PRESENTING SPATIAL INFORMATION:
GRANULARITY, RELEVANCE, AND INTEGRATION

International Workshop in conjunction with COSIT 2009
Aber Wrac’h, France
21 September 2009

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Preface

This volume collects the papers presented at the International Workshop *Presenting Spatial Information: Granularity, Relevance, and Integration* held in conjunction with the Conference on Spatial Information Theory, COSIT, on 21 September 2009 in Aber Wrac’h, France. These papers underwent a thorough peer review: The three papers by Howald, Harrie *et al.*, and Wang & Schwering as full papers, and the two papers by Seifert & Richter and by Dahinden & Sester as abstracts. Sabine Timpf contributed an abstract of her keynote talk.

In recent years, the availability of automatically generated spatial information of various kinds has developed dramatically. Nowadays, virtually any kind of information is obtainable via the Web. Route descriptions of diverse kinds can be obtained from many different sources and across different modalities. Views of maps and geographic information can be accessed in various ways, and local spatial or spatial-related information is provided for diverse interests and in a multitude of ways.

Although this is already a fantastic situation in terms of information availability and accessibility, Web users may not always be comfortable with the ways in which the information is presented. Recent research has shown that automatically generated information exhibits fundamentally different features from information provided naturally by humans when asked about spatial information, for example, in route directions. Therefore, it is our contention that substantial work still needs to be done in order to render spatial information services more supportive and cognitively suitable.

The workshop addressed issues pertaining to *granularity, relevance, and integration*. Spatial information is presented to information seekers on various levels of granularity, ranging from coarse high-level information concerning geographic areas to detailed low-level information concerning spatial actions in small-scale space. Not all of this information is relevant for all purposes, and so decisions concerning granularity are directly intertwined with issues of relevance across interaction scenarios. On top of that, web-based services typically present information on one level of granularity at a time, providing access to other granularities or other types of information via various hyperlinks. In contrast, humans manage to present information in an integrated and coherent way, switching flexibly and smoothly between levels of granularity according to the expected relevance for the information seeker. Such processes are substantially supported by dialogic interaction.

Each of the papers in this collection contributes to this research field in a different way. The collection starts with an abstract of the keynote talk by Sabine Timpf. She is focusing on the integration of spatial references at different levels of granularity. Blake Stephen Howald addresses the granularity structure of spatiotemporal information as presented in crime narratives. Tobias Dahinden and Monika Sester assess the relative importance or relevance of geocoded ob-
jects in terms of their frequency of mention in Wikipedia. Lars Harrie, Sébastien Mustière, Heiner Stuckenschmidt and Hanna Stigmar discuss various ways in which the readability of maps presented in geoportals can be improved by automatic methods. Jia Wang and Angela Schwering discuss how automatic sketch map-based querying may be improved by taking systematic cognitive errors into account. Inessa Seifert and Kai-Florian Richter address how the sense of orientation of digital library users, when “navigating” in the virtual data space, can be supported by appropriate visualization. Together, these papers provide a broad and multifarious insight into ongoing research in the exciting area of spatial information presentation.

Bremen and Melbourne
21 September 2009

Thora Tenbrink and Stephan Winter
Workshop Chairs
Organization

The International Workshop *Presenting Spatial Information: Granularity, Relevance, and Integration* was organized in conjunction with COSIT 2009, Aber Wrac’h, France.

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Institutional support from the the SFB/TR8 (Tenbrink) and the University of Melbourne (Winter) are acknowledged. Also, many people dedicated their time and funding to this workshop, most notably the program committee and the keynote speaker.
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Constructing Spatial Information for Presentation

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Abstract. Humans are good at presenting integrated spatial information, much better than computers are at the moment. In a dialogue between humans, the necessary granularity and relevance of spatial infobits are negotiated, i.e., spatial information is presented at different levels of granularity to probe the spatial knowledge of the other person and to determine the relevance of these spatial infobits. At the end of such a negotiation, selected infobits are presented in an integrated fashion using a tailored structure.

The information provider constructs the information to be presented from infobits using a structure he or she perceives as appropriate for the recipient. However, spatial information in our memory is not necessarily integrated. Most of our knowledge about space is in infobits that we can use to construct the type of representation we need to carry out a task. As a recipient of spatial information, do we accept the information construct of the provider or do we construct our own representation from infobits gleaned from the information provided? Do we use the structure inherent in the construct or do we provide our own structure?

The process of integrating spatial information is highly individualized and takes place within each person. If we accept that our brain is an extended network of neurons or nodes, then integration by the recipient could be described as the process of defining new nodes (containing infobits) and connecting these with the existing network. The more such connections can be made, the better the integration.

What can we learn from this process for the presentation of spatial information as a spatial information service? How can we determine and store the necessary infobits? In which way do we need to organize infobits to provide different levels of granularity? How does the construction process work? Which structures can we use as backbone for the information construction?

In my talk I will argue that selecting the appropriate infobits at the appropriate granularity and putting them into context, i.e., adapting them to location, time, activity and emotion, will provide the flexibility for the presentation of spatial information we lack so far. Thus, I presume that negotiation and context determine the successful presentation of spatial information.
Granularity Contours and Event Domain
Classifications in Spatially Rich Narratives of Crime

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Abstract. The role of space in narrative structure has been considered minimal at best and, consequently, has received little attention as compared to the role of time. However, recent research has suggested that space is more critical to narrative structure than may be readily apparent. This paper analyzes narratives of crime, from legal institutionalized settings, which have a high proportion of explicit spatial language. In contrast to narratives without such high proportions, a granularity contour (which characterizes the ground information) emerges and transitions between larger and smaller spaces—providing boundaries between groups of narrative events. As will be demonstrated, granularity and temporal ranking information can be used by classifiers to delineate Pre-Crime, Crime and Post-Crime event groups with 84% accuracy. Overall, by suggesting a spatiotemporal-event narrative structure, a challenge is presented to the traditional temporal-event perspective.

