Characterization of the Urban Street Network and its Emerged Phenomena

Aisan Kazerani

SUBMITTED IN TOTAL FULFILMENT OF THE REQUIREMENTS OF THE DEGREE OF MASTER OF APPLIED SCIENCE GEOMATIC ENGINEERING (BY RESEARCH)

Department of Geomatics
The University of Melbourne, Australia
January 2010

Supervisor:
Associate Professor Stephan Winter
Abstract

An urban environment can be abstracted in form of a street network in order to be further analysed structurally. The urban street network can be represented in various ways by taking different principles and constraints into account. Therefore the aim of this work is to investigate human behaviour and communication in emerged urban phenomena, namely traffic flow and wayfinding, by structural characterization of an appropriate representation of an urban street network and modifying the conventional methods.

In order to characterize the depicted urban street network, centrality measure and specifically betweenness centrality is utilized. This analysis is then implemented to characterize the studied urban phenomena with respect to their structural, temporal and dynamic properties. In case of studying only the structural properties of the phenomena such as route description or self localization the conventional betweenness centrality is performed. But in case of studying the dynamic and temporal properties of a phenomenon such as traffic flow a modified version of betweenness centrality is proposed which considers dynamic and temporal aspects of human travel behaviour.

Experiments are designed to test the implementation of the suggested methods in the studied urban phenomena. The results of experiments demonstrate the efficiency of the proposed model in characterization of the studied urban phenomena in this thesis and then mention some of the problems and potential areas for future works.
Declaration

This is to certify that

i. the thesis comprises only my original work towards the Masters except where indicated,

ii. due acknowledgement has been made in the text to all other material used,

iii. the thesis is 24,980 words in length, inclusive of footnotes, but exclusive of tables, maps and bibliography.

Aisan Kazerani
Acknowledgments

When I first started my master, I had no idea of doing research and was not really sure whether I should do that by research. But now after 18 months I am so grateful that I chose to do my master by research to gain such amazing experiences. This would not have been possible without the contribution of many people. First, I would like to express my gratitude to my supervisor, Dr. Stephan Winter. He showed me how to observe and think like a researcher and guided me through all scientific obstacles. Many people have contributed directly or indirectly to this thesis and I apologize for mentioning only a few. I would also like to thank other members of our research group especially Yunhui Wu, who was a nice friend and a helpful colleague.

I would like to express my deepest gratitude to a few very special people - my parents, who were always encouraging and supportive in all steps of my research and supported me from all the possible aspects so that I can focus on my research, and also my brother and his wife whom without their love and understanding I couldn’t have finished this thesis. Special thanks to my amazing friend, Farhad Goodarzy who not only assisted me with his wonderful scientific ideas, but also supported me emotionally so much so that I could keep going.
When you are far from home, writing a thesis can be a hard experience, but I should thank all of my friends specially my friends in penthouse of the Geomatics department who created such a friendly atmosphere that I always felt like being home.
Publications

Conference Papers


Submitted Journal Paper

Contents

Front Matter

Conference Papers ........................................................................................................ vi
Submitted Journal Paper ........................................................................................... vi
Contents ....................................................................................................................... viii
List of Tables ............................................................................................................... xi
List of Figures .............................................................................................................. xii

1 Introduction .............................................................................................................. 1
   1.1 Problem and Motivation .............................................................................. 1
   1.2 Hypothesis ................................................................................................. 5
   1.3 Methodology ............................................................................................... 6
   1.4 Expected Outcomes ................................................................................... 7
   1.5 Structure of the Thesis .............................................................................. 8

2 Literature Review .................................................................................................. 10
   2.1 Urban Street Network Representation ..................................................... 10
       2.1.1 Space Based Representations of Urban Environment .............. 14
       2.1.2 Geometric and Topological Representations ............................ 17
       2.1.3 Segment Based Representation ................................................ 18
       2.1.4 Named Street Representation .................................................. 20
       2.1.5 Good Continuation Representation ........................................... 21
       2.1.6 Primal and Line Graph Representations .................................. 26
2.2 Centrality Measures for Structural Analysis of Urban Street Network

2.3 Basic Centrality Measures for Network Analysis

2.4 Spatial Network Analysis and Space Syntax Tools

2.4.1 igraph

2.4.2 Mindwalk

2.4.3 Pajek

2.4.4 Axwoman

2.4.5 AJAX

3 Selection of an appropriate Street Network Representation

3.1 Requirements of the Studied Phenomena for Selection of an Appropriate Representation

3.1.1 Limitations of an Axial Lines Representation

3.1.2 Limitations of Segment Based and Named Street Representations

3.2 The Selected Appropriate Street Network Representation

3.2.1 Angular Analysis for Applying Good Continuity Principle

3.2.2 Correlation of the selected representation with the studied phenomena

4 Analysis of Urban Street Network and Its Emerged Phenomena

4.1 Characteristics of Betweenness Centrality in Various Representations of a Street Network

4.2 Edge Betweenness Centrality of the Primal Approach for Characterization of the Studied Urban Phenomena

4.3 Investigating Various Aspects of Human Travel Behaviour and its Effects vs. Network Effects in Urban Movement

4.4 Developing a Model of Modified Betweenness Centrality
5 Implementation and Test

5.1 OpenStreetMap Data Extraction ........................................................ 73
5.2 Modified Betweenness Centrality for Explaining Traffic Flow ....... 75
5.3 Situated Local and Global Mobile You Are Here Map ................. 85
5.4 User tailored Route Description Systems ........................................... 93

6 Conclusion

6.1 Summary ............................................................................................ 101
6.2 Discussions ......................................................................................... 104
6.3 Outlook ............................................................................................... 106
Bibliography ............................................................................................... 109
List of Tables

Table 4-1: Betweenness centrality of the edges $e_i (=v'_i)$ in Figure 4-2, right .................. 68
Table 4-2: Modified betweenness centrality algorithm parameters ....................................... 70
Table 5-1: Individual travel demand between 9am and 10am on a weekday....................... 79
Table 5-2: Origins and destinations of people in the morning (left), during the day (centre) and in the afternoon (right).................................................................................. 82
List of Figures

Figure 2-1: Grid like (left) and hierarchical (tree like) (right) structure ....................... 11

Figure 2-2: Axial map representation on convex map .................................................. 16

Figure 2-3: The street segment representation ............................................................ 19

Figure 2-4: An example of named street representation ............................................. 20

Figure 2-5: A simple example of good continuation principle .................................. 22

Figure 2-6: Every-best-fit representation .................................................................. 24

Figure 2-7: Self-best-fit representation ...................................................................... 25

Figure 2-8: Self-fit representation .............................................................................. 25

Figure 2-9: Primal (blue) and line (green) representations ........................................ 26

Figure 4-1: Edge betweenness of the primal (blue) is different from node betweenness of line (pink) representation ............................................................................... 60

Figure 4-2: Street centerline graph in primal (left) and line representation (right, dashed) ........................................................................................................................................... 68

Figure 5-1: The street centerline graph enriched with places and split edge weights..... 78

Figure 5-2: A street network with Central Business District (CBD) and suburbs .......... 81

Figure 5-3: People’s origins and destinations in the morning (blue arrows), at noon (green) and in the afternoon (orange) ........................................................................................................... 83
Figure 5-4: Comparison of conventional and modified edge betweenness centrality in three different time periods........................................................................................................ 84

Figure 5-5: The three levels of detail in a visual YAH presentation on a mobile display 87

Figure 5-6: Bremen city street network before (first) and after applying good continuity principle (second) and only the merged streets highlighted with black (bottom)......... 90

Figure 5-7: Streets of different betweenness range of values with different colors........ 92

Figure 5-8: Bremen city street network before (first) and after applying good continuity principle (second) and only the highlighted merged streets (bottom) ............................. 96

Figure 5-9: Streets of different betweenness range of values with different colors........ 98
Chapter 1

Introduction

1.1 Problem and Motivation

Urban form (Abelson et al. 2002) is usually represented as a pattern of identifiable urban elements such as locations or areas whose relationships to one another are often associated with linear transport routes such as streets within cities. These elements and their relations or associations depending on the type of analysis, can be thought of as forming nodes and edges in a graph. This graph can be represented in various ways in terms of structure and topology. Depending on the type of studied phenomenon emerged from the street network namely traffic flow prediction, human wayfinding modelling or pedestrian modelling, we can depict the most appropriate representation. The urban street network representations can be categorized into topological and geometric representations. Urban street patterns can be represented geometrically as spatial networks embedded in Euclidean space whose nodes occupy a precise position and whose edges are real physical connections. In a topological approach mainly the
accessibility and connectivity of the network is taken into account. It actually considers individual street segments for better understanding the underlying structure of urban street networks. The main difference between the two approaches is subject to whether or not geometric distance plays an important role in the graph theoretical representations. Since there exist various topological representations, an appropriate representation of the urban street network should be picked up which considers the structural and dynamic requirements of the studied phenomenon. The current existing urban environment representations which will be discussed in detail later in this work are not able to fully express and satisfy the requisites of the studied phenomena to be structurally characterized. Therefore the first research question in this thesis investigates *which type of street network representation should be depicted to be able to explain people’s travel behaviour in an urban environment and also to improve traffic flow and wayfinding assistance systems, as the studied emergent phenomena in this thesis, more appropriately.*

An urban street network can be characterized with respect to its structural properties: such as identification of salient streets of a city or the average level of integration or segregation of a street network. Centrality measures have revealed crucial for understanding the structural properties of complex networks and are also relevant for various spatial factors affecting human life and behaviours in cities (Crucitti et al. 2006a). Centrality measures and specifically betweenness centrality are suggested often in the literature for the characterization of a street network and studying human movement pattern in this urban environment (Hillier and Iida 2005; Crucitti, Latora et al. 2006; Jiang 2007). In this thesis, these measures are used to characterize the emerged studied
phenomena from the urban street network, namely traffic flow or improve the functionality of some wayfinding assistant systems used in this environment, namely a self localization device (mobile You-Are-Here (YAH) map) or a user-tailored route description system which are discussed below.

Traffic flow, in mathematics and engineering, is the study of interactions between vehicles, drivers, and infrastructure (including highways, signage, and traffic control devices), with the aim of understanding and developing an optimal road network with efficient movement of traffic and minimal traffic congestion problems (Lieu 1999). The central points of network flow have often been identified using graph theoretical centrality measures. In real networks, the state of traffic density arises from interplay between the dynamics of the flow and the underlying network structure (Holme 2003). So far centrality measures have been used to express the most relevant physical, topological and static properties of networks but dynamic and temporal aspects of the studied phenomena such as traffic flow are mostly disregarded. But since humans show autonomous, purposeful, flexible, and volatile attributes in urban movement, the traffic flow becomes a function of time and therefore these dynamic and temporal aspects of people’s travel behaviour should be considered in the analysis of the underlying street network. Therefore the second research question is how to modify conventional centrality measures by considering the dynamic and temporal attributes of travel demand in the characterization of underlying street network to be able to predict urban movement patterns such as traffic flow.

Self localization devices or specifically YAH map is usually designed to assist people to be able to orient themselves and have a general idea about their surroundings in an
1.1 Problem and Motivation

unfamiliar environment. On the other hand route description systems assist people by giving instructions to find their destination in an urban environment. In both of these systems, when the structural properties such as the prominence of the streets in terms of the frequency of using them or connectivity of the streets of an urban street network is identified, it becomes easier to guide the user through more prominent or better known streets or present the prominent streets around the location of a person to reduce the level of confusion. For instance we can mention the route description systems or localization devices which consider structurally prominent streets for routing purposes. Therefore the third research question is how to structurally characterize an urban street network in order to improve wayfinding assistance systems such as route description systems or self localization devices.

In brief, the objectives of this research can be summarized as:

1- Investigating different existing representation of the street network and comparing them in order to find out about their potentials and limitations.

2- Selecting an appropriate representation and address a method to overcome its deficiencies for characterizing each of the studied phenomena according to their limits and requisites.

3- Considering the dynamic and temporal attributes of travel demand and traffic flow, as one of the studied phenomenon, in characterization of underlying street network by modification of conventional centrality measures.

4- Investigating whether structural characterization of an urban street network can assist us in improving wayfinding assistance systems such as You-Are-Here maps or route description systems.
1.2 Hypothesis

The goal of this research is first to come up with an appropriate representation of an urban environment for each of the studied phenomena or patterns and second to characterize the urban street network and also phenomena emerged from this urban environment in a way that the structural, temporal and dynamic nature of these phenomena would be taken into account. The research presented in this thesis builds on the hypothesis that it is possible to explain people’s travel behaviour to improve the emergent phenomena such as traffic flow or wayfinding, by characterization of an appropriate representation of the urban street network. For such characterization, the main tool utilized in this thesis is either the conventional centrality measures or the modified one in case the studied phenomenon is temporal or dynamic, such as traffic flow. This thesis investigates possible topological and geometric representations (Hillier 1982; Hillier and Hanson 1984a; Thomson and Richardson 1999; Jiang and Claramunt 2002; Jiang and Claramunt 2004b; Jiang et al. 2008; Jiang and Liu 2009) of a street network in terms of their efficiencies and efficiencies, then picks up the one that has the highest correlation with the requirements of the studied phenomena and furthermore is closer to human mental representation of an urban environment. This representation will be considered in case of any shortage and a novel method will be proposed to overcome its deficiencies. The selected representation of the street network will be then analysed depending on the studied pattern, for instance in case of phenomena such as route direction and navigation purposes, the structural characterization will be applied but in case of analysis of dynamic phenomena such as traffic flow both aspects means the
physical and dynamic aspects would be analysed. Centrality measures (Freeman 1977) which define the relationship between particular structural features of a network are used as a basic measure for such analysis in this thesis. The conventional version of centrality measures is applied when only dealing with the physical properties of the street network in studying a user-tailored route description system or a mobile YAH map. Furthermore a modified version of centrality measure is suggested to study the temporal aspect of dynamic spatial patterns in order to predict traffic flow of a street network.

1.3 Methodology

The approach taken in this research starts from the classification of urban environment representation, allowing the research hypothesis to be formulated. The comparison of the characteristics of geometric and topological representations of the urban street network is provided. By studying various topological representations the most appropriate representation with the highest correlation to the studied phenomenon such as traffic flow or the properties of the studied system such as self localization or route description systems is chosen. The specified representation clarifies the definition and the extension of what was considered as “street” in the studied urban street network and in this way the first research question will be answered accordingly.

The selected representation of the urban environment is then characterized by the use of centrality measures from both the physical aspects and the dynamic aspect of the studied phenomenon. In case of studying dynamic and temporal aspect of human travel behaviour with the aim of predicting traffic flow a modified version of centrality or more
1.4 Expected Outcomes

specifically a modified version of betweenness centrality will be suggested which considers specific origins and destinations for different time periods of the day of human's travel demand. This modified version of betweenness centrality is then compared to the conventional one to observe if and to what extent the modified version can improve the results in terms of explaining the properties of this environment or improving the functionality of the systems utilized in this environment. By introducing a modified version of betweenness centrality and considering temporal aspect of human travel behaviour the second research question will be covered.

In the structural analysis of the physical network, centrality measures are used to characterize the physical street network to identify the streets with high value of centrality. The identified streets with high value of centrality are considered to be prominent to improve the functionality of the related studied wayfinding phenomena in form of a user-tailored route description system or a mobile self localization device.

