp will be retained.

7.2.3  The role of information depositories

This chapter assumes the indoor space has also been deployed with disconnected static information depositories. Such static depositories are capable of the same peer-to-peer communication with their surroundings and hence work in two ways.

- As a repository. The static information depositories work as repositories that collect the awareness of evacuees that pass by.
- As a service station. A static information depository shares with passing-by evacuees the collective awareness in its repository.

Such a concept of static information depositories enables the space itself to maintain awareness information and interact with passers-by.

7.3  EVACUATION SIMULATION MODEL

7.3.1  The building

Simulations adopt a five level departmental building, which has already been used for testing (purely) decentralized evacuation (Zhao and Winter, 2016). This building consists of three rectangular blocks. Each block includes the ground floor, level one, level two, level three, level four and the roof level. There are mainly four staircases starting from the ground floor and ending at the roof level, two of which are located on the left side and the right side of this building, and the other two are located near the joint parts of two blocks (Figure 51). These four staircases direct to the four main exits of this building. There are another six exits accessible only to evacuees on the ground floor. This building is mostly dedicated to staff use (offices), apart from labs on level one, two lecture theaters on level four, and a computer lab on the ground floor.

![Figure 51: The 3D model of the five level departmental building. It is the same model as in Figure 10.](image-url)
7.3.2 Route graph

A route graph associates evacuation routes with the building structure. This chapter adopts the method developed by Stahl (2010) and Wang et al. (2014), to generate a route graph. The nodes of the route graph are mainly placed pair-wise on both sides of an entrance, at the beginning, end, and turning points of staircases, or at the shifted boundary vertices of concave regions. The graph for this building consists of 1739 edges and 1120 nodes (Figure 52). Before the emergency, all the edges are initially unblocked and are allocated with a weight of their actual length. However, during the emergency, the edges of this graph will be continually affected by the emergency events: Some edges will become blocked by allocating a weight of infinity.

Figure 52: The route graph of the departmental building.

7.3.3 Emergency event

The simulation assumes that the building is affected by a spatially-extended and temporally-varying event such as a fire emergency, and adopts the emergency simulation developed by Zhao and Winter (2016). This emergency simulation assumes a virtual sensor network covering the whole area of the indoor environment (Figure 53). Each sensor captures the environmental factors within a circular detecting area (radius \( r = 6 \) m) if no walls shield the reception of this sensor. Otherwise, the detection area of the sensor is the intersection between the circular area and the boundary of the region where the virtual sensor is located. The sensor network is generated by adding an edge between two sensor nodes if their detection areas are intersecting. Two sensor nodes are neighboring each other if they are connected with an edge. Each sensor node has two possible states: normal and active. A sensor stays in the normal state when its detecting area is safe, and will shift to active when its detecting area is blocked by the emergency event. Before the event, all sensors should be in the normal state. The event is marked by setting one sensor to be active. As the event expands, the next active sensors should be one or more neighbored sensors of the already active one. Every two steps, this simulation randomly picks up one of the already active sensors, and set all its neighboring sensors as active. Thus, an extended emergency process has been simulated through simulating the state transfer of the virtual sensors. The main parameter that differentiates a simulated emergency event is the location where the first virtual sensor that detects the emergency events.
The emergency event is modeled independently from the route graph, so that the virtual sensors can be distributed equidistantly and can cover also spaces that are not directly covered by the route graph. Such simulations represent spatially-extended events, starting from a single location and continuing to expand. Events of other characteristics, such as earthquakes that impact at multiple locations at the same time or bomb explosions that do not expand after going off, will not be covered by this particular simulation, but could be tested in the same way in differently designed simulations.

7.3.4 Mobile agent

100 agents (evacuees) are randomly located in this building before the emergency. Each agent is capable of simulating an evacuee carrying a mobile device equipped with sensors. Each mobile device saves a local version of the graph of the building, which will be used to compute the shortest route independently during evacuations. The local graph can be updated by:

- Identify whether the edge being visited by this evacuee is blocked (e.g., by temperature, smoke, or visibility, or by the fact that the owner turns around and seeks alternative routes (Komatsu, Sasabe, and Kasahara, 2016)), and save this updated awareness in their memory.

- Communicate ad-hoc with devices that have come close (e.g., 3 m in the simulation), and exchange their individual awareness of the environment. These other devices can be other evacuees’ mobile devices, or static information depositories.

- Fuse the received awareness of another agent or depository with its own awareness. The merging operation ensures that among duplicates only the awareness with the more recent time stamp will be retained.
During evacuations, each mobile device computes a shortest route locally using A* algorithm, and provides evacuation guidance to the evacuee. The evacuee is supposed to follow the route suggested by the mobile device unless the evacuee finds the edge in front has been blocked. The mobile device senses this situation, allocates the blocked edge with a weight of infinity, and recalculates a new shortest route.

In the simulation, each device has been initialized with awareness of the complete original graph of this building. Such awareness is valid until a disaster strikes and the emergency evacuation is initiated. During the evacuation, the individual agents’ awareness will be updated by continuously sensing the environment and exchanging knowledge with peer agents and depositories.

7.3.5 Evacuation strategies

In order to find out (a) whether adding static information depositories will improve the evacuation performance, and (b) whether deployment of these depositories in staircases or corridors makes a difference, simulations compare three evacuation strategies during evacuation:

- Decentralized evacuation with no static information depositories (denoted by NoDepot), in order to establish the baseline. Evacuees update awareness of the dynamic environment only through exploration and peer-to-peer communication with other agents.

- Decentralized evacuation with information depositories at staircases (denoted by DepotSt). Evacuees update awareness of the dynamic environment not only through exploration and peer-to-peer communication with other agents, but also through peer-to-peer communication with close information depositories. In this strategy, twenty static depositories have been deployed, placed at each floor at locations near the four staircases of this building.

- Decentralized evacuation with information depositories in corridors (denoted by DepotCr). In this strategy, twenty static depositories have been deployed at random locations along the corridors of this building.

The locations of the information depositories are labeled with red squares (for DepotSt) and blue circles (for DepotCr) in Figure 54. Level one has been occupied by spacious labs. In this case, information depositories for DepotCr have been placed at graph nodes that are close to the doors of the rooms.
7.3 EVACUATION SIMULATION MODEL

7.3.6 Evacuation simulation

There are mainly four components in the evacuation simulation (Figure 55): the route graph, the emergency event, the mobile agents and the depositories. The route graph represents the indoor space of the building. All the edges are unblocked before the emergency. The emergency event acts as a stimulus that changes the states of the edges in the route graph. The emergency event and the route graph together create a route graph with changing states over time, which forms the ground truth of the dynamic indoor environment in the simulation. Each mobile agent senses the dynamic changes by visiting certain part of the environment, and keeps a partially out-of-date version of this graph, which forms their local knowledge. Their local knowledge can also be updated by the short-range communication with encountered peer mobile agents and depositories. Information depositories also save a local version of the dynamic graph, but they cannot sense the blocked edges and are immobile. Information depositories are considered to be set up before any event, as a fix part of the infrastructure of a building. In contrast to any centralized communication infrastructure, local depositories are robust towards any type of event and capacity. In this simulation, mobile agents are only blocked by blocked edges. Since this chapter assumes that the density of evacuees is low, the effect of congestions between mobile agents will not be considered. The route graph, the simulated emergency events, the locations of mobile agents, and the locations of depo-
tories have been predefined and saved to files, so that each pair of comparison simulations refer to identical experiment conditions.