1 Introduction

The predominate temporal focus on narrative, for example, embodied in Labov’s definition, as “a sequence of two clauses which are temporally ordered [such that] a change in their order will result in a change in the temporal sequence of the original semantic interpretation” [16], has rendered the analysis of space in narrative comparatively underdeveloped and of secondary concern. However, recent research has suggested that space plays an integral role in defining narrative structure as its temporal counterpart [10]. This paper evaluates this possibility by focusing on narratives which have, as revealed by explicit spatial language (e.g., prepositions, motion verbs), a qualitatively high proportion of spatial information—ten narratives of serial crime from several different genres from the United States legal system.

The presented analysis demonstrates that not only is space ubiquitous in crime narratives, but a similar pattern emerges across each narrative. In particular, the spatial referents classifiable as ground (within Talmy’s figure/ground/path trichotomy [35]) can be represented on a scale of descriptive granularity (following Montello [22]) such that the entire narrative adopts a granularity contour
which ‘zooms’ from larger to smaller to larger spatial perspectives. Further, different windows on a narrative’s granularity contour correspond to different narrative event groupings. The accuracy of these correspondences are subsequently tested in a machine learning task, the success of which is dependent on the ability to resolve granularity patterns in the crime narratives; suggesting that the spatial information available in narrative contributes to its overall (i.e., macro) structure.

This paper is arranged as follows. Section 2 presents the theoretical assumptions made about space and narrative taken in this paper and discusses differences between the spatial characteristics in ten crime narratives and ten non-crime narratives selected from the American National Corpus Charlotte Narrative and Conversation Collection (ANC) [13]. Section 3 describes the theory and methodology behind analyzing granularity information in narrative and presents the representation of granularity information as a zooming contour. Section 4 exploits this information in a machine learning task for determining boundaries between larger narrative event groupings which correspond to groupings of Pre-Crime (PRE), Crime (CRI) and Post-Crime (POS). Section 5 concludes the paper.

2 Space in Narrative

I adopt several theoretical postures in this paper which I now define. First, use of the term space will mean the explicit linguistic description which corresponds to the actual physical environment of the narrative events. Second, I will follow a Labovian definition of narrative (given above) which is primarily temporal\(^1\). This is in opposition to alternative narrative-like structures such as list structures (e.g., [30]), past tense descriptions of habitual actions, or, more crucially spatial, route directions and map descriptions. Lastly, as research on granularity and the spatial aspects of narrative suggest a strong link between individual spatial cognition and perspective taking in spatial language, I am focusing only on narratives of personal rather than vicarious experience.

Analytical frameworks subsequently developed by Labov and others based on the noted temporal-based definition of narrative have regarded space as non-critical for narrative understanding, definition or analysis (i.e., space is not necessary for the recognition of a Labovian narrative text-type [40]). Under temporal frameworks, space is typically relegated to providing background or setting information (e.g., Orientation in Labov’s model [16]) and, in later developments, aiding in verb and thematic role-based analyses of event resolution (i.e., V subcategorization for a PP or DP [17, 18]). Thus under the temporal view, temporal progression and past-time events are critical earmarks of narrative structure.

\(^1\) There are a number of competing perspectives to Labov (e.g., ethnomethodological [14] contextual [24] and identity [21]). However, it is important to note that despite potential theoretical differences, most perspectives adopt a similar core temporal definition [1].
Building off the temporal event structure of narrative, in the spatial domain, research has focused on the role of space beyond the contribution of setting information. For example, deictic approaches [7, 45]; cognitive approaches [36]; cross-disciplinary (literary and cognitive) approaches [3, 4, 28, 29, 44]; and computational approaches—Shapiro and Rapaport’s SNePS system which included spatial information in knowledge representation and inferencing [31–33] and Yuhan and Shapiro’s approach to frame of reference resolution [42]. However, while these approaches seek to leverage spatial information for a particular problem, it is still secondary in terms of defining the linguistic structure of narrative. The core structure of narrative is still temporal progression and events under these approaches. Space, when available, is used for derivative purposes. However, most relevant for the present discussion is Herman’s perspective that narratives can be viewed as a collection of temporally linked narrative domains [10]. Narrative domains are “mental construct[s] that encompass ... the history of spatial relationships between storyworld objects” [10]. Further, narrative domains are spatial localizations consisting of “sets of verbal or visual cues anchored in mental models” [10]. This is an interdisciplinary approach as narrative domains are defined relative to the cognitive map—our internal representation of the external environment [38, 9]. Linguistically, narrative domains are defined by (spatial) discourse cues such as: deictic shift; figure and ground relationships; region, landmark and path relationships; topological/projective locations; motion verbs; and what/where systems [19].

Herman’s insights are concerned with what role space plays in narrative structure, arguing for a reassessment of the temporal perspective such that narratives are a spatiotemporal progressions of past-time events. However, as indicated, space is minimized in narrative and is, for all intensive purposes, optional on the linguistic surface. Therefore, the ability to account for the spatial discourse cues indicated by Herman or any spatial language for that matter, is potentially limited because of this optionality—the possibility exists that a given narrative could be completely devoid of, or completely suffused with, spatial language. Consequently, before moving to an analysis of the high proportions of spatial language in the aforementioned crime narratives, and in order to get a sense of what the range of spatial language across other ‘non-crime’ narratives is, I will compare the crime narratives to a selection of narratives from the ANC corpus.

2.1 Analysis of Space in Narrative

Ten narratives, each describing one crime, were randomly selected from a corpus of serial offender narratives. While there is undoubtedly some influence on the narratives from the institutional contexts (e.g., the inclusion of spatial information for purposes of jurisdiction determinations) the offenders in these narratives

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2 Of course, the deictic center is omnipresent—something is being said by someone, at some time, at some place [5, 20]—the surface realization of this state of affairs, either through deictic words or otherwise, is not always present nor crucial for narrative structure.
are relatively unrestricted in their ability to respond—often speaking for long stretches of time with minimal to no interruption. For purposes of comparison, eight ANC narratives were randomly selected as well. Each ANC and crime narrative conforms to the minimal definition of narrative discussed above.