1.4 Expected Outcomes

The main objective of this research is to choose an appropriate representation for studying each phenomenon or system existing in the urban environment to be characterized by centrality measures and then implementing this method for improving the studied phenomena by taking their different physical and dynamic aspects into account. This characterization would reveal some hidden properties of the urban street network such as the prominence of the streets to be described or shown in navigation assistance systems or the prominence of streets as a measure of traffic absorption with the
aim of traffic flow prediction. Generally it is expected that by characterization of the appropriate representation of the urban street network from structural, temporal and dynamic aspects, the phenomena studied in this work namely, traffic flow or wayfinding in the forms of route description or self localization systems could be better studied and explained with the aim of improving their functionalities.

1.5 Structure of the Thesis

This thesis is structured as follows: the next chapter provides an overview of the relevant concepts and existing literature in the field of different possible geometric and topological representations of the urban street network. Then the basic centrality measures for network analysis will be discussed and compared. At the end some spatial network analysis tools are introduced and compared to each other to study their potentials and deficiencies.

Chapter 3 studies the characteristics of different street network representation and investigates their efficiencies and deficiencies to be able to select the most appropriate presentation for the studied phenomenon. Furthermore the angular analysis will be discussed in order to apply the good continuation principle on the street network. At the end the most appropriate representation for studying the urban phenomena in this thesis will be depicted and explained.

In the following chapter (Chapter 4) characteristics of betweenness centrality in different structural representations is investigated. Then the validity of network analysis on line representation and the impact of psychological aspect in urban movement are
investigated to highlight the necessity of introducing a modified version of betweenness centrality for analysis of dynamic and time-dependant phenomena.

In Chapter 5 first OpenStreetMap is introduced in order to extract spatial data and test the proposed methods. Then the proposed methods will be implemented to improve traffic flow prediction, mobile You-Are-Here map and also route description system. The application and efficiency of these methods in each of these works will be explained in detail. After each implementation, they will be tested through some experiments and then come up with the results. The experiments will be designed on studying and improving the studied phenomena emerged from the urban street network such as testing the proposed modified betweenness centrality for studying the dynamic and temporal aspects of travel demand with the aim of traffic prediction, characterization of the Melbourne street network for improving spatial orientation devices and route description systems.

The thesis concludes with Chapter 6, where first a summary of the whole work is described and the main contributions of the thesis are discussed afterward, then an outlook to future research is drafted.
Chapter 2

Literature Review

This chapter reviews previous work in the fields of different existing urban environment representations and also different categorization of representations such as geometric and topological representations. This introduction leads us to the selection of the appropriate representation later according to their potentials and disadvantageous. Then different centrality measures will be reviewed to observe their ability to characterize structural property of a street network. At the end some of the existing spatial analysis tools will be introduced and compared together to be able to choose the useful tools for the analysis in this work.

2.1 Urban Street Network Representation

Most real world networks can be considered complex by virtue of features that do not occur in simple networks. If cities were perfect grids where all lines have equal lengths and the same number of junctions, they would be described by regular graphs presenting sheer similarity independent of the part of the studied environment. One may argue that
since pure grid systems are highly accessible in terms of connectivity of the nodes and there exists multiple paths between any pair of locations, therefore minimizing the number of necessary navigation instructions they are easy to navigate (Rosvall et al. 2005). However, if we assume that such paths are equally probable, we see that morphology of the perfect grid does not differentiate main spaces and movement tend to be dispersed everywhere. On other hand, if cities were purely hierarchical or in tree shape, they would basically have a main space, like a single route between many pairs of locations, that connects all branches and controls movement between them. This would create a highly segregated system that would cause tough social consequences. It creates either systems of short descriptions and high randomness, i.e. disorder in their underlying spatial organisation, or systems of long descriptions and no randomness (Hillier and Hanson 1984b).

![Grid like (left) and hierarchical (tree like) (right) structure](image)

*Figure 2-1: Grid like (left) and hierarchical (tree like) (right) structure*

Cities seem to be a result of a process of negotiation, through which the paradigms of equality-freedom and hierarchy-control generate a structure of a different kind. The urban
grid minimises descriptions as long as possible while maintaining enough differentiation to establish a hierarchy, resulting from the interplay between the public processes, such as trade and exchanges, and the residential process preserving their traditional structures. The emergent urban street network usually possesses a very complex structure which is naturally subjected to the complex network theory analysis (Hanson 1989). Therefore, cities are neither trees nor perfect grids, but a combination of these structures that emerge from the social and constructive processes. Incorporating the spatial characteristics of an urban environment to a data model involves choosing an adequate representation for each one of them, i.e., a way to code their location, geometric shape, and topological behaviour (Davis Jr and Laender 1999).

The very first problem of graph theory was solved in 1736 by Leonard Euler. He formulated the problem of routing by abstracting a case of a particular city, by eliminating all its features except the landmasses and the bridges connecting them, by replacing each landmass with a dot, called a node (also vertex in graph literature), and each link with an edge. The message beyond Euler’s formulation was that topological properties of graphs (or networks) may limit or, quite the contrary, enhance our aptitude for travel and action in them. A large number of social, biological and man-made systems can be represented in the form of networks. A network similar to what Euler suggested consists of a finite set of nodes \( N \) and a finite set of edges \( E \). A graph is often denoted as a pair \( G(N, E) \), where \( N \) is the set of nodes \( n = \{n_1, n_2, \ldots, n_n\} \), and \( E \) the set of edges, is a subset of the Cartesian product \( N \times N \).

Although graphs are usually shown diagrammatically, they can also be represented as matrices. The major advantage of matrix representation is that the analysis of graph
2.1 Urban Street Network Representation

Structure can be performed using well-known operations on matrices. For each graph, there is a unique adjacency matrix (up to permuting rows and columns). If we assume that the spatial graph of the city is simple (i.e., it contains neither loops, nor multiple edges), the adjacency matrix is a \{0, 1\}-matrix with zeros on its diagonal \((i, j \in N)\):

\[
A_{ij} = \begin{cases} 
1, & i \sim j, \ i \neq j, \\
0, & \text{otherwise}.
\end{cases}
\]  

(2.1)

If the graph is undirected, the adjacency matrix is symmetric, \(A_{ij} = A_{ji}\). If the graph contains twin nodes, the corresponding rows and columns of \(A\) are identical.

In graph theory, connectivity of a node is defined as the number of edges connected to it in the graph. The degree of a node \(i \in V\) is the number of other nodes adjacent to \(i\) in \(G\),

\[
\deg(i) = \text{card}\{j \in N : i \sim j\} = \sum_{j \in N} A_{ij}
\]

(2.2)

The society is made by individuals connected by social interactions (Wasserman and Faust 1994), while the cell functioning is guaranteed by an intricate web of metabolites and chemical interactions. Equally, communication and transportation critical infrastructure systems, as the Internet (Pastor-Satorras et al. 2001), can be modelled as a network. The characterization of the topological properties of such networks has been the subject of attention in the recent literature (Albert and Barabasi 2002). Graph-based approach has been investigated for linear object generalisation such as street networks where the objective is to reduce the complexity of a network in a scale reduction process while retaining its general structure.

The network approach which represents an urban environment in form of a network has been broadly used in urban studies. Since the early sixties, some research has been spent to link the allocation of land uses to population growth through lines of transportation
(Wilson 2000), or seeking the prediction of transportation flows given several topological and geometric characteristics of traffic channels (Larson and Odoni 1981) or eventually investigating the exchanges of goods and habits between settlements in the geographic space even in historical eras. Planar graphs have long been regarded as the basic structures for representing environments where topological relations between components are embedded into Euclidean space. The widespread use of graph theoretic analysis in geographic science had been reviewed in Chorley and Haggett (1968), establishing it as central to spatial analysis of urban environments. The basic graph theory methods had been applied to the measurements of transportation networks by Kansky (1963).

Representing an urban environment by a network can be performed in various ways. The type of representation can be depicted according to the structure of the environment and the kind of analysis that is supposed to be performed on the selected representation. Therefore depending on the type of studied phenomenon in the urban environment, an appropriate representation of the street network should be analysed. In the following sections some of these representations will be discussed.

2.1.1 Space Based Representations of Urban Environment

Space syntax (Hillier 1982; Steadman 1983; Hillier and Hanson 1984a; Hillier 1985; Peponis 1985) is a set of techniques for the representation, quantification, and interpretation of spatial configuration in buildings and settlements. Configuration is defined in general as, at least, the relation between two spaces taking into account a third, and, at most, as the relations among spaces in a complex, taking into account all other spaces. Spatial configuration is thus a more complex idea than spatial relation, which
need invoke no more than a pair of related spaces (Hillier et al. 1987). Being developed as a tool to help architects simulate the likely social effects of their designs, the approach became instrumental in predicting human behaviour i.e., pedestrian or vehicular movement in urban environments (Jiang 1998).

Space syntax has been proven to be successful as a tool for understanding spatial structure, and its social and cultural role in human life, particularly the impact of spatial configuration on human movement in space from a topological point of view (Hillier 1996; Hillier and Hanson 1984b). A popular variant on this theme treats the streets containing one or more junctions, with the equivalent graph representation being more abstract, based on relations between the streets which themselves are treated as nodes.

Configurational models quantify the pattern properties of the street network by creating an axial map. An axial map of the open space structure of the settlement is the least set of axial lines which pass through each convex space and makes all axial links. Figure 2-2 presents an example of an axial map on the convex space. The term axial line is defined as the longest visibility line that can be drawn through an arbitrary point in the spatial configuration. Similarly, the term convex space is a convex polygon around a point and the term convex map consists of the least number of largest possible convex spaces needed to cover the entire area (Turner et al. 2005; Hillier and Hanson 1984b). A unique set of axial lines for any particular configuration would not be produced, because of the dependency to the human judgment.

The process of axial map derivation starts from the identification of the longest axial line and then the next longest one and so forth so that the whole convex space is covered by the intersected axial lines. There are a number of measures of the graph which can be
2.1 Urban Street Network Representation

used to describe configurational properties of the axial map. Most of these measures are based on topological distances, i.e. the number of steps (edges) between two intersections.

![Figure 2-2: Axial map representation on convex map](image)

The simplest are those that describe the local properties of a node in a graph:

- *connectivity* for example merely measures number of lines that directly intersect that given axial line or the number of neighbourhoods of this axial line that are directly joint to it.

- *Control value* (Hillier and Hanson 1984b) measures the degree to which an axial line controls its neighbours.

A similar measure taking into account the relations between each space and the whole system is *global choice* which shows how often each line is used on topologically shortest paths from all lines to all other lines in the system. But empirically, by far the most important global measure is called *integration* which measures the mean depth of every other line in the system from each line in turn. This measure of accessibility is calculated over the connectivity graph on the basis of a topological, non-Euclidean concept of distance (the so-called step-distance), in the connectivity graph each axial line
2.1 Urban Street Network Representation

is turned into one node, while each intersection between any pair of axial lines is turned into one edge (Hanson 1989; Hillier et al. 1993). Depending on the depth used, that is, local versus global, the matching integration parameter is called local versus global integration. Local integration considers both immediate and non-immediate neighbourhoods: that is lines that intersect each immediate neighbourhood and so on recursively up to a few steps away. Global integration considers both immediate and non-immediate neighbourhoods up to $K$ steps away (Jiang and Claramunt 2002).

2.1.2 Geometric and Topological Representations

Urban street networks can be represented as an interconnected graph from two different and contrasting perspectives; topological representation, in contrast to geometric approach refers to a description of the relationship between geographic objects or locations. In geometric representation identifiable urban elements with a certain mass (residential population, traffic flow and so on) are associated with locations in Euclidean plane, whose relationships to one another are usually based on Euclidean geometry providing spatial objects with precise coordinates along their edges and outlines, so the distances between the pairs of points are considered. The difference between the two approaches is subject to whether or not geometric distance plays an important role in graph analysis. Geometric approach considers the embedded graph in the Euclidian space; the edges (street segments) are weighted by the distance between the two corresponding junctions. In contrast in the topological approach distance does not play an important role, although other weighting functions might be considered. The geometric approach have some advantageous in some areas of network analysis, but it is not
suitable for illustrating the structure of urban street networks, since the structure captured by the geometric approach is simple, i.e., 3 or 4 links for most road junctions (Jiang 2008).

The topological properties of a street network are the properties that are invariant in a homeomorphic rubbersheet transformation. Examples of such properties are intersection and connectedness. Streets are not locations in this interpretation and thus the relations between any two streets can never be uniquely embedded in Euclidean space. This makes the analysis of the topological relations between streets entirely abstract; it forces the representation of distance between two streets to be distance in the graph-theoretic rather than the Euclidean sense, thus removing the relational graph from the physical space in which it is defined in the first instance (Batty 2004). The topological network model supports a street-oriented computational analysis of the properties of an urban street network. Topological representations and analyses help to uncover some hidden structure or patterns, which cannot be illustrated by the geometric representation and analysis (Jiang and Liu 2009). It highlights the accessibility and connectivity of a network, for instance in a street network it reveals to what extent the streets are connected to each other by focusing on the accessibility of them and ignoring their exact locations and hence representing a simpler approach in terms of their connectivity.

2.1.3 Segment Based Representation

Segment based approach represents intersections as nodes and the street segments between each two intersections as the edges. In order to analyze each of these street segments individually, this type of network representation might have some advantageous
2.1 Urban Street Network Representation

but it does not necessarily show the extension or the properties of a “street”. A street can be defined as a linear geographic entity that stretches in two dimensional space, and is often given a unique name so it should not be confused to a street segment between two junctions (Jiang and Liu 2009).

The structure of segment based approach is simple, for instance most of the nodes have the same number of links to others which makes the structural analysis of such representation boring. In other words structural analysis of this approach assigns similar results for most of the nodes or edges. Figure 2-3 presents an example of the street segment representation.

![Street segment representation](image)

**Figure 2-3**: The street segment representation

The nodes are defined in a Euclidian space, and the distances are taken by the matrix as its elements. Although the distance matrix can be further abstracted topologically into a node-node connectivity matrix, it might not be regarded as a true topology because of a lack of an interesting structure or pattern. It is obvious that such networks or graphs have similar connectivity structure, because of the lack of variation in connectivity for individual points.
2.1.4 Named Street Representation

Named street approach is one of the topological methods of representing an urban environment that supports a street-oriented computational analysis of the properties of an urban street network and is proposed by Jiang and Claramunt (2004b) (Figure 2-4). Named streets represent a functional modelling element of large urban street networks whose structure should be retained by a structural analysis. In this representation it is possible to evaluate the degree to which streets are interconnected versus segregated in a given city by designing a graph in which the nodes model those named streets and edges model links between those named streets. It should be noted that in such a view an edge (in primal approach) or a node (in line approach) represents not a street segment but an entire named street (Jiang and Liu 2009).

![Figure 2-4: An example of named street representation](image)

The major advantage of this type of representation is that compared to other geometric approaches a named street is never truncated at one end or broken into separate pieces in
2.1 Urban Street Network Representation

the course of selection and that the structure of a street network is retained with subsequent filtering of streets according to their names (Jiang and Claramunt 2004a). It is shown by Jiang and Liu (2009) that the street-based topological representation and analyses are superior to the conventional axial map in predicting traffic flow. It is also shown that the topological representations, in comparison to conventional geometric oriented representation, can help to uncover some hidden structure or patterns. They suggest that the street-based topological representations are better representations, not only for traffic prediction, but also for other well studied issues in space syntax such as pedestrian modeling, crime analysis, human wayfindings modeling etc. For instance, Tomko et al. (2008) used named streets for exploring hierarchies of human spatial knowledge in route descriptions, proving that topologically central streets are indeed more likely to be known. However this approach has its own limitations and deficiencies that will be discussed in the next chapter.