![Evacuation simulation model](image)

Figure 55: Evacuation simulation model. A square with a capital letter M represents a mobile agent. A circle with a capital letter D represents a depository.

The agent-based simulation tool Repast Simphony has been used. Figure 56 shows a flow chart of the simulation process. Before an emergency, the states of edges in the (global) route graph are unblocked, and the mobile agents are placed at predefined locations. All the mobile agents are initialized with the complete graph of the building as their prior knowledge. Evacuees are assumed to start evacuation simultaneously and immediately after the emergency alarm. The emergency event expands every two steps, and affects certain edges of the (global) graph, making them blocked. Also the information depositories will be destroyed if the emergency event expands to where the depository locates. The independence of each depository contributes to the robustness of the “system”.
The flow in Figure 56 describes necessarily a simplified model of human behavior. In a real evacuation scenario, people may not evacuate immediately after they hear the emergency alarm, which causes pre-evacuation delays. The start time of evacuation for each evacuee is uncertain, and can be affected by physiological and psychological factors. For example, some people may insist on gathering family members (known as kin behavior (Yang et al., 2005)) before they start evacuation. Such human behavior aspects are not modeled in this chapter since they would add some noise to the results, conflicting with a desire to control the parameters of a simulation for comparison purposes.

Figure 57 describes the subprocess of how a mobile agent acts in each step. Each mobile agent who has not finished the evacuation
tries to compute a shortest route from the current local knowledge. If no route is available, evacuation of this mobile agent is considered to be failing, otherwise this mobile agent tries to move along the evacuation route for 1.5 m unless it encounters blocked edges. The mobile agent updates its knowledge with the current states of the edges that have been visited in this step. Updating happens by overriding older information with newer ones. If other mobile agents or depositories are found within the communication range, they exchange and fuse their knowledge. If the mobile agent has arrived an exit, the mobile agent is considered to be successful. A mobile agent is considered to have finished the evacuation if it has failed or has been successful.

![Flowchart](image)

Figure 57: The subprocess of the simulation for each mobile agent to move in one step.

In this simulation, the moment when the emergency starts is considered as time zero, and the time for each step is considered as one second. The evacuation time of a mobile agent is represented by the steps consumed by this mobile agent. The timestamps of edges in the
knowledge of a mobile agent are represented by the step counts when those edges were visited.

The experiments simulate each of the three evacuation strategies with 100 independent but identical emergency events, i.e., the evacuees start always from the same locations, but the emergency events start from different locations and spread continuously in some random fashion that has been recorded.

7.4 Results

The simulations evaluate the performance of the different strategies in three dimensions:

- **Success rate.** It is measured by the total number of successful evacuees for each emergency event.
- **Evacuation time.** It is measured by the total evacuation steps of all successful evacuees.
- **Currency of situation awareness.** It is measured by the average number of edges that have been updated during evacuations.

The success rate and the situation awareness have been measured based on all the 100 emergency events, while the evacuation time has been compared only when the success rates for different strategies were the same.

7.4.1 Success rate

Success rate measured by the total number of successful evacuees, is the uppermost factor to be used for evaluating the performance of different evacuation strategies.

7.4.1.1 NoDepot vs. DepotSt

Figure 58 shows 100 paired comparisons of DepotSt and NoDepot in their evacuation success. Each point in the scatter plot corresponds to a simulated emergency event. The coordinates of each point shows the evacuation success of the two compared evacuation strategies simulated under that emergency event. Points on the red line indicate the two evacuation strategies have saved equal number of evacuees in those emergency events. The histogram shows the distribution of evacuation success for the 100 emergency events.

Comparing NoDepot and DepotSt, for 87 events (i.e., 87% of the total 100 events) both strategies have saved the same number of evacuees, while for the remaining thirteen events (i.e., 13% of the total 100 events) the number of successful evacuees shows differences (Figure 58). For these thirteen events, DepotSt on average saved 3.4 more people than NoDepot. Specifically, in eleven of these events (84.6% of the thirteen events showing differences in the number of successful evacuees) DepotSt saved more people (4.4 people per event on average) than NoDepot, and only in the other two events (15.4% of the thirteen
events showing differences in the number of successful evacuees), DepotSt saved less people (two people per event on average) (Table 18).

Table 18: The advantages of DepotSt and NoDepot in terms of success rate when the numbers of the successful evacuees for DepotSt and NoDepot differ.

<table>
<thead>
<tr>
<th>Advantageous</th>
<th>Number of Cases</th>
<th>Proportion</th>
<th>More Saved Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>DepotSt’s</td>
<td>11</td>
<td>84.6%</td>
<td>4.4</td>
</tr>
<tr>
<td>NoDepot’s</td>
<td>2</td>
<td>15.4%</td>
<td>2</td>
</tr>
</tbody>
</table>

Figure 58: The number of successful evacuees of each emergency event with depositories at stairs (DepotSt) and without depositories (NoDepot).

7.4.1.2 NoDepot vs. DepotCr

Comparing NoDepot and DepotCr, in 97 events (i.e., 97% of the 100 events) both strategies have saved the same number of evacuees, while in the remaining three events (i.e., 3% of the 100 events) the number of successful evacuees shows differences (Figure 59). DepotCr has saved more people in each of these three events (on average 1.3 more people per event) (Table 19).
Figure 59: The number of successful evacuees of each emergency event with depositories in corridors (DepotCr) and without depositories (NoDepot).

Table 19: The advantages of DepotCr and NoDepot in terms of success rate when the numbers of the successful evacuees for DepotCr and NoDepot differ.

<table>
<thead>
<tr>
<th>Advantageous</th>
<th>Number of Cases</th>
<th>Proportion</th>
<th>More Saved Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>DepotCr’s</td>
<td>3</td>
<td>100%</td>
<td>1.3</td>
</tr>
<tr>
<td>NoDepot’s</td>
<td>0</td>
<td>0%</td>
<td>0</td>
</tr>
</tbody>
</table>

7.4.1.3 Combined depositories

A combined depository scenario has also been simulated. In this scenario, 40 information depositories have been deployed, twenty of which have been placed at the same locations as DepotSt, and the other twenty depositories were placed at the same locations as DepotCr. Result shows that in the cases (eleven emergency cases) where DepotSt has saved more people than NoDepot and the two emergency cases where DepotCr has saved more people than NoDepot, a combined depository scenario also saved more people than NoDepot. In the two emergency cases where DepotSt has saved fewer people than NoDepot, a combined depository scenario also has saved fewer people (Table 20).

Compared with DepotSt, a combined depository scenario shows advantages over NoDepot in three more emergency cases, which at-
tributes to the contribution of the additional twenty depositories near corridors.

Table 20: The advantages of a combined depository scenario in terms of success rate when the numbers of the successful evacuees differ.

<table>
<thead>
<tr>
<th>Advantageous</th>
<th>Number of Cases</th>
<th>Proportion</th>
<th>More Saved Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depository’s</td>
<td>14</td>
<td>87.5%</td>
<td>3.7</td>
</tr>
<tr>
<td>NoDepot’s</td>
<td>2</td>
<td>12.5%</td>
<td>2</td>
</tr>
</tbody>
</table>

7.4.2 **Evacuation time**

The evacuation time has been compared only when different evacuation strategies have saved the same number of evacuees. It is always preferable to save more people even with increased average evacuation time. Therefore, the evacuation time has been considered as a supplementary factor of success rate to evaluate the advantages of different evacuation strategies. Simulation results indicate that deploying depositories has generally accelerated the evacuation process in many simulated emergency cases.