Each narrative was first broken into independent clauses and then evaluated for the existence of explicit spatial language; determined by the presence of: (1) a deictic verb or adverb (e.g., went, here); (2) a spatial preposition (as defined by The Preposition Project [25]); (3) a particle verb (e.g., put on, got out); or, (4) a manner of motion verb [23, 26] (e.g., Move (drive, fly); Move External (drive around, pass); Move Internal (walk around the room); Leave (leave, desert); Attach (cover up, put on); Detach (take off, disconnect); State (had, was); Stay (remain, stay); Follow (follow, chase); Reach (arrive, reach); Deviate (flee, run from) and Hit (land, hit)).

These decisions were based on a cognitive semantic view of space. In particular, English is predominately a ‘satellite-framed’ language [37], meaning spatial relationships are syntactically triggered by spatial P—either a Path (e.g., to, from, off), Place (e.g., at, on, behind) or Axial Part (e.g., middle of, top of) type [34, 15]. The inclusion of manner designations was permitted as English also exhibits characteristics of ‘verb-framed’ languages (spatial relationships syntactically triggered by the verb). To illustrate, consider the following short narrative in (A):

(A) (1) I drove to Leeds
(2) I was looking around the car for my coffee
(3) and I saw her standing in the intersection
(4) I pulled my sunglasses from the back of the driver’s seat to get a better look

In (A1), to is a Path preposition and drove is a Move manner. In (A2), around is also a Path preposition and looking (in addition to around) is a Move Internal manner. In (A3), in is a Place preposition and standing is a State manner. Lastly, in (A4), from is a Path preposition, the back of is an Axial Part of the driver’s seat and pulled is a Detach manner.

Looking first at the ANC narratives (1-8) in Table 1, there is quite a bit of variability in the length of a narrative, and, proportionally, how much space is included. The ANC narratives range from 6 (ANC-1) to 56 (ANC-8) total independent clauses; 1 (ANC-1) to 22 (ANC-8) of which include spatial information with proportions ranging from 4.35% (ANC-1) to 66% (ANC-3) with a 32.48% average. For those ANC narratives which have a seemingly high proportion of space (ANC-3, and -7) the total number of clauses is well below the average. In contrast, the crime narratives exhibit some variability in the inclusion of space but are, by and large, consistent—ranging from 42 (Crime-5) to 162 (Crime-4) total independent clauses, 21 (Crime-6) to 89 (Crime-4) of which include spatial information. The proportions range from 33.33% (Crime-7) to 76.56% (Crime-10) with a 51.69% average.

Assuming a normal distribution, the crime narratives exhibit a broader distribution in the length of narrative (20.09 independent clauses) and the inclusion
of spatial information (33.48) as compared to the ANC narratives (19.64 for total independent clauses and 7.86 with spatial information). However, for independent clauses with space as compared to those without, the distributions are much more narrow for the crime narratives (11.80) for a higher average percentage (51.69%) as compared to the ANC narratives (20.11 for a 32.48% average percentage).

Table 1. Percentage of Independent Spatial Clauses in Crime and ANC Narratives.

<table>
<thead>
<tr>
<th>Narrative</th>
<th>Spatial / Independent Clause</th>
<th>Proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crime-1</td>
<td>32 / 61</td>
<td>52.46%</td>
</tr>
<tr>
<td>Crime-2</td>
<td>43 / 100</td>
<td>53.00%</td>
</tr>
<tr>
<td>Crime-3</td>
<td>33 / 74</td>
<td>44.59%</td>
</tr>
<tr>
<td>Crime-4</td>
<td>89 / 162</td>
<td>54.94%</td>
</tr>
<tr>
<td>Crime-5</td>
<td>26 / 42</td>
<td>61.90%</td>
</tr>
<tr>
<td>Crime-6</td>
<td>27 / 66</td>
<td>40.90%</td>
</tr>
<tr>
<td>Crime-7</td>
<td>21 / 63</td>
<td>33.33%</td>
</tr>
<tr>
<td>Crime-8</td>
<td>28 / 58</td>
<td>48.27%</td>
</tr>
<tr>
<td>Crime-9</td>
<td>39 / 78</td>
<td>50.00%</td>
</tr>
<tr>
<td>Crime-10</td>
<td>49 / 64</td>
<td>76.56%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>297 / 768</strong></td>
<td><strong>51.69%</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Spatial / Total</th>
<th>Proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>29.7 / 76.8</td>
</tr>
<tr>
<td>SdDev</td>
<td>20.09 / 33.48</td>
</tr>
</tbody>
</table>

| ANC-1 | 1 / 23 | 4.35% |
| ANC-2 | 11 / 48 | 22.92% |
| ANC-3 | 4 / 6 | 66.67% |
| ANC-4 | 4 / 31 | 12.90% |
| ANC-5 | 20 / 55 | 36.36% |
| ANC-6 | 6 / 22 | 27.27% |
| ANC-7 | 5 / 10 | 50.00% |
| ANC-8 | 22 / 56 | 39.29% |
| **Total** | **73 / 251** | **32.48%** |

<table>
<thead>
<tr>
<th>Spatial / Total</th>
<th>Proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>9.13 / 31.38</td>
</tr>
<tr>
<td>SdDev</td>
<td>7.86 / 19.64</td>
</tr>
</tbody>
</table>

Whether or not, in terms of the inclusion of spatial information, this is the result of a genre effect, the crime narratives seem to be different in kind as compared to the ANC narratives. In the next two sections, I will argue that the high proportion of spatial information in the crime narratives follows a spatiotemporal pattern of aggregate shifts in granularity across a given crime narrative. In particular, each crime narrative progressively moves from broader spatial granularities (e.g., I was in New York, She looked around the streets, We parked the car in front of the restaurant) to finer granularities of spatial description (e.g., I put the keys in the glove box, She pulled the hat off of her head, I tapped him on the shoulder) and back to broader spatial descriptions. In Section 3, I demonstrate these aggregate shifts (initially based on an qualitative observations of the crime narratives [11, 12]) through a simple tracking of the frequency distributions of four types of granularities (following Montello [22]) across a given Crime narrative in comparison to a given ANC narrative. In Section 4, I explore the utility of this spatiotemporal information (e.g., the aggregate shifts) through a machine
learning task which will attempt to classify *narrative domains* of PRE, CRI and POS events.