2.1.5 Good Continuation Representation

Slightly modifying one standard definition to reflect the importance of spatial databases and GIS, generalisation could be described as the selection of detail appropriate to the scale and/or purpose of a dataset. Generalisation is a fundamental procedure in cartography and spatial data analysis and integration (Weibel 1996). A consideration of sample road and street networks made it clear, however, that generalisation is usually possible (by a human cartographer) in the absence of a site selection process: generalisation is achievable purely on the basis of the network’s geometric, topological, and thematic properties. This generalisation capability follows from the human visual
system’s ability to spontaneously perceive certain groupings of image features as natural units – i.e. figure-ground discrimination (Thomson and Richardson 1999). This idea led to a novel method of network analysis based on the decomposition of the network into linear elements found by the principles of perceptual grouping – most clearly the principle of good continuation which proposes elements that appear to follow in the same direction tend to be grouped together (Coren et al. 2004). If the process of drawing a given line is going smoothly, i.e. the direction and/or curvature of pen’s movement are not changing much, or do not change at all (straight line), then the continuation of the drawing is easy, and this line could be called a line of “good continuation” at any point of the line (lines /ab/ and /cd/ at Figure 2-5). So, the good continuation principle – one of the basic principles of Gestalt psychology – assumes that perception of a drawing includes the imaginable process of recreating (or imitating) the drawing. This principle explains the tendency for smoothly connected elements to be naturally “grouped” and considered as single objects, perhaps intersected by others.

![Figure 2-5: A simple example of good continuation principle](image)

If a road network is viewed as a planar graph, with junctions and dead ends representing nodes and the corresponding connective road segments representing arcs, then a stroke is a set of one or more arcs in a non-branching, connected chain (Thomson 2004b). Good
continuation representation, self-organized natural roads proposed by Jiang (2009), or continuity maps proposed by Figueiredo and Amorim (2005) are joined road segments based on the Gestalt principle of good continuity. All these approaches have the same basic principles in nature but are different in terms of area of applicability.

Figueiredo and Amorim (2005) introduced the idea of continuity map in which a continuity line is the aggregation of several axial lines to represent an urban path in its longest extension, respecting a maximum sinuosity previously defined. It is based on two main arguments: first, that the notion of continuity is already embedded in the axial system; and second, that the continuity lines reinforce the relationship between configurational properties and the hidden geometry of the axial maps. The implementation of the aggregation process is based on the angle between the linear continuation of an axial line and the real continuation provided by another axial line closer to one of its extremities. This angle of intersection is called angle of continuity. If an axial line has more than one intersecting line to one of its extremities, the line that has the smallest angle of continuity is chosen as the best continuation for aggregation. However, when standard axial maps are drawn, intersecting lines do not always share the same intersecting point, creating several trivial rings. As a result, the aggregation procedure has to implement an approximation margin that ignores small distances between intersections to correctly choose the best continuation. This margin can be defined by measuring the distance created by the trivial rings of the map. This procedure works recursively for both extremities, starting from the longest to the shortest lines, with the interest to create the longest, but also the straightest paths available.
In order to refine axial lines representation, the use of smoothly continuous road centre-line segments—which are termed strokes—, can be presented as a useful basis for the analysis of street and road networks. The decomposition of networks into linear strokes, which show good continuation of direction and continuity of character (width or type), has been found to provide a basis for robust, effective, and efficient automatic generalisation of road networks (Thomson 2004b).

Jiang et al. (2008) has proposed the idea of formation of natural roads in a way that every segment at each end chooses one most suitable neighbouring segment with a smallest deflection angle to join together; and this process goes on until the deflection angle is greater than a preset threshold. They have presented three different join principles for determining how each segment joins with one of its neighbouring segments by self-organized process. The first is called every-best-fit, and it works like this. Every pair of segments at a junction point have to negotiate with each other to have best fit (i.e., the one with a smallest deflection angle), in terms of which one joins which one (Figure 2-6).

![Figure 2-6: Every-best-fit representation](image-url)
The second is called self-best-fit. Instead of *every*, each segment only considers *itself* to find a best fit, and does not care about others in the process. Thus it is rather selfish or capitalism in nature. Or it can be deemed a natural selection (Figure 2-7).

![Figure 2-7: Self-best-fit representation](image)

Similar to the previous selfish principle, there is another one called self-fit. Obviously each segment tries to choose arbitrarily one fit, i.e., the one with a deflection angle less than a preset threshold, to join, but not necessarily to be the best fit (Figure 2-8).

![Figure 2-8: Self-fit representation](image)

By comparing these three topological representations of natural roads, we observe that the first principle always leads to a unique set of natural roads, while the other two
principles would generate various sets of natural roads, depending on the search order of the segments. But by arranging some conditions in the search order, it is possible to generate a unique set of natural roads even for the last two selfish representations which will be discussed in the next chapter.

2.1.6 Primal and Line Graph Representations

Graph representation can be divided into two other major categories called primal and line graph representations. Network analysis has mostly followed a primal approach, where in case of a street network geographic entities, street intersections and settlements are turned into nodes and their linear connections, which are the streets and infrastructures turn into edges. Figure 2-9 presents an example of a simple primal (blue) graph with four nodes and four edges, while the green lines present a line graph with four nodes and five edges. Primal representation seems to be more suitable for networks characterized by a strong connection to the geographic dimensions, which is to say networks where distance has to be measured not just in topological terms (steps) – for instance in social systems – but rather in metric distance (Porta et al. 2005).

![Figure 2-9: Primal (blue) and line (green) representations](image)
In a line representation of a street network, the equivalent graph representation is more abstract, streets or edges are treated as nodes and intersections are represented by edges. Therefore one street in spite of its length will be represented in the line graph as one node. This type of representation can assist us with the understanding of the connectivity and accessibility if the graph visually, because the whole edge is abstracted as a node and by a short glance at the links the level of its connectivity can be perceived. However, since any of the discussed representation such as named streets or good continuation representations can be abstracted as a line graph, the identity of one street might be assigned to a conceptually unlimited number of real intersections; it is possible to find one node (street) with a conceptually unlimited number of edges (intersections) in the line graph, a number which mainly depends on the actual length of the street itself (Porta et al. 2006).

The metric problem differentiates the primal and the line representations of street systems, because in the primal approach the metric distances between nodes or intersections can be considered beside the topology of the network. In contrast in the line representation only the topological characteristics of nodes and edges are considered and geometric properties, e.g. Euclidean distances, are not stored in this representation. Moreover distance based concepts are here purely graph-based and should not be confused with their counterparts in a geometric network. However, it should be considered that the edges of a line graph can be assigned various types of weights representing different cost functions.

The advantage of the topological distance approach is one that can make the difference: because streets are mapped as nodes no matter their metric length, and because the
intersections between every two streets are mapped as edges, one can have many – conceptually countless – intersections for each street, which means many – conceptually countless – edges for each node in the line graph. This makes the line graph of a geographic network comparable in its structure with most other networks recently investigated in social and biological systems, which in fact do not exhibit any geographic constrains (Porta et al. 2006). On the other hand the problem of the unique identity of an urban street throughout a number of intersections should be taken into account as well. In addition although the line graph can be an appropriate representation in terms of visualisation of street connectivity, it might have some limitations for analysis of the graph that will be discussed in the next chapters. However for every primal there is a line and vice versa and whether or not one measures accessibility in the primal (or the line), it is possible to translate consistently from one to the other (Batty 2004).

2.2 Centrality Measures for Structural Analysis of Urban Street Network

The network approach has been broadly utilized in urban studies. Since the early 1960s, a lot of research has been spent trying to connect the allocation of land uses to population growth through transportation lines (Wilson 2000), or challenging prediction of transportation flows by taking into account several topological and geometric characteristics of traffic passages (Larson and Odoni 1981) or investigating the exchanges of goods and habits between settlements in the geographic space even in historical eras (Pitts 1979). Various practical studies related to the city and intercity
routing problems have been a permanent issue of inspiration for graph theory. For instance the shortest path searching algorithms and minimum spanning trees originated in 1926 for the purpose of efficient electrical coverage of Bohemia (Nesetril et al. 2001). Routing studies underwent a rapid progression due to the development of probability theory and the implication of random walks in particular (Blanchard and Volchenkov 2008).

A street network can be characterized with respect to its structural properties: such as identification of salient streets of a city, the average level of integration or segregation of a street network or overall the way the streets are interlinked. All these characteristics deal with topological, logical, and structural properties that are the scope of urban morphology. Historically, centrality indices were developed to analyze social networks. Bavelas (1948) was the first to realize that central individuals in a social network very often play a prominent role in the group, or in other words a good location in the network structure corresponds to power in terms of independence, influence and control on the others. He applied the idea of centrality to human communication; he was interested in the characterization of the communication in small groups of people and assumed a relation between structural centrality and influence and/or power in group processes (Wasserman and Faust 1994). From this application, the emphasis lay on the analysis of the most central persons in social networks. Centrality measures serve to quantify that in a network some nodes or edges are more important (central) than others. Since then, various measures of structural centrality have been proposed over the years to quantify the importance of an individual in a social network and the issue of centrality has found many applications also in biology and technology (Crucitti et al. 2006b). Centrality has
revealed crucial for understanding the structural properties of complex relational networks. When dealing with urban street patterns, centrality has been investigated in both relational (topological) and also geographical (geometrical) aspects, each aspect clarifies some hidden properties of the urban street network. It is also relevant for various spatial factors affecting human life and behaviours in cities and can be used for characterizing the structural properties of an urban street network or for the selection of important streets. These measures consider both local and global structuring properties of street network that correspond to basic functional elements in the city (Jiang and Claramunt 2004a).

A spatial analysis, grounded on a set of different centrality indices, allows an extended comprehension of the city structure, capturing the skeleton of most central routes and subareas that has an impact on spatial cognition and on collective dynamical behaviours. The centrality analysis opens up to the in depth investigation of the correlation between the structural properties of the network and the relevant dynamics on the network like pedestrian and/or vehicular flows (Crucitti et al. 2006a). By using different centrality indices (multiple centrality assessment), extended or defined on purpose for spatial graphs, it is possible to spot the relevant places of a city. Relevant places means, places that are structurally made to be traversed (betweenness centrality), places closer to other places (closeness centrality), places that have more number of links to others (degree centrality), and places whose deactivation affects the structural properties of the system (information centrality) (Crucitti et al. 2006a).
2.3 Basic Centrality Measures for Network Analysis

Many centrality indices are based on shortest paths linking pairs of nodes, measuring, e.g., the average distance from other nodes, or the ratio of shortest paths a node lies on (Brandes 2001). Therefore here first the idea of shortest path will be discussed and then three basic centrality measures will be introduced and explained.

In graph theory the shortest path problem consists of finding the quickest way to get from one location to another on a graph. For a path $p$ in a graph $G (N, E)$ with edge weights $w$, the weight of the path, denoted by $w(p)$, is defined as the sum of the weights of the edges on $p$. A path from nodes $i$ to $j$ in $G$ is a shortest path (with respect to $w$) if its weight is the smallest possible among all paths from $i$ to $j$. The length of the shortest path from $i$ to $j$ also called the shortest path distance (also: depth) between $i$ and $j$, is denoted by $d_{G, w}(i, j)$, where the subscripts $G$ and/or $w$ are usually dropped if no confusion can arise.

It should be noted that Euclidean distances, are not stored in a line graph. Concepts such as shortest path and shortest distance are here graph-based and should not be confused with their counterparts in a geometric network. Here the topological distance is the number of edges between two different nodes.

High centrality scores generally indicate that a node can reach others on relatively short paths, or that a vertex lies on considerable fractions of shortest paths connecting others. The inhomogeneity of a centrality index is used to define the centralization of a graph with respect to that index (Freeman 1979). Three basic centrality measures allow the
2.3 Basic Centrality Measures for Network Analysis

The structural significance of a network element to be characterized: degree centrality, closeness centrality and betweenness centrality.

Degree centrality

In a graph \( G \) consisting of \( N \) nodes and \( E \) edges, the degree centrality of a node \( i \in N \), in space syntax called connectivity, is a measure specifying the number of direct neighbours (nodes connected by edges) of a node:

\[
C_i^D = \sum_{j \in N} e_{ij}
\]

(2.3)

Degree centrality is a local measure, determining the characteristics of a node only within the context of its direct neighbours.

Closeness centrality

\( C_i^C \) measures to which extent a node \( i \) is near to all the other nodes along the shortest paths and reflects the average length of the shortest paths from the node \( i \) to all other nodes of the graph, where \( d_{ij} \) denotes the length of the shortest path between the nodes \( i \) and \( j \).

\[
C_i^C = \frac{N - 1}{\sum_{j \in N, j \neq i} d_{ij}}
\]

(2.4)

Nodes with high closeness centrality have low average length of the path to all other nodes in the graph. When applied to a given urban network, this measure reflects global properties of the structure of the city, revealing its core. In space syntax this measure is known as global integration, or relative asymmetry, and is applied on line graph representations of the axial graph as discussed before (Hillier and Hanson 1984b).
2.3 Basic Centrality Measures for Network Analysis

Betweenness centrality (also choice in space syntax) $C_i^b$ quantifies the likelihood a graph node lies on a shortest path between two other vertices of the graph and therefore has the potential for control of communication (Freeman 1979). In a graph $G (N, E)$ consisting of $N$ nodes and $E$ edges, let $|SP_{jk}|$ denote the number of shortest paths between nodes $j, k \in N$, and $|SP_{jk(i)}|$ the number of such paths leading through node $i \in V$. Betweenness centrality of the node $i$ is defined as follows:

$$C_i^b = \sum_{\substack{j,k \in V \setminus \{i\} \atop j \neq k}} \frac{|SP_{jk(i)}|}{|SP_{jk}|}, \text{ or normalized: } C_i^b = \frac{\sum_{\substack{j,k \in V \setminus \{i\} \atop j \neq k}} |SP_{jk(i)}|}{(|N|-1)(|N|-2)/2} \quad (2.5)$$

In betweenness centrality the shortest paths ending or starting in $i$ are explicitly excluded. The motivation for this is that the betweenness centrality of a vertex measures the control over communication between others. This centrality index was introduced because it is problematic to apply the closeness centrality to a disconnected graph: the distance between two vertices in different components is usually set to infinity. With this, the closeness centrality in disconnected graphs will give no information because each vertex is assigned the same centrality value. The betweenness centrality does not suffer from this problem: Any pair of nodes $i$ and $j$ without any shortest path from $j$ to $k$ just will add zero to the betweenness centrality of every other vertex in the network.

Most centrality indices for edges, e.g., the shortest path betweenness centrality, were only developed as a variant of the centrality index for vertices. Here, the centrality index for vertices is transformed into a centrality index for edges. An extension of betweenness to
edges is obtained by replacing $SP_{jk(i)}$ in the definition of node betweenness by $SP_{jk(e)}$, the number of shortest paths from $j$ to $k$ containing the edge $e$.

$$C_e^b = \sum_{\substack{j,k \neq k \neq \ell \neq i \neq j \neq k \neq i}} \left| \frac{SP_{jk(e)}}{SP_{jk}} \right|$$

(2.6)

The concept of betweenness as a measure of centrality (Freeman 1977) evolved into a broad class of diverse measures that consider different types of network flow. It is one of the most significant and applicable measures of centrality which provides a global value of a network element and therefore allows us to compare its structural characteristics with all other nodes in the graph. In an urban street network betweenness centrality of a node or an edge is calculated by generating shortest paths for all pairs of possible origin and destination locations and then incrementing the betweenness value of an edge or node, whenever this edge or node is passed through on a path from origin to destination. Thus, frequently used nodes take high values, while those that fall on fewer paths take low values. Many researchers have noted betweenness seems to be a more intuitive model for movement than the traditional space syntax measure of integration. Network effects on movement flows are to be expected in spatial configurations in general, and the syntactic measures of betweenness can be expected to capture them. It is shown that betweenness centrality is less affected by the choice of the study environment than local characteristics of centrality and correlate very well with both pedestrian and vehicular aggregate movement levels and beside the greater the graph length of the trip, the more it will reflect the choice, or betweenness, structure of the graph, rather than the integration, or closeness, structure (Hillier and Iida 2005). In the context of this thesis, in order to study
the emergent phenomena of an urban environment, urban street network analysis is performed based on betweenness centrality.