For the 87 events (i.e., 87% of the 100 events) where DepotSt saved the same number of evacuees as NoDepot, the total steps for each event show differences in 28 events. In 27 events (i.e., 96.4% of the 28 events showing differences in the evacuation time), DepotSt reduced the total steps of all successful evacuees by 70 steps. Only in one event (i.e., 3.6% of the 28 events showing differences in the evacuation time), DepotSt used one step more than NoDepot (Table 21).

Table 21: The advantages of DepotSt and NoDepot in terms of evacuation time when the numbers of the successful evacuees for DepotSt and NoDepot are the same.

<table>
<thead>
<tr>
<th>Advantageous</th>
<th>Number of Cases</th>
<th>Proportion</th>
<th>Fewer Steps Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>DepotSt’s</td>
<td>27</td>
<td>96.4%</td>
<td>70</td>
</tr>
<tr>
<td>NoDepot’s</td>
<td>1</td>
<td>3.6%</td>
<td>1</td>
</tr>
</tbody>
</table>

For the 97 events (i.e., 97% of the 100 events) where DepotCr saved the same number of evacuees as NoDepot, the total steps for each event show differences in ten events (i.e., 10% of the 100 events). Compared with NoDepot, DepotCr allowed evacuees to consume less time in all the ten events and has decreased the total steps by 15 steps on average for each of the ten events (Table 22).
Table 22: The advantages of DepoCr and NoDepot in terms of evacuation time when the numbers of the successful evacuees for DepoCr and NoDepot are the same.

<table>
<thead>
<tr>
<th>Advantageous</th>
<th>Number of Cases</th>
<th>Proportion</th>
<th>Fewer Steps Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>DepoCr’s</td>
<td>10</td>
<td>100%</td>
<td>15</td>
</tr>
<tr>
<td>NoDepot’s</td>
<td>0</td>
<td>0%</td>
<td>0</td>
</tr>
</tbody>
</table>

7.4.3  Situation awareness

7.4.3.1 NoDepot vs. DepotSt

Situation awareness of an evacuee is measured by the number of edges that have been updated in knowledge during the evacuation. Figure 60 compares the average updated edges for each evacuee. The line is the boundary where the figure for DepotSt and NoDepot are identical. In all the 100 events, DepotSt allowed evacuees to update more of their knowledge. Compared with NoDepot, DepotSt leads to an increase of 15% on average of the edge updates (15.4 more edges updated per person for each event) (Table 23).

Table 23: The advantages of DepotSt and NoDepot in terms of situation awareness when the numbers of the updated edges for DepotSt and NoDepot differ.

<table>
<thead>
<tr>
<th>Advantageous</th>
<th>Number of Cases</th>
<th>Proportion</th>
<th>More Updated Edges Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>DepotSt’s</td>
<td>100</td>
<td>100%</td>
<td>15.4</td>
</tr>
<tr>
<td>NoDepot’s</td>
<td>0</td>
<td>0%</td>
<td>0</td>
</tr>
</tbody>
</table>
Figure 60: The average number of updated edges in knowledge for each evacuee in 100 emergency events with DepotSt and with NoDepot.

7.4.3.2 NoDepot vs. DepotCr

Figure 61 shows that in no event people with DepotCr were less aware of changes in the environment. In most of the events (77% of the 100 emergency events as in Table 24), people with DepotCr had more updates of their awareness than with NoDepot. On average, DepotCr allowed evacuees to be more updated by 3.3% (3.3 more edges per person on average for each of the 100 emergency events).
Figure 61: The average number of updated edges in knowledge for each evacuee in 100 emergency events with DepotCr and with NoDepot.

Table 24: The advantages of DepotCr and NoDepot in terms of situation awareness when the numbers of the updated edges for DepotCr and NoDepot differ.

<table>
<thead>
<tr>
<th>Advantageous</th>
<th>Number of Cases</th>
<th>Proportion</th>
<th>More Updated Edges Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>DepotCr’s</td>
<td>77</td>
<td>100%</td>
<td>4.3</td>
</tr>
<tr>
<td>NoDepot’s</td>
<td>0</td>
<td>0%</td>
<td>0</td>
</tr>
</tbody>
</table>

7.4.4 Staircase vs. corridor

Figure 62 compares static depositories deployed at staircases and static depositories deployed in corridors. For strategies with depositories, in eleven events (i.e., 11% of the 100 events) DepotSt saved more people than DepotCr (4.4 people per event on average). In five events (i.e., 5% of the 100 events), DepotCr saved more people (1.6 people per event on average) (Table 25). A Wilcoxon signed ranks test shows that the differences between the successful evacuees of DepotSt and DepotCr are statistically significant with a confidence interval of 95% ($p = 0.0352$).
Table 25: The advantages of DepotSt and DepotCr in terms of success rate when the numbers of the successful evacuees for DepotSt and DepotCr differ.

<table>
<thead>
<tr>
<th>Advantageous Number of Cases</th>
<th>Proportion</th>
<th>More Saved Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>DepotSt’s</td>
<td>11</td>
<td>68.8%</td>
</tr>
<tr>
<td>DepotCr’s</td>
<td>5</td>
<td>31.2%</td>
</tr>
</tbody>
</table>

Figure 62: The number of successful evacuees of each emergency with static depositories being deployed at staircases or in corridors.

Generally, deploying depositories at staircases has allowed people to be more situational aware than deploying the sensors in corridors (Figure 63). Specifically, DepotSt demonstrated advantages over DepotCr in 98% of the 100 events (by 12.4 edges per person). Only in 2% of the 100 events, DepotCr was better than DepotSt, allowing on average 1.5 more edges to be updated (Table 26). Overall, deploying depositories at staircases allowed evacuees to be more updated about the environment by 11.7% (12.1 edges per person per event). To find out whether the differences between the average edge updates for DepotSt and DepotCr are significant, a Wilcoxon signed ranks test has been applied. Test results reject with a confidence interval of 95% ($p = 3.6782 \times 10^{-5}$) the null hypothesis that DepotSt and DepotCr are not significantly different in their average number of updated edges.
Table 26: The advantages of DepotSt and DepotCr in terms of situation awareness when the numbers of the updated edges for DepotSt and DepotCr differ.

<table>
<thead>
<tr>
<th>Advantageous Number of Cases</th>
<th>Proportion</th>
<th>More Updated Edges Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>DepotSt’s 98</td>
<td>98%</td>
<td>12.4</td>
</tr>
<tr>
<td>DepotCr’s 2</td>
<td>2%</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Figure 63: The average number of updated edges for each evacuee in 100 emergency events with depositories being deployed at staircases (DepotSt) or in corridors (DepotCr).

7.4.5 Information depositories vs. fading memory

Information depositories improve evacuation by enhancing the knowledge exchange and thus allow for more current awareness. The current awareness, however, has been acquired based on visiting certain parts of the environment by some agent. This means, any agent’s situation awareness has some age, compared to a continuously changing environment. In order to introduce the information age into decision making, a ‘fading memory’ model has been proposed (Zhao and Winter, 2016): It improves evacuation success by relying more on more recent information.

To find out whether information depositories improve evacuation in a more robust way than the fading memory, additional simulations have been run implementing the fading memory model and applying the same 100 emergency events.
Figure 64 shows the number of successful evacuees for NoDepot and the fading memory strategy. The line separates the pairs of comparison for each emergency event. On the left side of the line, fading memory saved more people than NoDepot. On the right side of the line, fading memory saved fewer people than NoDepot.