3 Granularity Contours of Narrative Spatial Clauses

As alluded to above, the aggregate shifts in spatial granularities convey a spatial contour which ‘zooms’ from larger to smaller to larger spaces across a given crime narrative. In terms of approaching the question as to how to capture this zoom in a measurable way, it is useful to rely on insights from environmental and cognitive psychology. However, while a number of different insights are helpful in this regard, some are much too broad to be functional (e.g., Tversky’s observation that, “[a]t the highest level [of organized spatial knowledge], indoor scenes are distinguished from outdoor scenes” [39]). For purposes of this paper, I will rely on Montello, who, drawing on the relationship between psychological perspectives and the linguistic realizations thereof, indicates four levels of spatial knowledge: Figural (F)—space smaller than the body; Vista (V)—space larger than the body from a single point of view; Environmental (E)—much larger than the body with multiple (scanning) point(s) of view; and Geographic (G)—even larger than the body and “learned via symbolic representations” [22]. But, linguistically, how are Montello’s different granularities conveyed and what is actually shifting?

Talmy indicates that spatial relationships can be distilled down to *figure*, that which is located, *ground*, that to which the relative location of the figure is situated, and *path*, the direction of motion or orientation between the figure and ground\(^3\) [10]. Primarily, granularities were determined by the ground information which is encoded by the referent DP of the preposition or verb. Consider the examples in (B):

(B) (1) I left my wallet at the Empire State Building
(2) I looked for my wallet all over the house
(3) I left my wallet on the counter
(4) I left my wallet in my pocket

G granularities were by far the simple case as the DP is a toponym or some proper noun/named location of a specific place (B1). F granularities (B4) were more difficult as, while the use of a personal pronoun (*her*, *him*), names (*Catherine*, *Richard*) and body parts (*hands*, *feet*) indicated a F granularity, reliance on intuition as to whether or not the DP has a typical size that is at or smaller than the human body was necessary. For the V (B3) and E (B2) granularities, the DPs were entities larger than the human body; however, reliance on intuitions and additional syntactic information was necessary to differentiate the two. In particular, there was a natural division in terms of E granularities co-occurring with prepositions and verbs indicating movement (*ran out of the house, went up*).

\(^3\) Other nomenclature has been used to describe similar concepts (e.g., trajector for *figure*, and landmark for *ground*) and varying levels of extensions from these concepts have emerged as well (e.g., regions, directions, measures, etc.) (see generally [43]).
the right hand side of the woodyard, running around the park) and V granularities co-occurring with stative verbs or simple prepositions (put in the trunk, sat on the bench, staying at the bus stop). These general observations captured the majority of granularities. Returning to our set of examples in (A), G, E, V and F granularities would be assigned to (A1)–(A4) respectively. Deviations from these observations were largely categorical. For example, some motion classes such as Move.External and Follow [20, 25] indicated an E granularity despite the DP (drove past her, followed the dog).

3.1 Analysis of Granularity Contour

To capture a given narrative’s granularity contour (and any zooming effect), each granularity was coded\(^4\) and calculated as a percentage distribution per independent clause. For example, in (A), for the first independent clause, the G granularity would have a value of 1.0, and the remaining three would have a value of 0. For the second independent clause, the E and G granularities would each have a value of .5 and the V and F granularities would have a value of 0. For the third independent clause, the E, G and V granularities each have a value of .33 and so on. As summarized in Table 2, if there is a uniform zoom in the granularity contour, we would expect (assuming a roughly equal distribution of all four granularity types), that, as the narrative progresses, all granularity types should approach equilibrium (here, .25) and then, at some point, G and E granularities should wax and V and F granularities should wane from the equilibrium point. However, the arrival at an equilibrium may not be, necessarily, as linear as Table 2 suggests.

<table>
<thead>
<tr>
<th>Clause</th>
<th>F</th>
<th>V</th>
<th>E</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
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<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>.50</td>
<td>.50</td>
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<tr>
<td>3</td>
<td>0</td>
<td>.33</td>
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<tr>
<td>4</td>
<td>.25</td>
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<td>9</td>
<td>.22</td>
<td>.22</td>
<td>.22</td>
<td>.33</td>
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</tbody>
</table>

\(^4\) Data were coded by the author and an additional coder. Cohen’s kappa coefficient indicates **substantial agreement** (.694). The largest disagreements were between V and E granularities.

In Table 3, which display the granularity contour for Crime-8, as compared to ANC-8 in Table 4, Crime-8 more conforms to the archetype granularity contour in Table 2 as each granularity approaches equilibrium which is actually the percentage distribution of the granularities (for Crime-8: F = 10/39=25.64%, V
= 11/39-28.21%, E = 6/39-15.38%, G = 12/39-30.77%). The difference between Tables 3 and 4 is not wholly unexpected as, observationally, the ANC narratives exhibit greater variability in the inclusion (or exclusion) of spatial information. Further, not every granularity type is necessary; ANC-8 has only two granularities and is a well-formed narrative.