2.4 Spatial Network Analysis and Space Syntax Tools

In this work different tools are implemented for generating different urban street network representations, space syntax, axial lines and continuity maps and performing network analysis and graph theory problems. Some of these tools both in the area of spatial network analysis and also space syntax, which were more applicable in this thesis, are listed below and their advantageous and weak points are discussed further.

2.4.1 igraph

The igraph software package\(^1\) (Csardi and Nepusz 2006) provides tools for researchers in network science. It is an open source portable library capable of handling small and large graphs with millions of vertices and edges and it is also suitable to grid computing. It contains routines for creating; manipulating and visualizing networks, calculating various structural properties, importing from and exporting to various file formats and many more. It is capable of reading files written in Pajek format. Via its interfaces to high-level languages like GNU R and Python it supports rapid development and fast prototyping. The library is written in ANSI C, it is thus portable to most platforms. It is tested on

\(^1\) http://cneurocvs.rmki.kfki.hu/igraph
different Linux, Mac OS X, MS Windows and Sun OS (Csardi and Nepusz 2006). In this thesis this library is used in the GNU R environment interface.

igraph has various functionalities for network analysis, but what is mostly utilized in this work are centrality measures, path length based properties and visualization. Being open source can be useful for the users, because in addition to the binary format of the program, the user can always get the source code format enabling additions and corrections (Csardi and Nepusz 2006). For instance in this work a modified version of both node betweenness and edge betweenness centralities has been programmed, using the source code of conventional betweenness centrality.

Another advantage of igraph is the ability to assign attributes and weights to edges and nodes and calculate some of the centrality indices according to edge or node weight, for example weighted betweenness centrality (Brandes 2001). The library lacks functionality in some areas compared to other network analysis packages for example graph visualization which is under development.

Generally the igraph library was developed because of the lack of network analysis software which (1) can handle large graphs efficiently, (2) can be embedded into a higher level program or programming language (like Python, Perl or GNU R) and (3) can be used both interactively and non-interactively (Csardi and Nepusz 2006). Since the latest package of this library is under development, there is the possibility to subscribe as a member in igraph mailing list and to contact and receive a helpful response from the authors about any problem or deficiencies.
2.4.2 Mindwalk

Mindwalk\(^2\) (Figueiredo 2005) is a application to perform spatial analysis on buildings and cities over axial (Hillier and Hanson 1984b) and continuity maps (Figueiredo 2005). It imports and exports maps as drawing exchange files (DXF) and simple coordinate files (text files), being able to create continuity maps by aggregating axial lines. Mindwalk was fully written in Java, a programming language designed to be platform-independent by using virtual machines. Before using Mindwalk, a Java Virtual Machine 1.4 or higher must be installed, which is available for Windows, Solaris, Linux and Mac operating systems.

Mindwalk implements all standard syntactic measures used to analyse axial maps, which are the same for continuity maps. Most of them were taken from the graph theory and later adapted for the space syntax context, measuring abstract topological properties (Figueiredo 2005). After building the graph, these measures can be applied to the map which some of them are brought here:

- **Connectivity:** which is the number of lines that directly intersect it (also called degree of a vertex in graph theory).

- **Global integration:** which is a measure of eccentricity, accessibility or centrality.

- **Fast choice:** which is the number of times \( n \) that a line \( i \) is used in the set of all shortest paths from all lines to all other lines in the system. This measure is equivalent to edge betweenness centrality in network analysis theory.

\(^2\) http://www.mindwalk.com.br
Apart from these measures Mindwalk has the ability to generate continuity maps as mentioned earlier. In order to apply the good continuation principle, it is possible to introduce a merging degree, so that the intersected lines with less than the threshold degree would be merged together. Obviously Mindwalk uses a self-fit principle according to (Jiang et al. 2008) because each segment tries to choose arbitrarily one fit, i.e., the one with a deflection angle less than a preset threshold to join. But the elegant point here is although this type of representations are not unique, Mindwalk generate a unique one by introducing an ordered search algorithm. The order of this searching algorithm is in a way that it actually first starts from the longest lines (edges) and then processes the shorter one so that a unique representation would be generated.

In spite of these features, Mindwalk has some disadvantages; the most troublesome issue is that it does not keep the identifications of the imported files, so that the whole lines have new identities assigned by Mindwalk itself. This is a critical issue, because it would not be possible to correlate the edges before and after importing. There are some other deficiencies such as not having drawing capabilities and only having the possibility to import DXF or text files as an input, which is not always accessible, and also the conversion process of each file into DXF is time consuming.

2.4.3 Pajek

Pajek\(^3\) (Batagelj and Mrvar 2003) is an open source Windows program for analysis and visualization of large networks. Pajek provides tools for analysis and visualization of

\(^3\) http://vlado.fmf.uni-lj.si/pub/networks/pajek/
networks and is applied by researchers in different areas such as social network analysis and chemistry.

Pajek can read network data in several plain text formats (Batagelj and Mrvar 2003). The type of flexible data format implemented in this work is Pajek networks. The Pajek network format (the file name extension is .net) is basically a list of nodes followed by a list of arcs and edges. It is the most flexible format because it allows for multiple lines and many properties of the vertices and lines can be specified (Batagelj and Mrvar 2006). One of the advantages of Pajek is the flexibility to visualize networks, it is possible to visualize different attributes of nodes and edges like name and weight and therefore comparing them visually. But on the other hand the network analysis features for centrality measures are not complete, like it is only possible to compute betweenness and closeness centrality. Apart from that although it is possible to assign attributes to nodes or edges, some of the features do not take them into consideration for computing the results. For example, although it is possible to enter weights for edges of a network, these weights would not be considered when computing centrality measures.

In brief, this software is more suitable for visualizing networks and their attributes and also performing general network analysis, since it has various range of functionalities in this area, but not for specialized analysis of networks like performing different centrality measures with specific conditions. As in this thesis this software has been mostly utilized for the visualization purposes and rarely for analysis and computation tasks.
2.4.4 Axwoman

Axwoman4 (Jiang 1998) developed using Microsoft C# and ESRI’s ArcObjects is an extension for ArcGIS 9.2. It supports space syntax analysis based on both axial lines and natural streets. It is actually an analytical tool based on space syntax for urban morphological analysis and implemented as an ArcView5 extension. Three functions are implemented using Avenue scripts with different interface modules: drawing with view, computation with view and table, and analysis with table and chart. All these Avenue scripts are packed as an extension named Axwoman3.0 (Axwoman30.avx). A set of icons is created and linked to respective Avenue scripts. It is essential that the user has already been through the ArcView and understand basic ArcView terminology and interface concepts. It is also expected that she would be familiar with the analysis capabilities of the standard ArcView product (Jiang 1999).

Three kinds of methods are implemented with version 3.0 of extension, namely polygon, line and point-based approaches. The approaches start with spatial partition, i.e. identification of each individual geometric shape to represent small-scale space that can be perceived from a single vantage point of view. According to how the geometric shapes are interconnected or visible to each other, a connectivity graph can be derived for computation of various morphological measures (Jiang 1998). The kind of space syntax analysis has been recently extended using individual streets. The streets referred to here include both named streets (Jiang and Claramunt 2004b), and natural streets or “strokes” in Thomson’s term (Thomson 2004b). The new Axwoman is implemented with some

---

4 http://www.fromto.itb.hig.se/~bjg/Axwoman.htm
5 http://www.esri.com/software/arcview/
efficient computation, thus it can handle large systems involving thousands of axial lines or streets.

A series of analyses can be done with the extension module. Users can use ArcView drawing tools to perform space partition. *Doit tool* calculates various measures from the axial and point map for example connectivity, control value, integration, local integration, depth. Computed results are stored in a table corresponding to the respective map theme. Users can explore data from different perspectives, or import observed data, e.g., pedestrian or other traffic flow rates for a cross analysis (Jiang 1999).

### 2.4.5 AJAX

AJAX⁶ (Batty 2005) is a Windows-based program for generalised space syntax. It enables users to perform traditional space syntax, called the *primal* analysis, which consists of describing a spatial configuration as a set of axial lines and working out their relative proximities, accessibilities or integration values. But the program also enables users to generate the *line* analysis, which consists in working out these same accessibilities with respect to the intersections between the lines that we call junctions or nodes. A key feature of the software is that when the user is engaged in the analysis of the axial lines/axial map, another window opens which gives her the accessibility or integration values by thickness of line or in space syntax colours. The same happens – another window opens – for the line analysis on the intersections or junctions (Batty 2005).

---

⁶ [http://www.casa.ucl.ac.uk/ajax/]
The program essentially lets the user input her own map and then draw axial lines on it so that the analysis can be generated. The program is restricted to 500 axial lines but it would take several minutes to process a problem this size.

In brief, this software is useful for drawing axial lines while we have our map in background, but one of the problems in drawing the axial lines here is lack of possibility to make changes after the axial lines are drawn, the only option is to delete the unconnected or dispositioned line which is not always desirable. On the other hand this software has the ability to analyse and visualize the primal and line representation, which the latter is being less considered in other space syntax softwares.

In brief this chapter presented some of the existing relevant representations of an urban environment so that the basics of the formation of these representations would become clear. This introductory will assist us to address the deficiencies and potentials of these representation and finally selection of the appropriate one. This chapter also had a review on the role of centrality measures in structuring urban street networks and introduced different measures of centrality. Some of the useful and applicable spatial analysis tools were also introduced and their features and specifications were discussed in detail. This comparison will later assist us in picking up the suitable spatial analysis tool.
Chapter 3

Selection of an appropriate Street Network Representation

In the last chapter some of the existing representations of an urban environment and their basics were introduced. In this chapter the requirements of the appropriate representation for the studied phenomena in this work are first addressed. Each of these representations are investigated in terms of their limitations and potentials afterward and at the end the appropriate representation is depicted according to the discussed requirements. Since two different phenomena are studied in this work, the Correlation of the selected representation with each of these phenomena is investigated later.

3.1 Requirements of the Studied Phenomena for Selection of an Appropriate Representation

The application of the network approach to the urban environment in terms of the representation and analysis brings up several questions in terms of how to deal with
3.1 Requirements of the Studied Phenomena for Selection of an Appropriate Representation

Metric distances, what kind of graph representation to use, what kind of measures to investigate, how to improve the correlation between measures of the structure of the network and the measures of the dynamics of the emerged urban environment phenomena. These questions will be discussed partly from the aspect of selection of the appropriate street network representation in this chapter and partly from the network analysis point of view in the next chapter.

Since in the previous chapter different possible representations of an urban environment or more specifically street network representations were collected, in this chapter these representations will be compared and investigated in terms of their limitations and potentials with the aim of selecting an appropriate approach which has the highest correlation with the studied phenomena. The selected representation might be different depending on the studied phenomena in this thesis, namely self orientation (You-Are-Here maps), route description and traffic flow. Therefore the selection of an appropriate representation in the study each of these phenomenon means depicting the type of representation that can reflect the characteristics and properties of that phenomenon or in other words an approach which correlates better with the structural and dynamic analysis of the urban street network.

In order to be able to depict an appropriate representation for each of the studied phenomena, it is necessary to first make ourselves familiar with the requirements of these phenomena in terms of the type of street network representation and then compare different street network representations to see which of these representation has a higher correlation with the studied phenomena to be depicted.
3.1 Requirements of the Studied Phenomena for Selection of an Appropriate Representation

The first urban phenomena studied here is traffic flow with the aim of predicting this pattern. People in an urban street network are highly dynamic; they enter this environment at any time, and leave as soon as they have reached their destination. In order to predict this pattern, the distribution of travel demand and the locations of the sources and sinks of their travel behavior along the streets should be considered. Furthermore, since the selected representation should be characterized in the next step, the selected approach should reflect the structural properties of the street network as well. For instance it should highlight the structural difference of different streets in terms of their significance.

Self localization in the urban street network is the second phenomena that will be studied in this work in form of a self localization or specifically (YAH) map. Since this device assists people to orient themselves in an unfamiliar system, the type of representation utilized for urban street network should not have a high level of detail or too informative, because the user only needs to have a general idea of her surroundings. Otherwise the redundant information of street names would make her confused. Therefore by reducing the number of street segments that can be perceived to be in the same direction from people’s point of view, the user can be guided through a unique street and in this way preventing different changes of directions.

The third wayfinding phenomenon is studied here in form of a route description system. Route description systems give the users some instructions in a street network in order to reach to their destinations. Since in this case similar to the previous case people prefer to receive informative and adequate not redundant information, the street network
3.1 Requirements of the Studied Phenomena for Selection of an Appropriate Representation

representation should be consistent but not contained with too much detail information to make the instructions confusing. For instance by representing two neighboured street segments with a low deflection angle (which will be defined later), the route description system should mention the change of slight direction and also their names which makes redundant turning instructions and consequently confuse the user.

Finally at the end of this chapter the appropriate representation which has a high correlation with at least the phenomena studied in this work will be depicted and the logic behind the selection of this representation will be discussed.

3.1.1 Limitations of an Axial Lines Representation

The limitations of axial lines can be discussed from two aspects: There are practical limitations in terms of computational operability and cognitive limitation from a spatial modelling point of view. Based on the principles of space syntax discussed before, it is obvious that the derivation of axial lines is time consuming and also complex. To our knowledge there exists a few tools that can handle the automatic generation of axial map, for instance one of the tools already exists can only deal with generation of a small number of axial lines. The manual derivation of axial lines is both time consuming perception based, which can have an impact on the space syntax analysis results. Furthermore, one of the requirements of axial lines is drawing the fewest and the longest number of lines possible, but it is not easy to make sure that the map is made of the least
numbers of axial lines and the longest ones, especially in large environments (Jiang and Claramunt 2002).

Another limitation of the axial maps to be brought to debate is the generation of long lines. It is common to find in large and complex urban systems long and straight avenues with kilometres of extension that cross large portions of the grid. Because of their length, these long axial lines tend to be highly connected and integrated; these “straight paths” are lines of movement but are not necessarily lines of sight. When these long axial lines are compared to long curved and long sinuous paths that offer similar conditions for long journeys within the grid, an important distortion of the axial model becomes evident: non-straight paths are broken into a sequence of short lines, therefore their importance is misled and further minimised by the presence of long and highly connected straight lines (Figueiredo and Amorim 2005). Apart from that, analysis of these lines of sight does not make sense for structural analysis of the axial map in certain cases. Because the whole line would receive a unique structural value regardless of the differences in structural characteristics of its different parts, but the point is that this property might differ in various parts of the axial line in reality. Therefore assigning a unique value to the whole axial line might hide some individual characteristics of its parts. On the other hand, results of the space syntax analysis are influenced by the extent of the city that is being considered. An edge-effect appears which has pervasive consequences over the whole urban network and affects results even in remote locations (Ratti 2004).

According to the provided evidences, it can be concluded that these limitations impose significant doubt on the validity of axial lines for at least its application in the studied
3.1 Requirements of the Studied Phenomena for Selection of an Appropriate Representation

urban phenomena in this work. However some work has been done in order to overcome some of the axial map’s limitations (Figueiredo and Amorim 2004; Thomson 2004a; Turner 2007) that can be helpful even in network analysis area and out of the context of space syntax which will be discussed later.