Generally, both the fading memory strategy and DepotSt saved more people than NoDepot. Fading memory outperformed DepotSt in both the quantity and the magnitude of evacuation success. Specifically, in 29 events (i.e., 29% of the total 100 events) fading memory has saved more people (6.1 more persons on average per event), which is more than twice the number of events when DepotSt saved more evacuees than NoDepot (Section 7.4.1). However, fading memory also saved fewer people than NoDepot (3 persons on average per event) in more cases (6 events). Thus in this simulation, fading memory is less predictable than DepotSt (Table 27).

Table 27: The advantages of NoDepot and fading memory in terms of success rate when the numbers of the successful evacuees for NoDepot and fading memory differ.

<table>
<thead>
<tr>
<th>Advantageous</th>
<th>Number of Cases</th>
<th>Proportion</th>
<th>More Saved Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fading Memory’s</td>
<td>29</td>
<td>82.9%</td>
<td>6.1</td>
</tr>
<tr>
<td>NoDepot’s</td>
<td>6</td>
<td>17.1%</td>
<td>3</td>
</tr>
</tbody>
</table>

Figure 64: The number of successful evacuees of each emergency without depositories, compared to applying a fading memory strategy.
Figure 65 compares evacuations with DepotSt and using fading memory. In 29 events (i.e., 29% of the total 100 events), fading memory saved more people than DepotSt (5.1 persons per event on average). In twelve events (i.e., 12% of the total 100 events), DepotSt saved more people than fading memory (2.8 persons per event on average) (Table 28). A two-tailed Wilcoxon signed-rank test shows that the differences between the number of successful evacuees for DepotSt and fading memory strategies are statistically significant ($p = 0.0011$).

Table 28: The advantages of DepotSt and fading memory in terms of success rate when the numbers of the successful evacuees for DepotSt and fading memory differ.

<table>
<thead>
<tr>
<th>Advantageous Memory</th>
<th>Number of Cases</th>
<th>Proportion</th>
<th>More Saved Per Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fading Memory's</td>
<td>29</td>
<td>70.7%</td>
<td>5.1</td>
</tr>
<tr>
<td>DepotSt's</td>
<td>12</td>
<td>29.3%</td>
<td>2.8</td>
</tr>
</tbody>
</table>

Figure 65: The number of successful evacuees of each emergency with depositories being deployed at staircases, or applying fading memory.

7.5 Summary and Discussion

Table 29 shows a summary of the comparisons among different evacuation strategies in three dimensions: success rate, evacuation time, and situation awareness. For the success rate, the figures show the
numbers of simulated emergency cases where one evacuation strategy has saved more evacuees than another evacuation strategy, and the figures in parentheses represent the numbers of the more evacuees saved per case. For the evacuation time, the figures are the numbers of simulated emergency cases where one evacuation strategy used less evacuation time than another evacuation strategy, and the figures in parentheses represent the numbers of the fewer steps used per case. For situation awareness, the figures are the numbers of simulated emergency cases where one evacuation strategy has more edge updates than another evacuation strategy, and the figures in parentheses represent the numbers of the more edges updated per case. The evacuation times were computed based on the cases when two evacuation strategies have saved the same number of evacuees but have consumed different evacuation times. Table 30 shows the average success rates and the average edge updates calculated from the total 100 simulated emergency cases. To find out whether the differences of success rates and edge updates between NoDepot and other evacuation strategies are statistically significant, the Wilcoxon signed-rank test has been applied.

Table 29: Comparisons among different evacuation strategies in three dimensions: success rate, evacuation time, and situation awareness. Each figure represents the number of simulated emergency cases where the evacuation strategy is advantageous over the evacuation strategy in the comparison base because of saving more evacuees (the number of the more evacuees saved per case in parentheses), or because it has saved the same number of evacuees but has consumed less time (the number of the fewer steps used per case in parentheses), or because it has allowed more edge updates (the number of the more updated edges per case in parentheses). The total number of simulated emergency cases is one hundred.

<table>
<thead>
<tr>
<th>Evaluation Factor</th>
<th>Comparison Base</th>
<th>NoDepot</th>
<th>DepotSt</th>
<th>DepotCr</th>
<th>FadingMemory</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Success Rate</td>
<td>NoDepot</td>
<td>–</td>
<td>11 (4.4)</td>
<td>3 (1.3)</td>
<td>29 (6.1)</td>
</tr>
<tr>
<td></td>
<td>DepotSt</td>
<td>2 (2.0)</td>
<td>–</td>
<td>5 (1.6)</td>
<td>29 (5.1)</td>
</tr>
<tr>
<td></td>
<td>DepotCr</td>
<td>0 (0.0)</td>
<td>11 (4.4)</td>
<td>–</td>
<td>29 (6.0)</td>
</tr>
<tr>
<td></td>
<td>FadingMemory</td>
<td>6 (3.0)</td>
<td>12 (2.8)</td>
<td>6 (3.2)</td>
<td>–</td>
</tr>
<tr>
<td>Evacuation Time</td>
<td>NoDepot</td>
<td>–</td>
<td>27 (70.5)</td>
<td>10 (14.6)</td>
<td>16 (120.4)</td>
</tr>
<tr>
<td></td>
<td>DepotSt</td>
<td>1 (1.0)</td>
<td>–</td>
<td>5 (25.6)</td>
<td>12 (68.4)</td>
</tr>
<tr>
<td></td>
<td>DepotCr</td>
<td>0 (0.0)</td>
<td>24 (75.0)</td>
<td>–</td>
<td>16 (117.4)</td>
</tr>
<tr>
<td></td>
<td>FadingMemory</td>
<td>5 (24.2)</td>
<td>13 (72.0)</td>
<td>9 (14.3)</td>
<td>–</td>
</tr>
<tr>
<td>Situation Awareness</td>
<td>NoDepot</td>
<td>–</td>
<td>100 (15.4)</td>
<td>77 (4.3)</td>
<td>33 (5.5)</td>
</tr>
<tr>
<td></td>
<td>DepotSt</td>
<td>0 (0.0)</td>
<td>–</td>
<td>2 (1.5)</td>
<td>4 (8.0)</td>
</tr>
<tr>
<td></td>
<td>DepotCr</td>
<td>0 (0.0)</td>
<td>98 (12.4)</td>
<td>–</td>
<td>9 (11.0)</td>
</tr>
<tr>
<td></td>
<td>FadingMemory</td>
<td>20 (3.1)</td>
<td>96 (15.1)</td>
<td>60 (5.1)</td>
<td>–</td>
</tr>
</tbody>
</table>
Table 30: The average success rate and the average edge updates calculated from the total 100 simulated emergency cases. Statistical significant differences (Wilcoxon p < 0.05) are indicated with (*), and standard deviations are labeled in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>NoDepot</th>
<th>DepotSt</th>
<th>DepotCr</th>
<th>FadingMemory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Success Rate</td>
<td>82.1 (9.3)</td>
<td>82.5 * (9.0)</td>
<td>82.1 (9.3)</td>
<td>83.7 * (8.6)</td>
</tr>
<tr>
<td>Average Edge Updates</td>
<td>100.3 (18.0)</td>
<td>115.7 * (28.2)</td>
<td>103.6 * (19.4)</td>
<td>101.5 (17.5)</td>
</tr>
</tbody>
</table>

Table 30 shows that the edge updates of DepotSt and DepotCr were significantly different from the edge updates of NoDepot, which means that integrating information depositories has made a significant difference in situation awareness. Table 29 shows that, in all the one hundred simulated emergency events, DepotSt has more edge updates than NoDepot, and DepotCr has improved edge updates in 77% of the simulated emergency events. In no cases, DepotSt or DepotCr has fewer edge updates than NoDepot. It is safe to conclude that integrating information depositories has improved the situation awareness in terms of the edge updates.