Table 3. Crime-8 Granularity Contour

<table>
<thead>
<tr>
<th>Clause</th>
<th>F</th>
<th>V</th>
<th>E</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0.33</td>
<td>0.33</td>
<td>0.33</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0.25</td>
<td>0.25</td>
<td>0.50</td>
</tr>
<tr>
<td>14</td>
<td>0.07</td>
<td>0.36</td>
<td>0.14</td>
<td>0.43</td>
</tr>
<tr>
<td>21</td>
<td>0.29</td>
<td>0.33</td>
<td>0.09</td>
<td>0.29</td>
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<tr>
<td>22</td>
<td>0.27</td>
<td>0.32</td>
<td>0.14</td>
<td>0.27</td>
</tr>
<tr>
<td>39</td>
<td>0.27</td>
<td>0.29</td>
<td>0.15</td>
<td>0.29</td>
</tr>
</tbody>
</table>

Table 4. ANC-8 Granularity Contour

<table>
<thead>
<tr>
<th>Clause</th>
<th>F</th>
<th>V</th>
<th>E</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>0</td>
<td>0.78</td>
<td>0.22</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0.80</td>
<td>0.20</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>0</td>
<td>0.82</td>
<td>0.18</td>
<td>0</td>
</tr>
<tr>
<td>24</td>
<td>0</td>
<td>0.79</td>
<td>0.21</td>
<td>0</td>
</tr>
<tr>
<td>25</td>
<td>0</td>
<td>0.76</td>
<td>0.24</td>
<td>0</td>
</tr>
</tbody>
</table>

A priori, narratives need not conform to a granularity contour which approaches equilibrium let alone move uniformly from larger (G, E) to comparatively smaller (V, F) granularities, yet all of the crime narratives do.

There was some variation in granularity ordering which was consistent with what the actual narrated (physical) environments was. However, one point of regularity within this variation emerged which provided the genesis for the classification task presented in Section 4. Namely, that F granularities were common in narrating the commission of the crime and whenever the actual criminal act (e.g., stabbing, strangling) or extensions (e.g., throwing the murder weapon away later) were referenced. Further, as narratives are broken up into PRE, CRI and POS groupings of narrative events⁵, boundaries between PRE and CRI event

⁵ Considering PRE, CRI and POS distinct narrative event groupings is consistent with investigative and environmental criminology literature which considers these
groups occurs close to or at the emergence of the F granularity (14-15 in Crime-8, cf. Table 3) and, more subtly, the boundary for CRI and POS groups corresponds to the beginning of a steady increase in E or G granularities through to the end of the narrative (21-22 in Crime-8 cf. Table 3). Consequently, a machine learning task was developed to determine if the spatial information in the granularity profiles (e.g., aggregate shifts of granularity types) corresponds to the (macro) event structure of the crime narratives.

4 Granularity Classifications of Narrative Event Groups

If there is indeed a zooming granularity contour in all crime narratives, we would predict that the patterned correspondence between granularity types and event groups could be discerned from the narratives. The more accurate (and ease) in making the determination, the stronger the argument that spatial information is contributing to the event structure of narrative—moving the core definition of narrative, at least for the sub-genre of crime narratives and possibly all ‘spatially rich’ narratives—closer to space, time and events rather than just time and events.

In the ten crime narratives, spatial clauses were coded with a G, E, V or F granularity and a PRE, CRI or POS designation—the Space Only instance group. As not every independent clause contained spatial language, two additional instance groups were created: Null Value—where non-spatial clauses only received an event group coding, but no additional information; and Fill Values—where the non-spatial clauses received the granularity coding of the previous spatial clause and event group coding. Table 5 summarizes the granularity and event group distributions of unigram and bigram instantiations of Space Only and Fill Value instance groups (Null Values have the same distribution of Space Only over 74% more clauses).

Using the Waikato Environment for Knowledge Analysis (v3.6.0) [41], the granularity unigram and bigram instantiations of the Space Only and Null/ Fill Values were used to classify the event groupings (e.g., can a classifier determine, with any degree of accuracy, that F or FF granularities corresponded to the CRI event group). C4.5 (J48), K*, and Naïve Bayes (NB) classifiers were used at 10-Fold Cross Validation.

4.1 Results and Discussion

Starting with Space Only, Table 6 indicates that, while modest, granularity information is providing some information about the event groups as K* classified 7.80 percentage points about the majority class (the CRI event group) for unigrams and 11.63 above the majority class for bigrams (NB classifier). The majority class provides a baseline of performance—i.e., if the classifier classified relevant categories for the analysis of behavioral patterns [27, 6] and routine activity spaces [2, 8] which have a given spatial architecture relative to an offender’s cognitive map.
Table 5. Granularity Unigram and Bigram and Narrative Event Group Distributions

<table>
<thead>
<tr>
<th>Unigrams</th>
<th>Fill Values</th>
<th>Unigrams</th>
<th>Bigrams</th>
<th>Fill Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space Only</td>
<td>N=418</td>
<td>N=795</td>
<td>Space Only</td>
<td>N=418</td>
</tr>
<tr>
<td>F</td>
<td>84 / 20%</td>
<td>158 / 20%</td>
<td>FF</td>
<td>46 / 11%</td>
</tr>
<tr>
<td>V</td>
<td>172 / 41%</td>
<td>366 / 46%</td>
<td>FV</td>
<td>26 / 6%</td>
</tr>
<tr>
<td>E</td>
<td>97 / 23%</td>
<td>156 / 20%</td>
<td>FE</td>
<td>7 / 2%</td>
</tr>
<tr>
<td>G</td>
<td>65 / 16%</td>
<td>115 / 14%</td>
<td>FG</td>
<td>5 / 1%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>VF</td>
<td>23 / 5%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>VV</td>
<td>90 / 23%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>VE</td>
<td>44 / 10%</td>
</tr>
<tr>
<td>Space Only</td>
<td>N=418</td>
<td>N=795</td>
<td>Fill Values</td>
<td>N=795</td>
</tr>
<tr>
<td>PRE</td>
<td>138 / 33%</td>
<td>254 / 32%</td>
<td>VG</td>
<td>15 / 4%</td>
</tr>
<tr>
<td>CRI</td>
<td>172 / 41%</td>
<td>335 / 42%</td>
<td>EF</td>
<td>14 / 3%</td>
</tr>
<tr>
<td>POS</td>
<td>108 / 26%</td>
<td>206 / 26%</td>
<td>EV</td>
<td>32 / 8%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>EE</td>
<td>35 / 8%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>EQ</td>
<td>16 / 4%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GF</td>
<td>4 / 1%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GV</td>
<td>25 / 6%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GE</td>
<td>9 / 2%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GG</td>
<td>27 / 6%</td>
</tr>
</tbody>
</table>