3.1.2 Limitations of Segment Based and Named Street Representations

Since the principles of these two street network representations namely the segment based and the named street representations are discussed previously, here the limitations and inconsistencies of these representations will be investigated to find out whether and to what extent they can be utilized as a suitable approach for representing the studied phenomena in an urban environment.

Segment based representation has sometimes been considered as a geometric one, based on the facts that (1) the junction points can have precise geometric coordinates referenced to the earth, and (2) the geometric distances between the pairs of points are a major concern for the representation. Apparently this representation lacks variation in connectivity for individual points because most of the nodes have similar connectivity structure. That is why it is not suitable for uncovering structures or patterns of the urban studied phenomena in this work. This issue becomes obvious in the network analysis of such representation, which is the next step through characterization of the urban street network and the studied phenomena in this thesis. The result of centrality analysis and in particular betweenness centrality reveals similar centrality values for both nodes and
3.1 Requirements of the Studied Phenomena for Selection of an Appropriate Representation

edges of this representation. Therefore this representation cannot assist us appropriately with identifying the prominent streets of an urban environment which plays an important role in characterizing the studied urban phenomena in this work.

However it should be mentioned that this representation can be appropriate when analysing street segments of a street network for a specific purpose, for example when the aim is to study traffic flow of a specific part of a street, segment based representation can be helpful to characterize the network. Because when a street segment is analysed, the structural properties of this individual segment will be revealed after the analysis. While in other representation like the named street or good continuation, a longer unit would be analysed and then would be assigned a unique value when analysing the network. For instance in cases like traffic flow, different segments of a street can attract different amount of traffic flow and hence different traffic congestion; therefore if the aim would be to study each segment individually, it is worth considering each individual segment for structural analysis of some specific phenomena. But since the interest of this work in characterizing the studied phenomena is to do some structural analysis on the streets and not on the individual segments, this approach will not be used here.

The named street (Jiang and Liu 2009) representation might be closer to what people consider as a street, because people usually distinguish a street from others by its name and that is the base of this type of approach which merges segments with the same name to form the streets. Therefore in contrast to axial lines, this representation tends to be more cognition based rather than perception based. However this approach relies on proper information about street names in order to merge the segments with the same
names. Finding such a comprehensive database with complete names for all streets is an issue itself. First in reality not all the streets need to be named and there also might be the probability that the incorrect names are assigned to some street segments. Furthermore valid names are not always reliable as the same street may be termed in different ways by different conceptualization, or in different contexts, at different scales. Time is another point which has a direct impact on the names of the streets and brings the issue of currency of dataset. Apart from that the name of streets could vary from one district or quarter to another within the same city. By considering all the mentioned deficiencies, named street approach has not been utilized in representing the street network for characterization of the studied phenomena in this work.

3.2 The Selected Appropriate Street Network Representation

So far we have provided some evidences for deficiencies of the mentioned approaches for characterizing the urban street network, in this section the appropriate representation will be selected and the requirements for applying this method will be investigated. Afterward the correlation of each of the studied phenomena in this work will be discussed. By considering people’s movement behaviour and their perception of direction in a street network, what is adopted in this work as an appropriate representation of street network is mainly based on the good continuation and angular analysis, except in case of small synthetic networks.
Since the good continuity principle is discussed already in Chapter 2, here only the representation itself will be explained. Actually the angular analysis, which will be discussed in the next subsection, is performed to identify a threshold in order to merge the street segments and form the streets in the new representation. Therefore the joint segments that have a deflection angle less than the preset threshold are merged to form the streets. The only critical point here with this representation is not being unique, because this merging process basically depends on the direction of performing this principle. In other words, moving from different directions and performing this principle creates different streets with different segments depending on the search order of the segment selection. In order to solve this problem and create a unique representation the search order of segment selection is set in a way that the segments would be selected from the longest to the shortest one with the interest to create the longest and straightest paths available.

3.2.1 Angular Analysis for Applying Good Continuity Principle

Angular analysis is a technique that recently has been used for studying urban phenomena such as traffic flow and wayfinding (Turner 2000). The aim of this method is to investigate the way people move in an urban environment by considering the turns they make and also their perception of different direction. This type of analysis can improve the prediction of people’s movement around the urban environment both in the form of pedestrian and vehicular flow and also help us to improve the navigation systems based on people’s perceptions and understanding of this environment. Since the
mentioned phenomena are studied here as well, this technique will be discussed in this section to see to what extend it can improve the functionality of them.

Impact of turns on cognitive distance plays an important role in decision making, even when a driver has good knowledge of the spatial network and also that minimization of route angularity is employed as a high-level navigation strategy. If a person is to travel from point A to point B, then she will attempt to turn as little as possible (rather than the more usual assumption that it will try to follow the shortest path between A and B). In other words, she attempts to minimize the angular distance. However, in transportation analysis the mechanism for route choice is almost universally assumed to be the shortest time between locations, and it is often assumed that the person has access to a map.

For most situations qualitative information of direction in the sense of a small number of equivalence classes is sufficient. Especially in city street networks, which constrain the environment, directional choices of exact angular information are rarely necessary (Klippel et al. 2004). Two of the major strategies that was presented by Golledge (1987) that occur in cognitive representation of a street network is straightening curved paths and aligning nonparallel streets. A set of six prototypical turning concepts corresponding to a functional conceptualization of route direction elements can be considered. For these primitives (plus the concept for “straight”) the term wayfinding choremes is adopted (Klippel 2003). Wayfinding, i.e. getting from some origin to a destination, is one of the prime everyday problems humans encounter. Wayfinding choremes presented an approach to route directions based on the idea to adapt route directions to route and environment's characteristics. Mental representation of direction concepts can revise formal models of spatial reasoning and navigation assistance systems. According to the
representation of direction concepts, it can be perceived that people would not choose
directions according to exact angular information but for example the “straight” direction
can be extended up to a range around the exact angular definition in people’s perception.
A hierarchical cluster analysis based on people’s perception of direction, can reveal an
angular domain to which “straight” direction can be extended to from human point of
view is extracted (Klippel et al. 2004). According to the experiences in navigating urban
systems, there are several situations in which these straight segments are immediately
recognised as single lines of movement, such as costal or riverside streets; paths rounding
an obstacle, such as a hill; or curved and sinuous paths that cross open spaces.
In this thesis in order to define a threshold for applying the good continuity principle and
forming the streets out of the segments, the definition of straight by Klippel, Dewey et al.
(2004) is utilized to merge the segments which can be considered straight in this
definition. Since this definition is extracted according to the perception of people of
straight, it assists us to improve the functionality of the phenomena and systems studied
in this work.

3.2.2 Correlation of the selected representation with the studied phenomena
According to the requirements of the studied phenomena studied in the first section of
this chapter for choosing an appropriate representation of an urban street network, here
we investigate whether the selected representation can satisfy these requirements of each
phenomenon. The urban phenomena studied in this work deal with people’s travel
behaviour in urban environment. Therefore in order to investigate the correlation of these
phenomena with the selected representation, it should be considered to what extent the selected representation take these aspects into account.

In an unfamiliar area where people need to orient themselves and receive a general view from their surroundings, they prefer to be guided by a self localization device which avoids too much detail and perform according to their own concept of direction. The selected representation for presenting You-Are-Here map joins the street segments according to people’s perception of straight direction discussed before. Therefore they would be guided with a unique straight street rather than several directions for some confusing and consequent joint segment with low deflection angles. In this way the amount of information required to be presented to the user would be reduced which helps the user to have a clearer idea of her location and her surroundings.

The same logic is true about the other wayfinding phenomena studied in form of a route description system. Because representing the urban street network with the selected approach would first reduce the number of turning actions which leads to less confusion and second the instructions are more cognitive in terms of people’s perception of straight and their tendency to minimize the turning actions. In this way the user would be able to interact with the instructions better and beside there would be no need for giving redundant instructions to reach them to their destinations.

The ultimate task in the study of the third phenomena, namely traffic flow is to be able to improve traffic flow prediction. The logic behind applying the selected good continuation representation for this task is that first segment-based analysis of an urban street network would bring up a large number of centrality values for the segments which are mostly similar to each other and not interesting to challenge or interpret. Furthermore usually in
3.2 The Selected Appropriate Street Network Representation

joined segments with low deflection angles, the distribution of traffic flow is almost even. For instance it can be observed during peak hours that the congestion is almost evenly distributed along a street. Since this street is made of some joint segments with low deflection angle, it is more appropriate to consider all these segments to the extent that can be called straight as a whole street, unless as discussed before the aim would be the segment based analysis of the street network which is not true in our case. Therefore the analysis of the selected representation would reveal some hidden structural properties of the network which is closer to real nature of traffic flow.

In summary this chapter first introduced the requirements and the limits of the selected representation for each of the studied phenomena and then compared the potentials and limitations of some of the applicable representations. At the end the appropriate representation was depicted according to the requirements of the studied phenomena. In order to select and define this representation, some of the principles are defined and the correlation of selected representation with each of the studied phenomena is evaluated. In the next chapter the structural analysis of the urban environment with centrality measures is investigated.
Chapter 4

Analysis of Urban Street Network and Its Emerged Phenomena

In the last chapter the questions about the requirements of the studied urban phenomena and also selection of the appropriate representation of an urban environment were answered. In this chapter we will discuss about the role of betweenness specifically in analysis of the urban street network and also investigate the characteristics of betweenness centrality in different type of representation. Furthermore betweenness analysis of the primal and line approach will be investigated. Various aspects of people’s travel behaviour will then be studied to compare network affects and travel behaviour affects in urban movement and also to investigate the correlation of betweenness centrality with the studied phenomena in this work namely traffic flow, self localization device (You-Are-Here map) and route description system. In the next step modification of betweenness centrality will be developed to improve this correlation and also the functionality of these phenomena. This investigation will assist us to identify the gaps and insufficiencies of the existing methods and addressing these gaps later in this work.
4.1 Characteristics of Betweenness Centrality in Various Representations of a Street Network

Betweenness centrality is sensitive to the conceptualization of the physical street network, whether it is created based on segments, axial lines, named entities or the selected good continuation principle. Furthermore, analyses can be applied to the primal or line graph representations of these conceptualizations and both aspects influence the observed values of betweenness centrality. Each of these approaches by defining different principles forms different type of representation with different numbers of edges and nodes. For instance in the axial representation the least number of visibility lines are considered while in the selected good continuation approach the defined straight edges form the street network. Therefore simply the street networks of these representations do not match, and thus, betweenness centrality measures of the nodes or the edges are different in each case. Another problem specifically with structural analysis of segment based representation is that the nodes have usually similar connectivities with for example 3 or 4 links, therefore the result of betweenness centrality of the nodes and edges will be respectively similar. That is why various structural properties of nodes and edges cannot be highlighted with this approach.

Additionally, betweenness centrality is sensitive to the chosen distance function. For example, topological distance would weight each edge by 1, geometric distance would weight each edge according to its length and angular distance weights each edge based on its angle with the neighbour edge and so on. The resulting shortest paths between two
nodes differ respectively; for instance topological shortest path chooses a path that has the least number of edges, geometric shortest path searches for the path which has the shortest distance and angular shortest path depicts a path which has the least angular changes or in other words the path which has the least turns. Accordingly, betweenness centrality would be computed from different sets of shortest paths which results in different results.

4.2 Edge Betweenness Centrality of the Primal Approach for Characterization of the Studied Urban Phenomena

In graph theory when the focus is on accessibility and connectivity of the graph the line representation is used. The primal approach is suitable for making the best use of large information resources developed and available in a broad variety of different fields. Moreover, the primal approach significantly reduces subjectivism in graph construction by excluding problems related to the generalization model (Porta et al. 2006).

In spite of the advantages of line representation both in graph theoretic issues and specifically in an urban street environment discussed in section 2.1.6, there exists some disadvantages in terms of structural analysis of this type of representation that is discussed.
4.2 Edge Betweenness Centrality of the Primal Approach for Characterization of the Studied Urban Phenomena

Jiang and Liu (2009) have adopted a line representation that encodes a street-street or node-node relationship for predicting traffic flow. It has been suggested in the previous study of Jiang and Claramunt (2002) that the primal and line representations are identical from the point of view of structural analysis. In other words, the structural properties of nodes along an edge are the same as those of the edge. It is perceived that there are equally good reasons for considering the line problem, perhaps more so because it is easier to map the accessibility of nodes rather than the accessibility of streets (Batty 2004). However although in the line representation of an urban street network, which represents the accessibility between nodes rather than between edges, it is easier to understand the connectivity and accessibility of the graph visually, some analysis problems might not be approached through it.

For instance in order to characterize the urban street network with the aim of studying movement patterns such as traffic flow, betweenness centrality has been performed on the line representation of the urban street network in some of the previous works such as Jiang and Jia (2009). But a critical point that is ignored in their analysis is that the approach via node betweenness in the line graph does not yield the same results with performing edge betweenness on the primal graph and also that the difference between the two approaches cannot be overcome. As can be seen in Figure 4-1 edge betweenness centrality of the primal graph is different from the node betweenness centrality of the line graph (Brandes 2007) and the node betweenness of the line graph is not a complete indicator of the betweenness of streets. In order to clarify this issue see edge ac in Figure 4-1 of the primal representation. In this case the shortest path from \( a \) to \( c \) would
necessarily pass from this edge and therefore the value of its betweenness would be added up. But if we want to compute the node betweenness of \( d \) in the line graph which is a representative of edge \( ad \), since the shortest path between \( d \) and \( e \) starts from node \( d \), but would not pass along it, the value of its betweenness would not be added up. As can be seen if Figure 4-1 the betweenness value of edge \( ac \) in the primal graph is 3 but the betweenness value of node \( d \) in line graph is 0. Koschützki et al. (2005) also give substantive reasons why the line graph approach, though elegant, may be inappropriate for many application scenarios.

**Figure 4-1**: Edge betweenness of the primal (blue) is different from node betweenness of line (pink) representation

One of the works in this context is a simulation that was performed on human movement in large street networks by Jiang and Jia (2009) to investigate whether the aggregate flow, assigned to individual streets, is mainly shaped by the underlying street structure or the human moving behaviour. They used a line representation of the street network and found out that weighted PageRank (Langville et al. 2008), betweenness and degree
4.3 Investigating Various Aspects of Human Travel Behaviour and its Effects vs. Network Effects in Urban Movement

centralities are the best metrics to capture aggregate flow and that betweenness centrality specifically appears the best for purposive walkers.

But based on the provided evidences it can be perceived that the value of edge betweenness received from the primal approach as a more comprehensive, objective, and realistic methodology for identifying the significant or prominent streets of an urban street network. Furthermore, usually the location of people’s source of travel originates from and ends along edges and not necessarily on the nodes (note that other travel networks, such as train networks, behave differently). Travel behaviour of people in an urban environment play an important role in traffic flow, route description and self localization, which is why in this thesis the analysis of the urban street network and also in characterization of the studied urban phenomena, edge betweenness centrality of the primal approach is performed.

4.3 Investigating Various Aspects of Human Travel Behaviour and its Effects vs. Network Effects in Urban Movement

Since in this work we are dealing with some emergent phenomena from the urban environment such as traffic flow and wayfinding that involve human travel behaviour, it can be helpful to investigate some aspects of people’s travel behaviour to be able to address them in our analysis. It is worth mentioning that although people’s travel behaviour has different aspects, here only the relevant aspects to our studied phenomena
will be discussed. People in an urban street network are highly volatile; they enter this environment at any time, and leave as soon as they have reached their destination. Also, the places where they emerge or disappear are distributed over space and time, but not in a random manner. In other words they leave a specific origin and reach a specific destination at a specific time. Additionally, people travelling in an urban street network are purposeful. They have individual travel, sensing and communication capabilities, maybe even preferences, and a specific travel demand to reach a destination by a specified time or specified costs. Especially, during travel they can interact with their fellow agents (communication) and their physical environment (sense and act), and thus, change their travel plans at any time to satisfy their travel demand. This means travel plans—if not the underlying travel demand itself—can be dynamic.