The Wilcoxon signed-rank test also shows that a significant difference between the success rate of DepotSt and NoDepot was observed. Table 29 shows that deploying information depositories at staircases has guaranteed to save no fewer evacuees in 98% of the simulated emergency events, and to consume no more evacuation time in 99% of the simulated emergency events. It has improved the evacuation results in 38% of the simulated emergency events, either by saving more evacuees (11 simulated emergency cases), or by reducing the evacuation time (27 simulated emergency cases).

Noticeably, although DepotSt has more edge updates in all the simulated emergency events than NoDepot, there are still two cases where DepotSt has saved fewer evacuees and one case where DepotSt has increased the evacuation time. This can be explained by the complexity of the evacuation problem per se. Evacuation dynamics is very complex, where multiple factors are involved and interact non-linearly to produce an output shown as features such as the success rate and evacuation time (Vermuyten et al., 2016). In some cases, even if the situation awareness has been more current due to the new strategy, such improvements may not always trigger an increased number of successful evacuees or decreased evacuation steps. In very few cases, such improvements of situation awareness may still accidentally lead to decreased evacuation success due to the effect of non-linear interactions between different evacuees, and the interactions between evacuees and the dynamically changing environment. This also explains why there are more cases where integrating information depositories has increased edge updates and decreased evacuation steps, but less so many cases where integrating information depositories has saved more people.

Compared with the significant improvements by deploying information depositories at staircases, depositories in corridors have made
less significant improvements. The comparison of the Wilcoxon signed-rank tests for DepotSt and DepotCr also indicates that the information depositories should be strategically distributed. Simulation results suggest information depositories at staircases lead to better evacuation outcome than information depositories in corridors. Compared with corridors where evacuees’ route choices are largely restricted, staircases may allow evacuees to have more alternatives towards the exits and more likely to make decisions that have a significant impact on the evacuation outcome. A combined depository scenario of DepotSt and DepotCr shares the advantages and disadvantages on both sides. Comparison of evacuation success between a combined depository scenario and DepotSt suggests that increased number of depositories leads to more evacuation success.

The fading memory, as another approach to bridging the temporal gap of knowledge exchange in decentralized evacuations, has also improved the evacuation success significantly. Compared with DepotSt, fading memory has improved the evacuation success in a larger number of cases (29 cases), and has a larger average success rate (83.7%). At the same time, in more cases (6 cases), it has saved fewer evacuees than DepotSt (2 cases), which fundamentally attributes to the mechanism of fading memory model per se: Fading memory devalues older knowledge because of losing trust in its continuing validity, which involves risks of devaluing knowledge that is still valid. In such life-critical situations as evacuations, the uncertainty of leading to fewer people saved should be minimized at strategic level. An evacuation strategy that almost guarantees saving no fewer people is much reliable than a strategy that involves large uncertainty. In this sense, deploying information depositories is more robust than fading memory method in terms of improving the evacuation performance.

DepotSt has also outperformed fading memory in the number of updated edges. In 96% of the cases, DepotSt has more edge updates than the fading memory, while only in four cases does fading memory have more edge updates. Compared with fading memory, DepotSt has added information depositories and allows asynchronous communication for awareness sharing in decentralized evacuations. More situation awareness contributes to better prediction, which is essential for fading memory method. So it can be anticipated that a hybrid model that integrates information depositories and fading memory can benefit from the advantages of both sides.

In summary, information depositories generally improve evacuation performance on all measures:

- In terms of the number of successful evacuees, information depositories guaranteed almost always no less successful evacuees than NoDepot. In a portion of events, information depositories saved significantly more people.
- In terms of the time consumed by the evacuees, information depositories allow evacuees to almost always use no more steps than NoDepot. In a number of events, information depositories allow evacuees to complete evacuation within fewer steps.

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• In terms of the update of knowledge, simulation results indicate that information depositories guaranteed that no fewer edges were updated during evacuations, especially when the information depositories were deployed at staircases, where the number of updated edges has increased by 15.3% on average.

• In terms of the location of depositories, deploying information depositories at staircases can improve evacuation more than deploying sensors in corridors.

The chapter develops a concept of information depositories for decentralized evacuation. The information depositories bridge the temporal gap of asynchronous communication for awareness sharing in decentralized evacuations. Depositories collect the environmental and risk information from passing by agents, maintain this information by fusion, and convey the fused information to passing-by evacuees. Simulations verify that information depositories enhance the spatial awareness of the environment and risk awareness by tracking states and updating information, thus raising the chance that people survive and or can reduce their evacuation time. This chapter also suggests that the information depositories should be deployed at strategic locations such as staircases. A comparison of the alternative approaches of fading memory and information depositories shows that information depositories are more reliable than the fading memory when improving the evacuation outcome. However, fading memory also has advantages that can be combined by information depositories. Overall, simulation results support the hypothesis that even a small number of information depositories will enhance risk awareness of evacuees and improve the evacuation results.

Without explicitly tested, it is anticipated that there will be an upper bound of the density of information depositories. Beyond that bound, no significant improvements will occur by increasing further the number of information depositories. Deploying information depositories at strategic locations such as staircases are advantageous possibly because staircases are “bottlenecks”, or, generally, have a high centrality in the evacuation graph, which can be investigated in the future. Future work may also explore whether information depositories work equally well in decentralized evacuation for events with substantially different behavior, such as earthquakes or a roaming sniper, and whether deploying depositories near staircases or in corridors are better options for these kinds of disasters. Since depositories improve situation awareness, and more situation awareness may contribute to better prediction, it is expected a hybrid model combining information depositories and fading memory will significantly improve the evacuation performance.
DISCUSSION

8.1 CONTEXT AWARENESS AND TIME AWARENESS

As described in Chapter 1, for evacuation the context awareness consists of two aspects:

- knowledge of the topological structure of the indoor space
- knowledge of the dynamic risk in the indoor environment

In this thesis, the topological structure of the indoor environment has been represented by a route graph. Each edge denotes a connection in the built environment (e.g., a corridor) that allows people to move from one location to another. Each connection in a building is considered as persistent over time during the evacuation process. An edge will be described by the risk attached with that edge, which is the second aspect of the context awareness. Evacuees may, at any time, have knowledge of the complete graph or only part of this graph depending on the strategies they have adopted.

The dynamic risk in the indoor environment describes whether an edge is safe to pass or has been blocked. Unlike the topological structure of the indoor space, during evacuations, the risk associated with edges in the indoor space (i.e., the state) is dynamically changing over time due to the emergency dynamics, thus the risk of an edge always refers to particular time stamp. The changes of the risk attached with an edge correspond to a trajectory of the states of that edge along the time dimension. Evacuees may have knowledge of the risk information of an edge at one or more time stamps. The time stamps has implication on

- whether this knowledge is likely to be still valid;
- how it has possibly changed; and
- how it will possibly change.

This constitutes the main concept of time awareness in this thesis and underpins the dynamic risk aspect of context awareness.