Each instance as a CRI and the classifier would be accurate 41% of the time. For the Null Values, the information, while providing something, is overall less effective in classification—unigrams and bigrams falling close to the majority class; the best being 5.6 percentage points above the majority class (bigrams with NB classifier). For the Fill Values, the bigrams get a boost to 15.82 above the majority class (J48). In sum, bigrams are outperforming unigrams, and Fill Values are outperforming both Space Only and Null Values. However, while the performance is above the majority class, the overall accuracy is low.

Table 6. Granularity Unigram and Bigram Classifications of Narrative Event Groups

<table>
<thead>
<tr>
<th>Unigrams</th>
<th>Bigrams</th>
<th>Unigrams</th>
<th>Bigrams</th>
<th>Unigrams</th>
<th>Bigrams</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space Only</td>
<td>N=418</td>
<td>N=795</td>
<td>Null Values</td>
<td>N=418</td>
<td>N=795</td>
</tr>
<tr>
<td>J48</td>
<td>45.21</td>
<td>44.94</td>
<td>44.82</td>
<td>46.33</td>
<td>57.82</td>
</tr>
<tr>
<td>K*</td>
<td>48.80</td>
<td>44.31</td>
<td>42.92</td>
<td>44.33</td>
<td>54.54</td>
</tr>
<tr>
<td>NB</td>
<td>45.93</td>
<td>42.63</td>
<td>47.6</td>
<td>46.33</td>
<td>56.81</td>
</tr>
</tbody>
</table>

In order to boost the accuracy of the classifier, I included more explicit temporal information in the form of ranks: (1) an ordinal ranking (1 through n, where n is the total number of independent clauses); (2) a proportional ranking represented as a percentage of the total narrative (.000 through 1); and (3) a centered rank where a 0 was assigned to the first occurrence of a F granularity—clauses from the F granularity to the beginning received a step-wise negative ordinal rank to the beginning of the narrative and a step-wise positive ordinal rank to the end of the narrative.
Table 7. Fill Value Granularity Bigrams and Rank Classifications of Narrative Event Groups

<table>
<thead>
<tr>
<th></th>
<th>Ordinal RBase</th>
<th>+ Granularity</th>
<th>Proportional RBase</th>
<th>+ Granularity</th>
<th>Centered RBase</th>
<th>+ Granularity</th>
</tr>
</thead>
<tbody>
<tr>
<td>J48</td>
<td>73.86</td>
<td>77.65</td>
<td>73.35</td>
<td>80.68</td>
<td>74.62</td>
<td>84.34</td>
</tr>
<tr>
<td>K*</td>
<td>75.12</td>
<td>82.07</td>
<td>77.02</td>
<td>82.95</td>
<td>74.62</td>
<td>83.33</td>
</tr>
<tr>
<td>NB</td>
<td>65.53</td>
<td>76.51</td>
<td>77.77</td>
<td>78.16</td>
<td>70.20</td>
<td>76.51</td>
</tr>
</tbody>
</table>

As shown in Table 7, the overall accuracy is greatly improved. However, comparing the results against the majority class is no longer an adequate performance measure. Because the boost in accuracy is obviously attributable to the ranking information, the new majority class becomes the rank baseline (RBase)—i.e., based either on the ordinal, proportional or centered ranking alone, how well does this (local temporal) information differentiate the event groupings. As indicated in Table 7, the worst RBase (65.53, ordinal NB classifier) outperformed the best bigram/fill value granularity (57.82, cf. Table 6). So, while the overall best accuracy increased to 84.34 (centered J48), the contribution of spatial information in the classifications dropped to about 10 percentage points over the RBase (74.62 centered J48).

Overall, the results suggest that the local discourse realization of temporal progression is comparatively more powerful than the granularity information for purposes of delineating event groupings. This is not surprising given the temporal structure of narrative accounted for above. Nonetheless, Tables 6 and 7 do indicate that granularity is contributing something to the spatial architecture of events across crime narratives. Despite the small contribution granularities are providing, the granularities do not have to pattern, even weakly, in this way. However, while the improvement in classification by including space and time cannot be ignored, the suggestion of these results that a macro spatiotemporal structure of events is tenable, at least in crime narratives, is guarded. Additional research will seek the inclusion of additional spatial information (e.g., including figure and path information, frames of reference) to ensure an accurate and comprehensive as possible spatiotemporal perspective on narrative structure.

5 Conclusions

Overall, I have accounted for a spatial phenomenon in narratives with a high proportion of explicit space. In particular, the tracking of ground information encoded with a certain granularity reveals a narrative long pattern which shifts from large to small to larger spaces as conveyed by the narrator’s perspective. Based on granularity information alone, this information is able to classify narrative event groups in all crime narratives, above the majority class proportions. However, because narrative structure is strongly temporal, the inclusion of rankings significantly improved performance. While, the generalizability of these findings remains to be seen, especially as explicit space is optional in narrative, this analysis works to provide empirical support for a potential redefinition.
of narrative which accounts for spatiotemporal structure. Further, these results provide interdisciplinary observations in environmental psychology and violent crime research by showing spatial cognitive architectures of narratives which are reflective of an individual’s perspective on spatially defined behaviors.