On the other hand there exist some cognitive aspects in human’s wayfinding behaviour. People find their way with bounded rationality, i.e., based on incomplete individual network knowledge, inaccurate and systematically distorted weights of edges (Stevens and Coupe 1978), a hierarchic cognitive map (Hirtle and Jonides 1985), and heuristics instead of optimal algorithms. For the same reason—cognitive efficiency in an uncertain world—they show a habitual wayfinding behaviour. For example, in case of a route description system, people prefer to be instructed with the streets that are better known or are mainly used by other people. This means that people do not (necessarily) follow topologically or geometrically shortest paths. They may have more complex cost functions in mind, but they also apply heuristics. A strong support of this claim is Braess’
4.3 Investigating Various Aspects of Human Travel Behaviour and its Effects vs. Network Effects in Urban Movement

paradoxon (1969), where he shows that a new shortcut in a network may lead—in a perfectly rational decision—to on average longer travel times, because everybody will try to use it and nobody is able to estimate the impact on capacity. The effects of psychology of navigation can be found for example in the concept of distance that underlies the use of measures such as betweenness centrality.

The nature of human movement has two aspects: the selection of a destination from an origin; and the selection of the intervening spaces that must be passed through to go from one to the other. The former is about to-movement, the latter through-movement. Therefore every trip is made up of a pair of origin-destination, or to-movement nodes, and a variable number of through movement nodes (Hillier et al. 1993). In the process of making decision for these selections, humans show autonomous, purposeful, flexible, and volatile attributes.

In the context of space syntax it is suggested that the configuration of the urban street network is in itself a major determinant of movement flows: that is, the number of people observed moving along the street segments, without regard to the origins or destinations, or to the reasons for choosing to move along that segment. The fact that strong correlations are commonly found between observed flow and configurational measures cannot be ignored and it can be concluded that geometric (from the use of lines) and topological (from the use of metric free graph measures) factors are critically involved in how people navigate urban environments (Hillier et al. 1993; Penn et al. 1998). Since the reported results are about aggregate human behaviour, it has always been unclear how far
they depended on individual spatial decisions, and how far they are simply mathematically probable network effects, that is emergent statistical effects from the structure of networks, relatively independent of the psychology of navigational choices. By using different concepts of distance in configurational analysis of urban networks, and correlating the results with real movement flows, it was shown how cognitive inferences can be made from aggregate movement data, and distinguished from network effects in Hillier and Iida (2005). The technique they propose was to extract cognitive information from real flows is to take urban street networks and subject them to different perception of distance by people, then to explore how well the different interpretations correlate with real movement patterns. Therefore, differences in movement correlations with the different definitions of distance cannot be network effects, since in each case the representation of the street network and its graph are identical, and all that differs is the mathematical interpretation by varying the concept of distance. It is then an unavoidable inference that people are reading the urban network in geometrical and topological rather than metric terms. Although it is perfectly plausible that people aim to minimise distance, their concept of distance is, it seems, shaped more by the geometric and topological properties of the network than by an ability to calculate metric distances. In general it can be concluded that the structure of the graph governs network effects on movement and that how distance is defined in the graph governs cognitive choices (Hillier and Iida 2005).

Jiang and Jia (2009) have simulated human movement in large street networks. They have also collected some dataset from taxi cabs, in order to find out about human’s
behaviour and their origins and destinations of their urban trips. They found that aggregate flow, assigned to individual streets, is mainly shaped by the underlying street structure, and that human moving behaviour (either random or purposive) has little effect on the aggregate flow. This finding implies that given a street network, the movement patterns generated by human beings (purposive walkers) and by monkeys (assumed to be random walkers) are the same. They have found what Hillier and Iida (2005) have concluded about the role of psychological aspect in aggregate flow is implausible and rather odd reasoning.

By taking Jiang and Jia’s (2009) simulation into account, it can be seen that what they have considered as human travel behaviour is solely purposive walkers who would randomly decide their goals and even if they would have a preference, it is only prioritizing closer locations, which is not true about all the trips people might take. It should be considered that purposive walkers do not randomly decide for their destinations and they might have various preferences apart from the distance to their destinations, such as cost of their travels or avoiding congested streets. In case of the collected data from taxi cabs, it should also be considered that the origins and destinations of taxi cabs are not necessarily the origins and destinations of people. For example some of the cabs might only give service from taxi stop to train station or other high demand spots. Apart from all this, people’s travel behaviour is time-dependant, which means majority of them would leave home for work or school in the morning and would come back in the evening, which are the traffic peak hours of the day. Therefore this thesis would take
these temporal and dynamic aspects of human travel demand into account to be able to study traffic flow of a street network.

4.4 Developing a Model of Modified Betweenness Centrality

So far we have provided some evidences to see why there is the need to consider dynamic and temporal aspects of human travel behaviour in studying an urban movement phenomenon such as traffic flow. Therefore since the depicted dynamics of travel behaviour cannot be found out of the characteristics of a static network, the urban street network should be characterized in a way that the dynamic aspect which is the specific origins and destinations of people and also temporal aspect which is travel behaviour in different times of the day would be taken into account. Because people enter traffic at any time, and leave as soon as they have reached their destination. The places where they emerge or disappear are distributed over space and time, but not in a random manner. Additionally, people in urban traffic are purposeful. Developing a modified betweenness centrality measure finally has to address any of the identified issues reflecting the locations of origins and destinations of human’s recorded trips in different time periods of the day. In this section we focus on theory and algorithm of this model, developing a preliminary model and demonstrating by this way the principle feasibility of this goal. The implementation of this model in traffic flow prediction will be discussed in the next chapter.
4.4 Developing a Model of Modified Betweenness Centrality

An environment that is large enough to discuss the details of the model and small enough to be understood completely is presented in Figure 4-2. On the left side a primal graph of a street centreline conceptualization and on the right side the line representation are shown with dashed lines. The graph consists of five vertices $V = \{v_1, v_2, v_3, v_4, v_5\}$ and five edges $E = \{e_1, e_2, e_3, e_4, e_5\}$. Since the graph is embedded, edges can be characterized by their geometric length, or by any other travel cost function. These costs are shown in Figure 4-2 as well. On the right side of Figure 4-2 the line graph $G'$ is added in dashed lines. Edges $E$ of the primal graph become vertices $V'$, and adjacent primal edges $e_i$ and $e_j$ become linked by edges $e'_{ij}$ in the line graph. Also these edges $e'_{ij}$ can be weighted, although the semantics of weights are different now. For the example let us choose travel costs from the centre of $e_i$ to the centre of $e_i$.

$$w(e'_{13}) = (w(e_1) + w(e_2))/2$$  \hspace{1cm} (4.1)

For the results in Table 4-1, the above equation is applied for uniform (topological) distance as well as for weighted (geometric) distance. For example, $e_1$ is on the topologically shortest paths from $e_2$ to $e_5$ and vice versa, and on one out of two topologically shortest paths from $e_3$ to $e_5$ and vice versa. In terms of weighted shortest paths, $e_1$ is on the shortest path from $e_2$ to $e_5$ and vice versa, and on the (single) shortest path from $e_3$ to $e_5$ and vice versa.
4.4 Developing a Model of Modified Betweenness Centrality

Figure 4-2: Street centerline graph in primal (left) and line representation (right, dashed)

Betweenness centrality basically considers shortest path from every node to every other node, and each time a node or an edge is passed, its betweenness value would be incremented. For one, this conventional betweenness centrality is not dynamic, although temporal dependency can easily be added by choosing weights as a function of time. But also it is still unsatisfactory in terms of considering travel from every edge to every edge happening with the same likelihood, and by using an unreliable geometric distance function.

Table 4-1: Betweenness centrality of the edges $e_i (=v_i')$ in Figure 4-2, right

<table>
<thead>
<tr>
<th>$C_i^b$</th>
<th>Topological distance (Line graph)</th>
<th>Geometric distance (line graph)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e_1$</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>$e_2$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$e_3$</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>$e_4$</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$e_5$</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>
4.4 Developing a Model of Modified Betweenness Centrality

In order to consider specific origins and destinations for cases like travel behaviour of people in an urban street network, we need to replace the number of shortest path from every node to every other node in the original definition of betweenness to shortest paths from specific origins to specific destinations in a specific time period. Therefore in the mathematical expression of modified betweenness centrality the number of shortest paths between \( j \) and \( k \), \(|SP_{jk}|\) is replaced by the number of shortest paths between origins and destination \(|SP_{od}|\) in the time period of \( \Delta t \).

\[
C_{mb}^i = \frac{\sum_{j,k \neq i} \frac{|SP_{od(i)}|}{|SP_{od}|}}{(|N|-1)(|N|-2)/2} \tag{4.2}
\]

The modified edge betweenness centrality can be also obtained by replacing number shortest paths that pass through node \( i \) or \(|SP_{od(i)}|\) with the number of shortest paths that pass through edge \( e \) or \(|SP_{jk(e)}|\) in the specified time period of the day. The result that is obtained from this equation either in case of modified node or edge betweenness centrality presents the betweenness value of each node or edge for the shortest paths between the specified origins and destination and in the specified period of time. It actually clarifies the prominence of the nodes or edges in the specified time duration. Eventually the values received by this version of betweenness are different from the conventional betweenness. The value obtained from the conventional betweenness first does not belong to specific time duration and second the shortest paths are from every node to every other node.
4.4 Developing a Model of Modified Betweenness Centrality

The input and output data for the modification of betweenness centrality performed for our analysis methods are specified in Table 4-2 and the algorithm is presented in Algorithm 4-1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>i, Int</td>
<td>Counting index, starting from 1 to the number of origin points in the N_o vector</td>
</tr>
<tr>
<td>2</td>
<td>j, Int</td>
<td>Counting index</td>
</tr>
<tr>
<td>3</td>
<td>k, Int</td>
<td>Counting index</td>
</tr>
<tr>
<td>4</td>
<td>O, Char</td>
<td>The specific origin point</td>
</tr>
<tr>
<td>5</td>
<td>D, Char</td>
<td>The specific destination point</td>
</tr>
<tr>
<td>6</td>
<td>SP, Vector&lt;Node&gt;</td>
<td>A route array, the first element is the start point, and the last element is the destination</td>
</tr>
</tbody>
</table>
### 4.4 Developing a Model of Modified Betweenness Centrality

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>Frequency <strong>Int</strong></td>
</tr>
<tr>
<td></td>
<td>The number of shortest paths between specific</td>
</tr>
<tr>
<td></td>
<td>origin and destination</td>
</tr>
<tr>
<td>8</td>
<td><strong>EB₀</strong> Vector&lt;Zeros&gt;</td>
</tr>
<tr>
<td></td>
<td>A zero vector with the dimension equal to the</td>
</tr>
<tr>
<td></td>
<td>number of edges that is used as the default value</td>
</tr>
<tr>
<td></td>
<td>for edge betweenness of a node</td>
</tr>
<tr>
<td>9</td>
<td><strong>EE</strong> Vector&lt;Node&gt;</td>
</tr>
<tr>
<td></td>
<td>A specific route array between two consecutive</td>
</tr>
<tr>
<td></td>
<td>nodes</td>
</tr>
<tr>
<td>10</td>
<td><strong>EB</strong> Float</td>
</tr>
<tr>
<td></td>
<td>An accumulating buffer to calculate the value of</td>
</tr>
<tr>
<td></td>
<td>edge betweenness by summing up</td>
</tr>
<tr>
<td>11</td>
<td><strong>EBW</strong> Float</td>
</tr>
<tr>
<td></td>
<td>Betweenness value of the edges</td>
</tr>
</tbody>
</table>

*Algorithm 4-1*: Edge Betweenness centrality for specific origins and destinations
4.4 Developing a Model of Modified Betweenness Centrality

Float edge betweenness (graph, origins, destinations)

Set the primary edge betweenness value of all the nodes to zero

For every pair of origin and destination in the graph do

   Find all the shortest paths from origin to destination

   Calculate the number of the shortest paths (frequency)

   For each edge in each path do

      Calculate the edge betweenness by adding the previous value to the inverse of the frequency

Return

This chapter investigated characteristics of betweenness centrality in different representation of an urban environment and then discussed human travel behaviour effects vs. network effects. At the end the suggested modified betweenness centrality was clearly introduced and developed according to the existing observations methods. The suggested methods in this chapter and also in the previous one will be implemented and tested in the next chapter to clarify the efficiency of these methods.
Chapter 5

Implementation and Test

In this chapter the implementation of the suggested model for selecting an appropriate representation and structural analysis of the urban street network in characterization of the studied phenomena will be discussed and tested in different experiments afterward. Each of these experiments includes the whole or part of the contributions to different papers. But since in these experiments the OpenStreetMap is often utilized as the source of the dataset, an introduction to OpenStreetMap and its application in this thesis will be first given.

5.1 OpenStreetMap Data Extraction

OpenStreetMap\(^7\) (OSM) creates and provides free geographic data such as street maps to anyone who wants them. This project was started because most maps actually have legal or technical restrictions on their use, holding back people from using them in creative, productive, or unexpected ways. User-contributed geographical information is a core part

\(^7\) http://www.OpenStreetMap.org/
of OSM that follows the peer production model that created Wikipedia; its aim is to create a set of map data that’s free to use, editable, and licensed under new copyright schemes. The OSM project’s hub is the main OSM Web site, which contains four parts. Visitors are first greeted with a Google Maps style online mapping interface, which lets visitors pan, zoom, and search the OSM world map and discover which geographical areas are completed. An export function allows users to download portions of the OSM information in different raster and vector formats for further use or processing. The editing tab allows anyone to contribute to the project by digitizing geographical features, uploading GPX traces from hand-held GPS units, or correcting errors they might have discovered in their local areas.

In this thesis the dataset needed for testing the implementation of the proposed model in self localization devices You-Are-Here (YHA) map and also route description system is provided from OSM dataset. In the first experiment which is the implementation of our model in mobile YAH maps two sets of shapefiles data is downloaded from OSM. Shapefile is a set of files that are a standard way of representing GIS vector data and although OpenStreetMap is not shapefile friendly, but here in this thesis the shapefiles are extracted due to the possibility of further analysis with our tools. These datasets are extracted from Bremen, Germany and also Melbourne in Australia which are the places where the proposed mobile YAH map is tested in.

The second experiment which is the implementation of our model in a route description system, has utilized the same shapefile dataset from Melbourne, Australia. Although OSM dataset is a helpful source of spatial data since it is open source and free for users, but apparently there exist some inconsistencies such as the missing names of some streets.
or not clearly specifying street from other features at least in the shapefile dataset which
is implemented in this work and therefore causing confusion in the analysis of the street
network. Because sometime some linear features which are not necessarily streets, are
included in the street shapefile of the dataset and therefore will mistakably be considered
as part of the streets in the street network analysis.

5.2 Modified Betweenness Centrality for Explaining Traffic Flow

This implementation is the combination of the contributions to two different papers
(Kazerani and Winter 2009a; Kazerani and Winter 2009b). It will first prove the
inadequacy conventional betweenness centrality for explaining people’s travel behaviour
and then proposes a method to modify betweenness centrality.

Traffic flow can be defined as the process of physical agents moving along an urban
travel network. The underlying physical street network in this context is assumed to be
static, although it can have relevant dynamic and temporal constraints such as current
traffic volume in comparison to capacity or night time closures. Since humans are
dynamic and purposeful, they have specific travel demands such as to leave an origin or
reach a destination at a specific time. Hence if they consider centrality of streets in their
route planning, their route planning problem becomes essentially a dynamic one.