8.1.1 Integrating sensing and routing

In Chapter 3, a centralized evacuation framework integrating sensing and routing has been provided. The indoor space has been modeled as a graph. Context awareness has been achieved by surveillance with sensor networks in real-time. Surveillance data converges in a central server and then will be sent to evacuees via a mobile device carried by each evacuee. Evacuation routes are computed based on a complete
graph of the whole building and its real-time updates. Experiments have compared three evacuation strategies: a blind evacuation strategy (BLIND), a static evacuation strategy (STATIC), and Sensor Tracking and Risk Aware (STRA). In terms of context awareness, the three evacuation strategies have the same complete graph, but the risk information has been unequally updated. STRA, featured by the real-time risk awareness, confirms that any available evacuation route is safe at the current moment. BLIND strategy, the baseline in the comparisons, has the least context awareness and plans a route based on the out-of-date knowledge. It can only update the risk information when the evacuee encounters blocked edges, or in other words, when the evacuee has been directed to a highly risky area. STATIC strategy is better context aware than BLIND only by knowing also the start location of the emergency. The advantage of STATIC strategy over BLIND strategy indicates that even a limited increase in the context awareness leads to improved evacuation results.

8.1.2 Integrating sensing, routing and timing

In Chapter 3, the real-time information may also expire over time, thus currently a safe route may also direct evacuees to a blocked area. This centralized evacuation framework has been improved in Chapter 4 by adding foresight to the real-time context awareness. Three strategies have knowledge of the same complete graph but update the risk information in different ways. No Foresight (NF) updates risk information in the same way as STRA, where risk information is available for time stamps in real-time and in the past. The foresight strategies Exact Foresight (EF) and Conservative Foresight (CF) also consider how the risk information will change in the future by trying to predict the future states of the graph. Compared with no foresight strategies, which makes decision with the most up-to-date risk information, foresight strategies look at the route planning in the picture of the whole process of evacuation, and aim to confirm the resulting route will not be blocked in the future. As foresight at a moment can be inaccurate, at each time steps, the foresight is adjusted with the most recent risk information as provided by the centralized evacuation system. EF, as an ideal situation of exact foresight, guarantees the optimal evacuation route for each evacuee. Simulation proves that prediction can improve evacuation result, and the improvement also shows a dependence on the accuracy of prediction.

8.1.3 Time-aware decentralized evacuation

Chapter 5 considers the time awareness in decentralized evacuation. Without a centralized system to provide real-time updates, the knowledge of evacuees is more likely to be out of date. A fading memory model evaluates the temporal aspect of risk information, and examines how much the knowledge is likely to be invalid and how it may have changed. The model uses threshold to select the knowledge that
is likely to be invalid. A smaller threshold corresponds a more selective criteria for the time-stamped risk information, and thus safer evacuation routes. However, a small threshold may cause that no route can be computed. To avoid over-selectiveness, when a small threshold yields no results, the threshold value is iteratively adjusted to allow also less recent knowledge to be considered as valid, until an evacuation route is found. Such adaptive threshold guarantees the adoption of the most recent knowledge. Although the threshold may be adjusted in each step, different initial thresholds also impact the evacuation process. For example, when evacuation routes are available, a smaller initial threshold allows only very recent knowledge to be trusted and impacts the selection of evacuation routes that the evacuees will follow. Such selection of evacuation route then directs the evacuees to areas of different risk level. Fading memory generally improves evacuation by evaluating the time awareness of risk information. However, this method cannot guarantee that the evacuation success will not be lower, due to its possibility of devaluing knowledge that may be still true.

Chapter 5 assumes evacuees have the complete graph of the environment, which is not always realistic. In reality, human activity may happen at anywhere which are not restricted to the buildings that they are familiar with. They may enter a building which they are unfamiliar with, or conduct activity in an outdoor environment. For example, a person may go to a city or a country as a first-time visitor, or a person may explore an outdoor space such as a mountain then the bush fire suddenly breaks out. To go a step further, Chapter 6 addresses the decentralized evacuation when the complete graph is not available. The findings would allow fading memory to be applicable to more generic circumstances. Simulation suggests evacuees in an unfamiliar environment may also benefit from the fading memory method. Compared with the previous chapters, which all assume a complete knowledge of the topological structure, Chapter 6 differs in that it assumes the least prior knowledge of the topological structure at the start of an evacuation. The complexity in this part of research has increased by the involvement of heuristics to explore the unknown part of the environment, as well as a balance of devaluing old knowledge and exploring unknown territories. Chapter 6 prioritizes the exploitation of existing knowledge over the exploration of the unknown environment, and adopts two exemplary heuristics that have been previously used in literature. Other sophisticated heuristics or reasonable balancing between existing knowledge and exploration can also be substituted for specific applications.

8.1.4 Information depositories

Both Chapter 5 and Chapter 6 focus on the time awareness, and examine whether the knowledge is prone to have changed or how it may have changed. Fading memory benefits from the exploitation of the existing knowledge without direct increase of the amount of existing
knowledge. However, existing knowledge is acquired and updated via self exploration and peer-to-peer communication. While self exploration in a hazardous environment should be minimized, peer-to-peer communications can be enhanced without additional time consumption. Chapter 7 compensates to *fading memory* by suggesting information depositories, thus fills the temporal gap of asynchronous communication in decentralized evacuations and allows evacuees to be more up-to-date of the state of the environment. Simulations indicate that depositories improve the context awareness of evacuees and save more people. Depositories function more effectively if placed at strategic locations which allow more chance of communications between depositories and evacuees.

8.1.5 *Evacuation strategies*

Figure 66 summarizes where the evacuation strategies in different chapters sit in context awareness and time awareness coordination. *EF* has the most context awareness and time awareness. In *EF* strategy, evacuees have the knowledge of the complete graph in a building, and also know the current and near future risk information of the indoor environment. *CF* has the same context awareness and time awareness; however, the near future risk of the indoor environment is not overestimated and may not coincide with the reality. *NF* in Chapter 4 and *ST&RA* in Chapter 3 are the same evacuation strategy. They have been named differently for better understanding in self-contained chapters.

![Figure 66: The position of evacuation strategies in terms of context awareness and time awareness.](image-url)
Compared with EF, CF, NF and STRA, which all assume a central infrastructure to support the system, STATIC and BLIND are evacuation strategies without a central infrastructure. Fading memory considers the time stamps when the knowledge has been last updated, and examines whether the knowledge has been changed or how it has been changed by prediction. As prediction can have different effects on the evacuation process:

- It can be accurate prediction of the situation, thus the effect equals to an evacuation strategy with real-time risk information.
- It can underestimate or overestimate the situation, thus misleads the evacuees and results in less evacuation success.
- It can, in rare cases, have an effect that is similar to the effect of an exact foresight or conservative foresight strategy. Because of this possibility, fading memory, which has no access to real-time information, is able to generate better evacuation results than an evacuation strategy that has real-time information. Such cases have been discussed in Chapter 5.

Evacuation without Depositories (NoDepot) in Chapter 7 is the same strategy as BLIND in Chapter 3. The depository strategy improves context awareness by enabling the chance of peer-to-peer communications. It relies on the perceived (out-of-date) reality, but makes no predictions. Therefore, its improvement is less so significant than fading memory, but also involves less uncertainty. Compared with fading memory, which improves evacuation results but also introduces risk of saving less people, a depository strategy improves the evacuation with less risk of being harmful to evacuation.

8.2 Evaluation Criteria

There are three factors used in this thesis to assess the advantages of different evacuation strategies:

- The success rate, which is measured by the total number of successful evacuees.
- The evacuation time, which is measured by the number of simulated evacuation steps.
- The knowledge update, which is measured by the number of updated edges during evacuations.