Acknowledgements

Thank you to my advisor Dr. E. Graham Katz for tremendous mentoring and support. A great deal of appreciation to Dr. Thora Tenbrink, Dr. Stephan Winter and two anonymous reviewers for insightful and productive comments. Thank you also to Vitaly Nikolaev and Lissa Krawcyk for numerous helpful discussions. All errors and omissions are solely my responsibility.

References

25. The Preposition Project, http://www.clres.com/cgi-bin/onlineTPP/find_prep.cgi
Categorization of Linear Objects for Map Generalization Using Geocoded Articles of a Knowledge Repository

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Abstract. One of the major tasks when generalizing a map is the classification of map objects according to their importance. The target of this task is to retain important objects and eliminate unimportant objects. In order to determine the importance of spatial phenomena we link the notion of importance with the fact and the frequency of their use. This approach has been proposed in vernacular geography to delineate objects with vague boundaries. To classify objects we therefore propose to use the article and link structure of a knowledge repository with geocoded articles. This is done by collecting the coordinates of the linked articles of a class of objects and drawing them in a map as points. Then we consider the importance of an object the higher the denser the points are. To illustrate this method we study an alpine river system. As knowledge repository with a link structure and geocoded articles the German Wikipedia is used. The result of this classification depends particularly on the kernel density estimation function and its parameter, such as the search distance. Furthermore the result may vary radical if multi-linked articles are weighted more than single-linked and if we take into account that the total of geocoded articles are not distributed equally. We describe the variation of the point density when the parameters are changed according to our example. In addition the results of our calculation are also compared to generalizations derived by traditional techniques.

1 Introduction

In cartographic generalization objects have to be presented according to their relevance and importance. In topographic mapping, there are rules which indicate the (relative) importance of topographic objects: e.g., roads are more important than boundaries of vegetation; therefore, they are emphasized at the cost of other less important objects. A new research direction in mobile cartography is to personalize cartographic visualizations; this also involves that the notion of relevance has to be introduced in a flexible and personalized way. The question is, how to define relevance.

In this paper we use crowd-sourced information as an indication for relevance. The idea is that data in public repositories like Wikipedia are introduced, if
they are of certain relevance—at least for the one who writes the article. A higher number of references to the same object and a more detailed description indicate a higher relevance. In this way, the counts or the distribution of spatial locations of an object are used as indication for the relative importance. We use the Epanechnikov kernel estimation to transform the discrete location data in a continuous form.

The paper is organized as follows. After a review of related work our approach is described in detail. Then we present examples and finish with a summary and outlook on open problems on future work.

2 Related work

The automation of cartographic generalization has been researched since more than 40 years (for a comprehensive overview see [5]). Methods for automatic realizations of most of the operators have been proposed and implemented (e.g. simplification, selection, enhancement, typification, displacement). All operations, however, need prior knowledge to determine the importance of features. Some measures can directly be determined from geometric measures like minimal visible sizes or distances, or pre-given rankings of features. However in the case of selection or typification, there are similar objects which have to be reduced in number, e.g. a set of buildings, roads or rivers of similar category. For solving this problem, density based approaches have been proposed, e.g. by [7] or [9].

Collaborative data and knowledge acquisition is becoming more and more frequent. Knowledge repositories like the German Wikipedia contain 950,000 articles, the English 3,000,000 articles with totally 650,000 coordinates associated (August 2009). Also, people are collaboratively editing spatial objects in project like Open Street Map. To exploit this crowd-sourced information has been proposed in several approaches. Jones et al. [4] have proposed to use the footprints of Websites in order to delineate the boundary of regions with uncertain or vague boundaries like the “Black Forest” or the “British Midlands”. They used websites which were scanned for geographical names, which in turn were georeferenced using gazetteers. The underlying idea is that the boundary can be found by inspecting how the location names are used by the people. Dahinden [1] used a similar approach to delineate areas. He, however, used a repository which already includes spatial references, namely Wikipedia as a basis; in this way he was able to determine the outline of Swiss cantons or the location of linear objects like a motorway. Hecht and Raubal [3] locate non-geographic expressions. They also use the Wikipedia Article Graph (WAG). In this graph all articles are nodes and the links are the edges of the graph. The edges of the graph are weighted by the semantic relatedness of the articles. This is a measure based on the number of links in article A and B and the number of links that point from A to B and from B to A. They describe why the WAG is easier to use than the Wikipedia-text-structure. The major technique is to follow the links of the page. If they find a geocoded article they add its weighted
coordinate to the non-geographic feature. The weight is calculated according to the semantic relatedness.

Piatti et al. [6] locate activity zones of literature. The works of fiction can be seen as knowledge repository. However the assignment of scenes to geographic places is not unique. This leads to some problems:

- First, there are several places with the same name (e.g., Santiago).
- Second, there are names of people that sound like places (e.g., Hilton, Paris).
- Third, some names are alienated or fictitious (e.g., Gotham City or Gottfried Keller's Seldwyla).

A problem is also to show uncertain areas. They are using fuzzy shapes and animations.

The exploitation of crowd-sourced data for digitization of spatial objects has been investigated by Sayda [8]: from a set of uploaded GPS-tracks of hikers, he determined the most probably and at the same time reliable track.

TomTom and Vodafone use the temporal distribution of mobile phones on highways for the prediction of traffic jams [2].

3 Approach

3.1 Knowledge repository and gazetteer used

In principle our approach works with any knowledge repository with an associated gazetteer. For our research we used the German Wikipedia as knowledge repository and the collection of coordinates of Wikipedia-World [11] as gazetteer.

The German Wikipedia contains more than 900,000, the English more than 3,000,000 articles. They contain texts about geographical features from all over the world. Thus it should be useful for all kind of maps. Yet some places are missing. For example the place Negenborn exists three times in Germany, but there are only two articles in Wikipedia by now (August 2009).