Furthermore, their time dependent demands contribute to the dynamics of centrality
measures. Therefore with all these behavioural observations of urban traffic at hand, in
this implementation first we will investigate what type of graph representation is
appropriate for studying this phenomenon and then will modify conventional centrality measures by considering the dynamic and temporal aspects of people’s travel demand to compare it with the conventional version to see to what extent it can improve and determine traffic flow prediction.

In this application the type of implemented representation is the primal approach, not the line one. The reason behind this selection is described in the previous chapters so here it suffices to mention that the node betweenness of the line graph is not a complete indicator of the betweenness of streets, because when we consider edge betweenness of the street or edge $e$ in the primal representation, every time the shortest path between two nodes pass from this street, it would be added up to the value of its betweenness. But when the node (represents the street) betweenness of the line graph is considered, the shortest path might start from these nodes, but not necessarily pass along them. Therefore the value of edge betweenness received from the primal approach can be a more realistic indicator of the significance of that street among others.

In terms of the analysis and characterization of the street network to study traffic flow, since the emergence of traffic means sources and sinks of traffic are irregularly distributed in space and change over the course of the day (see, for example, the daily commuting patterns) or other temporal cycles. A spatially irregular distribution of traffic demand contradicts the fundamental assumption of betweenness centrality that traffic happens between nodes, and equally likely from all nodes to all nodes. One can expect that nodes on many shortest paths in the urban travel network attract much traffic, and by this way, betweenness centrality can characterize the patterns of traffic flow or traffic density. This view is supported by evidence reported in the literature (Hillier et al. 1993;
5.2 Modified Betweenness Centrality for Explaining Traffic Flow

Penn et al. 1998; Jiang et al. 2008). But two factors are shaking our confidence in this argument. First, we know that human agents act at most bounded rational and second, the depicted dynamics of travel behaviour cannot be found out of the characteristics of a static network. Therefore, whether betweenness centrality can explain traffic flow is a valid question. Therefore a modified version of betweenness centrality as was theoretically described before is proposed in this thesis to be able to take the dynamic and temporal aspects of human’s travel behaviour into account with the aim of traffic flow prediction.

Traffic flow has a behaviour over time; apparently there is more travel demand in peak hours, when people travel to work or come back home from work. On weekday mornings the places where people live are the sources of traffic, and the workplaces are the sinks. This pattern reverses for their commuting trip back in the afternoon. While commuting is the major factor in generating urban traffic, other travel demands are superimposing the resulting traffic patterns, travel demands such as shopping or leisure.

Hence here a modified edge betweenness which considers people’s specific origins and destinations in different time periods of the day is generated for this task. The reason why we have implemented edge betweenness is that since people’s travel demands are distributed along each edge or in other words originated from and ended along edges and not necessarily from node to node, edge betweenness centrality can be a more reliable measure for this analysis. Apart from that defining the prominence of an edge in terms of betweenness is more useful in terms of predicting traffic flow rather than prominence of a node.
5.2 Modified Betweenness Centrality for Explaining Traffic Flow

As an example let us assume that we know the travel demand of a population, specified in time. Figure 5-1 shows a street centreline graph enriched with all places \( P = \{ p_1, \ldots, p_{10} \} \) that are relevant for a particular time window, let us say, 9am to 10am on a weekday. For convenience the figure also shows the edge weights split by the locations of the places. In this graph true weighted shortest paths can be computed.

\[ C_{mb}^i(\Delta t) \]

Now a modified betweenness centrality measure \( C_{mb}^i(\Delta t) \) for primal edges \( e_i \) can be computed by counting all shortest paths through \( e_i \) divided by all shortest paths possible in \( \Delta t \) time period. This is a simple example which shows the basic requirements and functionality of this method.
In order to test whether and to what extent conventional betweenness centrality can explain traffic flow and also to test our proposed modified betweenness for improving this method, the following experiment is designed.

We previously hypothesized that since human movement is planned from a specific origin to specific destination and is not from every node to every other node, the number
of visits to each edge or the travel demand of each edge cannot be determined by the traditional edge betweenness centrality. Therefore, here a modified betweenness centrality which considers people’s specific origins and destinations in different times of the day is considered in a synthetic network.

Apparently there is more travel demand in peak hours, when people travel to work or come back home from work. On weekday mornings the places where people live are the sources of traffic, and the workplaces are the sinks. This pattern reverses for their commuting trip back in the afternoon. While commuting is the major factor in generating urban traffic, other travel demands are superimposing the resulting traffic patterns, travel demands such as shopping or leisure.

Since we did not have access to real data about people’s travel behaviour means the places of works and their homes in different times of the day, a simple synthetic network is designed so that the results would be clearer to analyse. This network includes a central business district (CBD) and seven suburbs around it. Figure 5-2 presents this network with streets as edges and intersections as nodes. A primal approach is used in this test, but the segment based representation is kept without any further change. The reason for that obviously is that since this street network is small, applying different principles on it such as good continuity would not make any significant change to the structure and also analysis of the network.
Specific origins and destinations are considered in three different time periods of the day. Although this is not driven from actual data, it is the dominant travel behaviour in the city during these times of the day on a smaller scale:

1. In the morning when people leave home for destinations like work, school and shopping centres. Usually people’s homes are located in suburbs and work, school and shops are located in central parts. Table 5-2 (left) shows an artificial data set reflecting such a distribution of origins and destinations for Figure 5-3.

2. During the day when they go for lunch or shopping or any other activity. Since people are expected to be at more central places, these travels usually happen within a CBD. Table 5-2 (centre) shows a data set reflecting this predominant pattern of movements.

3. In the afternoon when people would travel mostly back to home. This behaviour is reflected in the data set of Table 5-2 (right).
5.2 Modified Betweenness Centrality for Explaining Traffic Flow

Table 5-2: Origins and destinations of people in the morning (left), during the day (centre) and in the afternoon (right)

<table>
<thead>
<tr>
<th>Origin</th>
<th>Destination</th>
<th>Origin</th>
<th>Destination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sub7</td>
<td>CBD4</td>
<td>CBD4</td>
<td>Sub3</td>
</tr>
<tr>
<td>Sub2</td>
<td>CBD1</td>
<td>CBD3</td>
<td>Sub6</td>
</tr>
<tr>
<td>Sub6</td>
<td>Sub2</td>
<td>Sub6</td>
<td>Sub7</td>
</tr>
<tr>
<td>Sub3</td>
<td>CBD3</td>
<td>CBD1</td>
<td>Sub2</td>
</tr>
<tr>
<td>Sub6</td>
<td>CBD1</td>
<td>CBD3</td>
<td>CBD2</td>
</tr>
<tr>
<td>Sub1</td>
<td>CBD3</td>
<td>CBD2</td>
<td>CBD4</td>
</tr>
<tr>
<td>Sub1</td>
<td>CBD4</td>
<td>CBD1</td>
<td>Sub6</td>
</tr>
<tr>
<td>Sub5</td>
<td>CBD2</td>
<td>Sub4</td>
<td>Sub2</td>
</tr>
<tr>
<td>Sub5</td>
<td>Sub3</td>
<td>CBD4</td>
<td>CBD1</td>
</tr>
<tr>
<td>Sub4</td>
<td>CBD2</td>
<td>CBD3</td>
<td>Sub4</td>
</tr>
</tbody>
</table>

Since people’s travel demands are distributed along each edge and not necessarily from node to node, edge betweenness centrality can be a more helpful measure for analysis of travel demand of the street network. Apart from that defining the prominence of an edge in terms of betweenness is more useful for predicting traffic flow rather than prominence of nodes. In order to compute the modified edge betweenness centrality in a network of travel demands, igraph package version 0.6[^6] (Csardi 2005), which is an open source library for network analysis, is employed in GNU R statistical environment[^9]. The algorithm used for this modification is discussed before, so here we solely observe and discuss the results. It is worth mentioning that the analysis methods applied in this experiment can be run on any other network.

[^6]: http://cneurocs.ruukki.hhu/igraph
[^9]: http://www.r-project.org/
5.2 Modified Betweenness Centrality for Explaining Traffic Flow

Figure 5-3: People’s origins and destinations in the morning (blue arrows), at noon (green) and in the afternoon (orange)

According to these origins and destinations the proposed modified betweenness centrality along with the conventional betweenness are computed. The results of applying the modified edge betweenness centrality for characterizing people’s travel demand in three time periods of the day is presented and also compared in a diagram in Figure 5-4 betweenness is referred to as $btwns$ here.
5.2 Modified Betweenness Centrality for Explaining Traffic Flow

A low correlation between conventional and modified edge betweenness centrality can be observed in the diagram. Basically this significant difference is logical because the shortest paths in the modified betweenness are not from every node to every other node, there for the number of the shortest paths is less than the conventional betweenness. For instance edge S5 has the most central edge in terms of conventional betweenness but it relatively a low score in modified betweenness in all three time periods of the day. This edge is actually located on one side of the street network so it is not a link between any important areas and one would not expect that it absorbs much traffic flow.

The opposite case can be seen for edge C2, which is the least prominent street in the conventional sense but not the same in modified one. This edge as can be seen in Figure 5-3

Figure 5-4: Comparison of conventional and modified edge betweenness centrality in three different time periods
is the linkage between the central part and the suburbs so one would expect relatively high amount of traffic flow on it. That is because in the conventional way of computing edge betweenness, some of the constraints like population of different parts of the city, concentration of business locations and demands of people would not be considered. Therefore it seems that the values received from the modified betweenness are more realistic in terms of the prominence of that street and its travel demand in different time periods. There even exists a noticeable difference among edge betweenness of travel demand in different periods of time throughout the day. For instance, SC2 is a prominent edge in terms of betweenness in the morning and evening, but has a zero value at noon. The reason is that in the morning and also evening people need to pass the edges which are between suburbs and CBD, but at noon they would be more in central areas and rarely pass other edges.

5.3 Situated Local and Global Mobile You Are Here Map

This experiment is part of the contribution to the joint paper (Schmid et al. 2010). Traditionally, You-Are-Here maps (YAH maps) are static maps of an environment, showing a You-are-here symbol and being displayed in the environment to support spatial orientation. YAH maps serve the purpose of orientation for people in an unfamiliar environment. Although the proposed YAH map develops a novel way of providing improved mobile YAH maps based on spatial hierarchies and relevance, here only the implementation of our proposed methods for selection of the appropriate representation and characterization of the urban street network will be discussed. The
motivation of this work is connecting local and global orientation zones with a network-connectivity zone to generate a mobile equivalent to traditional YAH maps.

The proposed mobile YHA map consists of three context zones as can be seen in the Figure 5-5:

1. **Self-Localization Zone**: This zone, realizing the ‘near’ zone of self-locating in Figure 5-5, depicts the complete street network and the last part of the latest trajectory. Streets are labelled selectively to avoid clutter on the small display. Streets are labelled if they are (a) along the trajectory, (b) likely to be in the direct surrounding of the user, based on the observed position, or (c) of high prominence in terms of centrality based on edge betweenness.

2. **Network-Connectivity Zone**: This zone, realizing the ‘not near, not far’ zone in Figure 5-5, relates the Network-Connectivity Zone to the network links of the larger street network. In the Network-Connectivity Zone only those streets that have a high centrality are depicted, addressing small-display problems as well as relevance principles. This zone starts at the Self-Localization Zone, has the same scale and covers the rest of the display.

3. **Global-Embedding Zone**: The Global-Embedding Zone, realizing the ‘far’ zone of pointing in Figure 5-5, is thus outside of the display.

The contribution of this thesis to this work can be observed partly in the Self-Localization Zone and mainly in Network-Connectivity Zone for characterization and identification of prominent streets in these zones. Actually, outside Self-Localization Zone the street network is simplified and reduced to the most important streets based on betweenness centrality. The appropriate representation selected in Chapter 3 based on Gestalt principle
5.3 Situated Local and Global Mobile You Are Here Map

of good continuation is implemented here to represent the street network. This principle is performed by joining the street segments according to the good continuity principle if they have small deflection angles. The threshold is chosen based on what people perceive as straight (Klippel et al. 2004). Once streets are formed according to good continuation representation the edge betweenness analysis is performed on the primal approach of the selected street network.

Figure 5-5: The three levels of detail in a visual YAH presentation on a mobile display

In the Self-Localization Zone the level of detail of the street network reflects the originally available granularity from the data set. However, street network information requires a noticeable amount of space and is proven to introduce a significant amount of visual clutter. As the task at hand is self-orientation, not the identification of a particular street or route, in the Network-Connectivity Zone those streets which are not important to be visualized are removed, as they are not necessary to describe the general structure of
the street network of the particular environment. Only streets with a betweenness above a certain threshold are depicted, i.e., streets that are prominent and support the street network structurally. As a consequence, thinned out street network will be obtained which contains all necessary information for gaining configurational survey knowledge, but has significantly improved cognitive processing properties due to reduced detail. The reason for that is first the representation in this zone shows the streets in a way that they would lead the user directly to the outer zone (Global-Embedding Zone) instead of representing a lot of number short neighboured segments with low deflection angle, and second here the prominent streets are preferred over the whole streets which prevents redundant and confusing information.

In the first experiment in order to implement betweenness centrality in characterization of the street network in mobile YAH, Bremen city shapefile data set are downloaded from OSM as was discussed in the last section. This analysis is performed mostly in the Network-Connectivity Zone to identify the prominent streets that can connect the Self-Localization Zone to Global-Embedding Zone. In order to apply the good continuity principle on the street network representation, Mindwalk software which performs spatial analysis on continuity and axial maps is used. Since this tool only accepts drawing exchange files (DXF) and simple coordinate files (text files) as an input, the shapefile had to be converted to DXF format. Mindwalk has the ability to merge the segments of a street network according to the defined angle by user. Therefore here this angle called angle of continuity in Mindwalk is chosen based on what people perceive as straight (Klippel et al. 2004). The result would be a street network with formed streets that fit into the defined straight rule but at the same time keeping the identifiers of its segments as
well. Figure 5-6 shows Bremen street network before and after merging process, in which the number of 699 segments decreased to 495 formed streets after applying the good continuity principle.
In order to perform betweenness centrality analysis on Bremen’s street network, Mindwalk implements a computationally efficient version of betweenness centrality, called fast choice. It considers only one random shortest path between each pair of nodes in a graph, instead of generating all the alternative shortest paths. In larger networks, the differences in centrality values resulting from fast choice are statistically insignificant, which can be simply verified by multiple analysis of the same network.

Edge betweenness values range between 0.004 and 0.3676. The mean value calculated from the sample was $\bar{x} = 0.011881$ with a standard deviation in the dataset $\sigma = 0.026216$. The plot of the fast choice values of streets in the city of Bremen is shown in Figure 5-7.
5.3 Situated Local and Global Mobile You Are Here Map

along with the visualization of the street network with streets of different betweenness range of values with different colours.

After performing the analysis the streets with the values above the mean are depicted as prominent ones to be shown in the Network-Connectivity Zone. One of the problems that we confront for this analysis in Mindwalk software is that this tool does not keep the original identifiers of the streets so that after analysis it makes it hard to identify the original ones. In this work the original identifiers are brought in the final result by having the coordinates as the common attribute of the streets and joining the original identifiers to the Mindwalk identifiers.