It is possible that not all people can successfully escape from a building in fire emergency, and it is always preferable to save more people than having overall shorter evacuation time. In this regard, the success rate should always be the first criterion when evaluating different evacuation strategies. Therefore, the number of success has been applied as a key criteria in all the experiments in this thesis, which also distinguishes this research from others, which only compares evacuation time. They may assume a disaster so that people
need to evacuate as soon as possible, but they have not simulated a spatially expanding disaster and the subsequent impact on the indoor environment.

Evacuation time has been compared when different evacuation strategies have saved the same number of evacuees. In this thesis, evacuation time only depends on the length of evacuation route of evacuee. The speed of evacuees has been assumed to be a same constant value. The speed can be different in reality, depending on the gender, age, or physical conditions. Since this thesis is not investigating the impact that different speeds have on the evacuation process, such details have been simplified to emphasize the impact caused by different evacuation strategies.

Knowledge update has been applied as a criterion in Chapter 7. In particular, depositories allow asynchronous communications for environment updates and enhance context awareness. Compared with the less evacuation time, which means people can be less exposed to the emergency risk, and the higher success rate, which means more people have survived, more knowledge updates is less so influential as to directly benefit evacuees. However, more knowledge updates may enable evacuees to make better decisions by choosing the safer and shorter evacuation routes, who may otherwise head to risky areas and get trapped or require a detour. Therefore, more knowledge update may indirectly benefit evacuees. It may lead to less evacuation time, or more people saved, or just more updated knowledge.

8.3 ADVANTAGEOUS STRATEGIES

Advantageous strategies do not always save more people. In each chapter, the evacuation success shows no differences between different evacuation strategies in a number of simulations. As discussed in Chapter 7, evacuation is a complex non-linear process, in which multiple factors interact. If the evacuation process is considered as a black box, the inputs of this process will be the initial locations of evacuees, the emergency spatiotemporal dynamics and the evacuation strategies, and the observable factors are the number of success and evacuation time. Although the evacuation strategy may have benefited the evacuation process, as evidenced by the more edge updates in Chapter 7, such improvement has not been sufficient to save more people. In this regard, saving the same number of evacuees does not imply the strategy shows no advantages.

Advantageous strategies do not always save no fewer people. On the other side, an advantageous strategy does not guarantee always save no less people. There are cases when an evacuee was more context aware and quickly chose a route heading to another staircase after knowing the current route was leading to danger. However, due to the specific circumstance of the emergency dynamics and the spatial structure, this evacuee got trapped. By contrast, an evacuee that was less aware of the situation firstly headed to the risk area until encountering a blocked edge, and then returned heading to another staircase.
This delay allowed this evacuee to find out that the other staircase had been blocked before going downstairs, and luckily avoided being trapped. Although the chances are low, a few simulations pick up the possibility.

In decentralized evacuation scenarios, no stochastic strategy can guarantee to be always advantageous in any specific simulations. There is always a possibility that a poor strategy produces a better outcome than a good strategy. Fortunately, this likelihood is low, so that the advantage of a strategy can be reflected by analyzing the statistics of distinct sets of simulations.

There is one exception in the discussed strategies, which guarantees to save *no less* evacuees. Since for EF, before the evacuation, the dynamics of the event as well as its impact on the environment has been precisely predicted, thus route planning become a deterministic problem. The solutions are deterministic and a route that will not block when the evacuees pass through (it may block after the evacuee pass there) can be found at the beginning of evacuation. However, up to now, it is unlikely people can predict exactly what will happen in the next moment, and predictions always inevitably deviate from the reality. In this sense, only in ideal circumstance when exact predictions are available EF can guarantee save no less people.
The thesis contributes to the knowledge of evacuation management in both centralized and decentralized manner by exploring spatio-temporal perspectives and testing conceptual models. Experiments suggest that context awareness and time awareness contributes to improved system performance of evacuation.

9.1 RESEARCH CONTRIBUTIONS

Overall, the major contributions of this thesis are:

- The suggestion of a centralized evacuation framework which integrates sensing and routing for providing real-time context awareness. Experiments demonstrate that such centralized evacuation strategies are prone to save more people and are also able to cut down the evacuation time;

- Consideration of emergency dynamics and addition of foresight to the centralized evacuation framework. Simulations verify that foresight improves evacuation success and the improvements are sensitive to the precision of foresight;

- The implementation of a decentralized evacuation framework where evacuees acquire knowledge based on exploration and peer-peer communications. This considers the time when the knowledge is lastly updated and trusts less the aged knowledge, which has been proved beneficial for decentralized evacuation; and

- The proposal of information depositories for decentralized evacuation. Experiments suggest that information depositories facilitate context awareness and improve evacuation success.

The limitations of this thesis are:

- The simulation assumes evacuees have the same walking speed, so the diversity of evacuees has been ignored. Specific group of evacuees such as visually impaired persons have different walking speeds.

- The simulation assumes simultaneous evacuation start time. In a real evacuation scenario, the start time of evacuation for each evacuee is uncertain, and can be affected by physiological and psychological factors. Human behavior aspects are not modeled since they would add some noise to the results, conflicting with a desire to control the parameters of a simulation for comparison purposes.
9.2 MAJOR RESULTS AND FINDINGS

9.2.1 Integrating sensing and routing

This thesis proposes an integrated data model for indoor evacuation on the basis of building sensor systems and building structure. With the purpose of employing real-time sensor data as references for evacuation route calculation, this thesis converts monitoring sensors to sensor graphs, and integrates these sensor graphs to a route graph. With this integration, sensor tracking and risk aware evacuation routes may be generated dynamically for evacuees. These have been shown to be superior to STATIC or BLIND evacuation plans. So far, hypothesis 1 has been verified. Integrating sensing and routing can save more evacuees compared with evacuation assisted only by static exit signs.

9.2.2 Integrating sensing, routing and timing

To provide additional support for the integration of sensor graphs and a route graph in an indoor environment for route planning in real time, this thesis deploys time expanded versions of the sensor graph and the route graph, and demonstrated that all principles of the integration process are immediately applicable. In particular, this thesis has investigated whether the time expanded versions, allowing route planning with foresight, are advantageous. Experiments show that risk-aware evacuation planning improves evacuation times and the number of saved lives. Experiments have also shown, though, that the impact of the model is sensitive to the accuracy of the foresight in the risk-awareness, and hence, good event spreading models are required. This result verifies hypothesis 2: The integration of time in evacuation facilitates risk-aware and time-aware evacuation planning, which significantly improves both evacuation times and the number of lives saved.

9.2.3 Time aware decentralized evacuation

Spatial knowledge of dynamic environments fades in decision making value over time because of the growing risk that it has become obsolete. This thesis challenges the general validity assumption of spatial knowledge in evacuation routing, and improves the existing decentralized evacuation method by a fading memory concept. Fading memory has been used here to represent the knowledge of a dynamic environment and applies it to route planning. Results show that this fading memory model can improve the evacuation success rates for expanding events or in general improve the decisions made in a dynamic environment. This result verifies hypothesis 3: Devaluing obsolete information in acquired knowledge is beneficial for agents’ decision making in a dynamic environment.
A decentralized evacuation paradigm has been developed. In this paradigm, each evacuee is equipped with one mobile device, which facilitates trajectory recording before the event and also communication and route calculation during the event. The evacuation processes with this mobile device involve two iteration steps. The device firstly tries calculating a route based on existing knowledge, where time-awareness has been considered to avoid potential risks. Then if a route is not available, the device suggests exploration of the environment with heuristics. Experiments show that decentralized evacuation will benefit from trusting more recently updated knowledge and less so the knowledge acquired a long while ago, independent from the prior knowledge of the agents. This experiment result verifies hypothesis 4: When complete prior knowledge is unavailable, fading memory improves the evacuation performance in decentralized evacuation services. Based on this conclusion, applying fading memory in decentralized evacuation is suggested. Such a concept, because of its independence from any central infrastructure, is transferable to any environment, e.g., being applied to any building, without revision of the system.