An experiment was designed to test the functionality of our proposed mobile YAH. To evaluate this approach, a user study with 10 participants was made (6 male, 4 female, mean age 31.2). Participants had diverse professional backgrounds (computer science students, biologists, law students, psychologists). In the first step the participants were informed about the self localization task they would have to perform and also the involved time constraints. They were introduced to the map styles and were allowed as much time they needed learn the interaction with our system. Then they were given 5 minutes to perform as much interaction with the respective map until they indicated that they could point to the correct location and orientation. Generally self-localization with respect to a virtual or real location consists of two parts: the correct identification of the location on a representation (the map) and correct interpretation of the heading (orientation). Here not all the results received for the basic functionality of this mobile YAH map will be discussed, but only the relevant results to this thesis.
An interesting finding of our study was that only one participant recognized the truncation of the street network by means of the edge betweenness measure. The
localization was not affected by reducing the level of details of the street network.

Presumably (although not explicitly tested) the reduced complexity of the map (especially on larger scales) supported the cognitive processing of the information and helped to focus on the relevant structural information.

5.4 User tailored Route Description Systems

This implementation is part of the contribution to another paper (Dethlefs et al. 2010). Basically the aim of this work is the generation of route descriptions that are as user-tailored and adaptive as possible given only information that is inferable from the route or the discourse context. To this end, a formal algorithm needs to be devised and implemented that integrates research on the cognitive principles that have been suggested to operate on human route descriptions, such as the hierarchical structuring of a route description, the classification of landmarks or streets as more or less salient, or the level of detail and granularity provided for certain segments and the kind of street, as well as the linguistic surface forms that typically function to structure and realise the route. Route descriptions can be classified into two categories. Turn-by-turn directions are describing turn by turn how to find to the destination. Destination descriptions describe where the destination is, assuming that the recipient has sufficient knowledge to find to this destination once located. In order to determine the geographical information that should be included in a route description, we suggest using ranking mechanisms for geographic features. Those adapted here concern landmarks as identified in business directories (Duckham et al. 2009), and streets as identified by centrality measures (Tomko et al.
2008). Depending on their ranking, these features will be selected where appropriate in the route context.

The implementation of the suggested methods in this thesis to this work is to come up with an appropriate representation of the street network in order to identify salient streets of the environment to be described by the proposed route description system. In this representation the good continuation approach is used with a preset threshold to merge the neighbouring segments together and form the streets. This representation satisfies human navigation strategies in two senses: first it is a topological representation and second we do not need to mention consecutive and redundant turning instructions for streets with low deflection angle, because they are already considered as one street.

In the next step in order to characterize the structure of urban systems and identify salient streets in the street network, betweenness centrality is used. Betweenness centrality of each street formed by good continuity principle identifies salient or even better known streets which were visited more frequently than others. Therefore selecting salient streets makes the route description cognitively more efficient in terms of relating to the users. Actually in this implementation the application of betweenness can be better observed in destination description rather than the turn by turn description.

In order to test our method a context sensitive and variable route description system in an urban environment, Melbourne street network dataset was extracted from OpenStreetMap. This dataset included central business district (CBD) and some suburbs such as Carlton, St Kilda and Parkville. Since in this experiment as the previous one, the good continuation representation is used, the same process was done for applying this principle on Melbourne’s street network in Mindwalk software. Figure 5-8 presents
Melbourne street network before and after merging process in which the number of 3834 segments decreased to 2988 formed streets after applying the good continuity principle.
After performing the street network analysis similar to the previous case, the results of edge betweenness values seemed to be ranged between 0.0007 and 0.1774. The mean value calculated from the sample was $\bar{x} = 0.002315$ with a standard deviation in the dataset $\sigma = 0.00825$. The plot of the fast choice values of streets in the city of Melbourne
is presented in Figure 5-9 along with the visualization of the street network with streets of
different betweenness range of values with different colours.

The problem that occurred here at this stage was that there were relatively large numbers
of unnamed streets in OSM data set and since we needed the names for giving route
descriptions, we used another data set of the same area to repair the incomplete names.
Although even with the new dataset there remain some unnamed streets, but the numbers
are very few. In the next step streets with the betweenness values above the mean were
selected as the salient ones and are prioritized for being used in route description.

Actually in order to determine the geographical information that should be included in
destination descriptions mainly and turn by turn descriptions partly, the selected salient
streets are utilized. In destination descriptions the most salient street around the
destination spot is used.

To evaluate the integrated model to generate route descriptions, an experiment is set up
collecting from participants ratings of given route descriptions for car drivers. The aim of
the experiment is to find out whether our automatically generated route descriptions are
as natural, helpful and appropriate as human route descriptions. Another goal which is the
aim of this work here is to figure out how to improve the algorithm, particularly from the
aspect of street names.
Figure 5-9: Streets of different betweenness range of values with different colors
The method of performing this experiment is in a way that questionnaires are distributed by email to 23 participants of this experiment. Each questionnaire provides eighteen sets of route descriptions: twelve sets of turn by-turn descriptions, and six sets of destination descriptions. Each set includes one route description automatically generated by the algorithm discussed in this paper (called CSDs), one descriptions by human (called HDs), and for turn-by-turn descriptions additional one by online routing services, here Google Maps (called GDs). First, participants indicate their familiarity of the environment. Then they point out the descriptions that they think are automatically generated. Finally, they select the most useful description and explain their reasons.

Since the focus of this thesis is not evaluation of the whole proposed route description system, it suffices to say that for the first question for turn-by-turn descriptions, 36% CSDs are identified by the participants to be computer generated. In other words, 64% CSDs are thought as natural as HDs. For destination descriptions, the difference between CSDs and HDs is smaller, which is 52% and 30% respectively identified as machine generated. Although the identifying percentage of CSDs for destination descriptions rises, the smaller difference against HDs indicates that it is harder to tell CSDs from HDs in terms of destination descriptions than turn-by-turn descriptions. Therefore, destination descriptions are more natural and closer to HDs than turn-by-turn descriptions. In the next question, participants are asked to choose the most useful description in each set. According to results in turn-by-turn descriptions, HDs are the most preferred ones at about 42%, while CSDs are least preferred at about 26%. In contrast, in the case of destination descriptions CSDs are more preferred than HDs, 57% vs. 40%. In the responses to plain language questions, various preferences can be observed but the ones
related to this work can be mentioned as for instance the use of street names. The way of using street names in the CSDs is accepted better in destination descriptions than in turn-by-turn descriptions. In both formats of descriptions more street names are expected. As can be seen, destination descriptions in which the use of the prominence of streets are obvious in them, gain a higher rate of preferences. In first question destination descriptions are considered to be closer to human way of describing a route and in the second one again destination descriptions are more considered to be as the most useful descriptions rather than turn by turn ones. Although there might exist some other factors apart from the selection of the salient streets, but in the verbal explanations in both questions participants have declared that they prefer the use of street names and also prominent streets. Therefore it is shown that use of street name plays an important role in route descriptions, furthermore, wayfinders depend on street names more than that what CSDs release.
Chapter 6

Conclusion

The final chapter will first summarize proposed model for an appropriate urban street network representation and also characterization of the suggested representation according to the studied urban phenomena. Then the studied phenomena will be evaluated according to the results and the conclusions will be drawn with regard to the hypothesis. In order to investigate the limitations and the open questions for future work, this chapter then discusses each of these urban street network phenomena individually.

6.1 Summary

A belief in the influence of the built environment on humans was common in architectural and urban thinking for centuries. Cities generate more interactions with more people than rural areas because they are central places of trade that benefit those who live there. Spatial organization of a place has an extremely important effect on the way people move through spaces and meet other people by chance (Hillier and Hanson 1984b).
Various practical studied related to the city and intercity routing problems have been a permanent issue of inspiration for graph theory. An urban street network can be represented in various ways for instance geometrically as spatial networks embedded in the real space whose nodes occupy a precise position in a two dimensional Euclidean space, and whose edges are real physical connections, or topologically in which only the connectivity and accessibility of the graph would be considered. The difference between the two approaches is subject to whether or not geometric distance plays an important role in the graph theoretical representations.

In order to select an appropriate representation for studying urban street network phenomena such as the ones studied in this work namely traffic flow, navigation assistance (route description) services or self orientation devices, it is important to consider their characteristics, behaviour and requirements. For example in this work good continuation representation was selected to characterize and improve route description system and mobile You-Are-Here maps. The reason for that is this type of representation can reveal some hidden structural properties of the urban street network that cannot be approached by other types. For instance by merging neighbour segments with low deflection angle and applying the “straight” definition of Klippel et al. (2004) the representation become closer to the perception of people from streets. Therefore they can interact better with either of these navigation assistance systems because what they receive as rout description or observe as their current place on a map is according to their perception of street. Since in the case of investigating traffic flow and travel demands of people, a simple synthetic network was utilized the basic segment based representation
was adopted because applying these principles on such a small network would not make major differences.

The next step toward characterization of these phenomena is the structural analysis of the street network. The main method suggested in this work is centrality measures and specifically betweenness centrality. Betweenness centrality (Freeman 1977) would reveal to what extend a node or an edge is between others or in others words significant. There for identified streets with high value of centrality are considered to be prominent to improve the functionality of the related studied phenomenon. In both cases of studying route description system and mobile You-Are-Here map, the conventional betweenness centrality is computed. In mobile You-Are-Here maps, identifying prominent streets in the network connectivity zone would reduce the number of streets and prevents the user from being confused. Apart from that user would be leaded from the self localization zone through NCZ to global embedding zone by the streets that are more prominent or sometimes better known. By describing the routes using highlighted salient streets in a route description system, the user would be able to interact with the system more cognitively. Because according to the results people prefer to be instructed by the streets names specifically the ones the ones that are better known or more salient.

The conventional betweenness centrality was revealed to be insufficient to explain the last studied phenomenon that is traffic flow. Since people’s travel demand are originated from specific locations to specific destinations and varies through different time periods of the day like in peak time, the conventional betweenness cannot predict this behaviour, because it considers travels from every node to every node. Therefore in order to take the dynamic and temporal aspects of people’s travel demand into account, a modified version
of betweenness centrality is proposed here in which people’s travel behaviour is considered to be from specific origins to specific destinations in different time periods of the day. The value received from this version of betweenness highlights the prominent streets with regard to people’s travel demand, but since this version considers different time periods, the values change for different time periods of the day.

6.2 Discussions

The methods discussed in this work were particularly proposed for characterization of urban street network with the aim of improving the emergent phenomena from this environment. For this task basically an appropriate representation was selected with regard to the studied phenomenon and then the phenomenon was investigated to see which type of analysis should be performed to characterize it properly. Therefore the first research question regarding the selection of an appropriate representation for the studied phenomena is addressed accordingly.

Three different urban phenomena have been studied here with regard to both their underlying structure of street network and also their behavioural aspects. The first two studied phenomena, namely the mobile You-Are-Here map and the cognition based route description system, the conventional betweenness centrality seemed to have a positive correlation with the conventional betweenness centrality. Actually in characterization of these phenomena time does not play an important role, hence cannot improve the functionality of them at least from the aspect that was studied in this work. The implementation of conventional betweenness improved the functionality of mobile YAH
map in sense of reducing the number of insignificant streets and highlighting the prominent ones in the network connection zone which connects the local zone to the global one. The interesting point is that the users did not realize the reduction of the streets in the experiment, because the major and prominent ones were already there. On the other hand implementation of the salient streets in the proposed route description system received users’ positive feedback. In users’ written responses, lots of references to the use of salient street names could be observed. Therefore the results show the positive role of the proposed method in improving the route description system which address the second research question.

The characterization of traffic flow was performed with regard to both its structural properties of the street network and also dynamic and temporal properties of people’s travel demand. The proposed method of modified betweenness centrality was performed on different synthetic networks due to the lack of access to real travel demand dataset, but here in this thesis only one of the simple examples was brought in. The significant difference among the conventional betweenness centrality and modified betweenness along with other evidences show the improper nature of conventional betweenness for predicting traffic flow. The results drawn from testing the modified betweenness on the synthetic network in this thesis and also from all the other street networks which are not brought in here, revealed a high correlation between human travel demand in street network and inconsequence prediction of traffic flow and the modified betweenness centrality. By addressing the third question, it seems that the values received from this version of betweenness can be a reliable indicator of prominence of streets according to dynamic and temporal aspects of human travel behaviour.
In summary, the proposed model both for street network representation and characterization of urban street network satisfy the requirements for improving the studied phenomena emerged from an urban environment. The proposed methods can also be performed on other movement patterns such as predictability of pedestrian movement, to see whether and to what extend it can improve them.

6.3 Outlook

This section will first point out the limitations of the proposed model, and then will come up with some potential solutions and open questions for future work.

In terms of the input of the tested phenomena, the dataset that was utilized for the implementation of the proposed model in improving mobile YAH map and a user-tailored route description system was extracted from OpenStreetMap. Although OSM is a free and helpful source of geographic data, in both cases the incomplete nature of street names in the street network brought up some major problems especially in route description system. Because in this case the instructions need to be given mainly according to the names of the streets and that was the reason why another dataset had to be used to repair the unnamed streets. Apart from that at least in the shapefile dataset which was used in this work, there are some features in the street network dataset that are labelled as streets but actually they are not, which makes confusion for the structural analysis of street network.

The threshold used for selection of salient streets is based on the average value of edge betweenness centrality. Since there were some comments in the written responses of the
related experiment regard to this issue, it is worth changing the threshold of the selection
criteria to see the effect of this change in route description and users’ feedback. Although
users’ feedback about the interaction with the mobile YAH is quite satisfying but the
same modification of threshold can be applied to this device as well to see whether the
functionality even improves better.

The routing algorithm performed in designing the proposed route description system is
based on shortest path algorithm and the value of edge betweenness centrality is only
used for the selection of the salient street especially in destination description. What
seems to be interesting to apply instead of shortest path algorithm is using the
betweenness value for routing purposes, which for instance means to choose the route
including the streets which have overall the highest value of betweenness. In this way the
route which has the most salient streets along it would be chosen to be described by the
system and consequently the user can interact with it easier.

The implementation of the proposed modified betweenness centrality for predicting
traffic flow is performed on several synthetic networks and one of the simple ones was
analysed in this thesis. The reason for that was the lack of access to travel demand data
set such as the location of work and home of people and also their temporal behaviour in
an urban street network. Therefore testing this method on real travel demand dataset and
in real street network can reveal some interesting results which shows to what extend this
method can be applicable for real travel demand dataset and whether the same results
would be drawn from it.

Another step toward improving this method from the cognitive aspect can be
implementing a routing algorithm which is cognitively closer to the route that people
would usually choose to reach to their destination. For instance the idea of “simplest” path proposed by Duckham and Kulik (2003) is suggested to minimize the complexity of a route description, based on the amount of information required to negotiate each decision point. This idea can be reflected in the routing algorithm by entering a weighting function based on for example a cognitive model of navigation instruction complexity which is implemented in the mentioned work. Therefore by considering the cognitive aspects of human travel behaviour and also other aspects that have not been considered in this work, the analysis performed for characterization of traffic flow would be more realistic. This could be a big step toward studying people’s travel behaviour and also prediction of traffic flow.


Hillier, B., J. Hanson and H. Graham (1987). "Ideas are in things: an application of the space syntax method to discovering house genotypes." Environment and Planning B: planning and design 14: 363-385.


Bibliography


Minerva Access is the Institutional Repository of The University of Melbourne

Author/s:
Kazerani, Aisan

Title:
Characterization of the urban street network and its emerged phenomena

Date:
2010

Citation:

Persistent Link:
http://hdl.handle.net/11343/35410

File Description:
Characterization of the urban street network and its emerged phenomena

Terms and Conditions:
Terms and Conditions: Copyright in works deposited in Minerva Access is retained by the copyright owner. The work may not be altered without permission from the copyright owner. Readers may only download, print and save electronic copies of whole works for their own personal non-commercial use. Any use that exceeds these limits requires permission from the copyright owner. Attribution is essential when quoting or paraphrasing from these works.