9.2.4 Information depositories

The thesis develops a concept of information depositories for an efficient collaborative mapping of the dynamic indoor environment during an evacuation. The information depositories bridge the temporal gap of asynchronous communication for awareness sharing in decentralized evacuations. Depositories collect the environmental and risk information from passing-by agents, maintain this information by fusion, and convey the fused information to passing-by evacuees. Experiments verify that information depositories enhance the spatial awareness of the environment and risk awareness by tracking states and updating information, thus raising the chance that people survive and/or can reduce their evacuation time. This chapter also suggests that information depositories should be deployed at strategic locations of high betweenness, such as staircases. A comparison of the alternative approaches of fading memory and information depositories shows that information depositories are more reliable than the fading memory when improving the evacuation outcome. However, fading memory also has advantages that can be combined by information depositories. Overall, experiment results support the hypothesis that even a small number of information depositories will enhance risk awareness of evacuees and improve the evacuation results.

9.3 Reflection and Future Work

9.3.1 Simulation

The simulations presented used a simple, randomized model of event spread. The event is modeled after a spatially-extended disaster such
as a fire disaster, starting from a single location and continuing to expand. Events of other characteristics, such as earthquakes that impact at multiple locations at the same time, or bomb explosions that do not expand after going off, or point-like processes such as a roaming sniper has not been covered by the particular simulations in this thesis. The treatment of risk could directly be replaced by more sophisticated event spread models, for example one that uses information about the building structure and materials.

The simulation in this thesis leaves aside any human behavioral factors, such as walking speed, visual ability or acting under stress. The risk assessment model can also be refined. For example, a formulation by probabilities of blocked edges can replace a threshold model more elegantly, and probabilities can be produced according to the type (or aggressiveness) of the event, e.g., fire spread compared to gas spread.

Both centralized and decentralized evacuation strategies are at risk of leading evacuees on paths that may lead to an emergent phenomenon: route congestion, which has not been implemented in all the simulations in this thesis. Upon occurrence of route congestion, the suggested evacuation path may take longer time than a path that is not congested. With congestion the speed along edges translates to different costs; the alternative routes become least costly. Congestion leads to increased evacuation time, but people are still safe. In order to minimize the evacuation time, future work may also include a module to assess the route congestion. For example, closed-circuit television can be setup around locations where congestion is likely to happen, so that data from the closed-circuit television can be used to analyze the route congestion. Since each evacuee carries a mobile device recording their locations, the trajectory data can also be used to analyze the route congestion. Including congestion assessment module would allow balanced flow of evacuees while avoiding the hazard from the disaster.

Centralized evacuation assumes that sensors are connected to a central server and are providing correct readings. In the case of an event some sensors may get disconnected, thus becoming not reachable anymore. Such unreachable sensors would have unknown status that cannot be simply considered as activated. Some sensors may provide wrong readings. Future work would investigate to what extent the uncertainty and measurement errors would affect the results of the evacuation strategies.

9.3.2 Fading memory

Fading memory tracks the state of an edge as well as the age associated with the acquisition or last affirmation of that state. One evacuee may visit the same edge multiple times at different instances. Different evacuees may also visit a same edge at different times, in which case they share the knowledge of this edge. In this regard, for a same edge, a list of states at different times can be available, exhibiting
rich information of the process how the state of an edge changes over time. When it is applied the entire route graph, the spatial and temporal dynamics of the graph can be partially demonstrated. The current fading memory model only retains the most recent state and age of the known edges, collapsing all the historic states in the process. In future research, an enriched fading memory model can be developed by retaining the rich information of the states. Upon an enriched fading memory model, further exploration and sophisticated computation are possible, for example predicting speed ranges of the event, as well as the near future states of the graph, in further support of risk avert decision making.

9.3.3 Information depositories

Without being explicitly tested, it is anticipated that there will be an upper bound of the density of information depositories. Beyond that bound, no significant improvements for evacuation success will occur. Locations at staircases are advantageous possibly because staircases are bottlenecks, or, generally, have a high centrality in the evacuation graph. The contribution of centrality and evacuation success with depositories can be investigated in the future, leading to informed placement of depositories. Since depositories improve situation awareness, and more situation awareness may contribute to better prediction, it is expected a hybrid model combining information depositories and fading memory will significantly improve evacuation performance.

9.3.4 Route graph

In this thesis, the graph is not directed. The thesis assumes that the only factor that impacts the accessibility of an edge is the fire disaster. Each edge is either accessible from both directions (when the edge has not been blocked by the fire); or is not accessible from either direction (when the edge has been blocked by the fire).

The direction of an edge can make a difference when other factors are also considered, such as:

1. Crowd congestion. When a path is congested, evacuees may be constrained to only one direction: the direction that the crowds are moving towards, so that moving against the direction of the crowds can be difficult.

2. Access restrictions such as locked doors. Accessibility through a locked door can be restricted to one direction: from the inside to the outside. The opposite direction may be accessible only if the evacuees have appropriate keys.

Stairs may be considered adding not a restriction but a direction-dependent weight, assuming different walking speeds upstairs or downstairs. Also, varying mobility of individuals may add individual weights to the edges. In this thesis these differences are neglected
since it is in the first instance interested to proof concepts for a general (or average) pedestrian. Only if the concepts have been proven it makes sense to implement services for varying user groups.

9.3.5 Sensor graph

Future research may also borrow the concept from a wireless sensor network (WSN), where sensors represent devices that can not only capture environmental stimuli, but also communicate with each other when they are within communication range. The sensor graphs in Chapter 3 and Chapter 4 are conceptual representations different from a WSN. In a sensor graph, a node represents a type of sensor (e.g., a sensor to detect temperature, or smoke density), and an edge represents the relation that two sensors overlap in their detection areas, rather than that they are within communication range, as in a WSN. In a sensor graph, each sensor directly connects to the central server and does not communicate with neighbored sensors. In this case, once the central server has been destroyed by the disaster, the whole system fails.

An improved system would suggest each sensor not only connects to the central server but is also enabled for wireless communication with neighboring sensors and passing-by evacuees. The appealing advantage of this system is that it is robust against failure. Firstly, even if the central server has been destroyed, the sensors can still work as depositories in a decentralized way. As suggested in Chapter 7, decentralized evacuation with depositories, even disconnected and of very limited number, is beneficial. However, a connected sensor network operating as depositories would provide a globally accessible depository of, in principle, total situation awareness. Secondly, the disaster may separate the global sensor network of the whole building into isolated small sensor networks that work locally, but communications between neighbored sensors allow still information to be shared in the isolated small sensor network, which continues to provide situation awareness to evacuees. Thirdly, the evacuees move between different local sensor networks, remedying the information gap between separated local sensor networks. The interaction between sensors and evacuees allow the information to flow around the global sensor network. Evacuees with such situation awareness are also expected to evacuate efficiently.
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