Analyses of Hecht and Raubal [3, p. 102] show a relation between the topics of the articles and the language, i.e., a domination of German topics in the German Wikipedia.

The names of the places with its coordinates are provided in a separate MySQL-Database. This Database is an extract of Wikipedia and thus the names in the database correspond to the links in the articles in a 1:1 relation. For this reason we do not have to use named entity recognition to match ambiguousness.

Yet the coordinates of several language versions may differ. For example the Turkish town Patara is located in the German Wikipedia with 36°16’ N, 29°19’ E, and in the English with 36°15’ 37” N, 29°18’ 51” E. There are also articles with missing coordinates (e.g., Schloss Neuenhinzenhausen) and the gazetteer could be out of date.

In the gazetteer about 72,000 entries have information about the dimension of the objects, where approx. 17,000 correspond to 2,500 m in diameter or smaller, 10,000 to 5,000 m, 27,000 to 10,000 m, 6,000 to 25,000 m and 1,000 to 50,000 m or larger. The mean value of this granularity of the object is approx. 13,000 m.
In addition there is also some information about the type of the object (e.g. city, monument, river) and the ISO-3316 Country Code of the area the coordinate belongs to.

3.2 Processing of the data

The investigation of an object has to be based on one article or on a list of certain articles that describe the object. Both article and list can be found in Wikipedia, e.g. for the river system Reuss you may use its category [12].

The link-list of a certain article can be requested through the Mediawiki API. This list has to be compared with the entries in the gazetteer. As a result a list with coordinates associated to the object is derived.

The list with coordinates can be seen as random variables of an unknown probability distribution describing the relevance of the object. To estimate the probability distribution we use the Epanechnikov kernel density estimation [10]. Unfortunately the parameters of the density estimation have to be selected according to the distribution of the coordinates. As a hint we may use the dimension of the objects.

The relevance of a linear system is determined by integrating the density along a line segment. This leads to a value that depends on the density and the length of the line segment. As a consequence the result is different if a long line is divided in segments. To avoid the influence of the length of the line segments, it is possible to divide the value by the length of the line segment.

4 Examples and results

The approach is tested with the linklist “Kategorie: Flussystem Reuss” [12] of German Wikipedia. A river system (Flussystem) is a collection of rivers that constitute a major river. For its cartographic representation, the different river sections have to be evaluated with respect to their importance. A classical approach is to calculate the so-called Horton order [5] to determine the relative importance. Here, we extract the importance value from the analysis of Wikipedia links.

A major problem is the occurrence of the same link in several articles. When using a single article as origin each link is usually unique. But when using a list, this is certainly not the case. In each article there is usually an entry about the country the object belongs to. Thus you get the centroid of the country from each article of the list. The same problem arises with objects that are superior such as the main river.

There are three possibilities to solve this problem. Either all links are used, or the links are weighted according to their dimension, or each link is used only once. If all links are used, it is assumed that superior objects are more important than inferior. But the superior object can be of a more abstract type than the investigated, e.g., in our example the centroid of the Switzerland lies in the investigated area. If the border of Switzerland would be changed also the
centroid would and thus the result of our calculation. Yet the border of a county seems irrelevant to the categorization of a river system. Unfortunately the dimension of river objects is often missing in the gazetteer. So most of the weight can only be guessed. This method may be investigated in the future.

The third possibility is to use each coordinate only once. Figure 1 shows the distribution of the footprints of the articles.

![Fig. 1. Distribution of the footprints of the articles about the river system Reuss in German Wikipedia. Geometry of waterbodies: geodata @ swisstopo.](image)

We estimated the kernel density of these points with a search distance of 6 km. In Figure 2 the kernel density estimation for the river system is depicted. The result seems to reflect the river system quite nicely.

On the basis of a vector dataset with river for each part of the river system Reuss the integral over the estimated density was calculated. This leads to a product of the relevance and the length. The relevance value can be calculated by dividing value of the integral with the length of the waterbodies. In Table 1 the ten waterbodies with the largest integral are named. A map with nine of these ten waterbodies is shown in Figure 3.

With this method it is possible to compare different kinds of categorization of vector data. For the river system under investigation we have the possibility
Fig. 2. Kernel density estimation of river system Reuss. In the dark blue area the density is high, in the light blue low. The blue lines correspond to all rivers shown in the national map of Switzerland 1:25.000. Geometry of waterbodies: geodata @ swisstopo.

Table 1. The 10 most relevant waterbodies according to the integral of the kernel density estimation along the waterlines.

<table>
<thead>
<tr>
<th>Name</th>
<th>Integral</th>
<th>Length</th>
<th>Relevance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vierwaldstättersee</td>
<td>6972047</td>
<td>130061</td>
<td>53.6</td>
</tr>
<tr>
<td>Reuss</td>
<td>6359911</td>
<td>152205</td>
<td>41.8</td>
</tr>
<tr>
<td>Zuger See</td>
<td>1944531</td>
<td>38226</td>
<td>50.9</td>
</tr>
<tr>
<td>Lorze</td>
<td>1534526</td>
<td>30633</td>
<td>50.1</td>
</tr>
<tr>
<td>Sarner Aa</td>
<td>1200075</td>
<td>30450</td>
<td>39.4</td>
</tr>
<tr>
<td>Rigiaa</td>
<td>1110433</td>
<td>22338</td>
<td>49.7</td>
</tr>
<tr>
<td>Lauerzer See</td>
<td>1076590</td>
<td>12190</td>
<td>88.3</td>
</tr>
<tr>
<td>Engelberger Aa</td>
<td>1045192</td>
<td>39526</td>
<td>26.4</td>
</tr>
<tr>
<td>Muota</td>
<td>951644</td>
<td>30107</td>
<td>31.6</td>
</tr>
<tr>
<td>Kleine Emme</td>
<td>846280</td>
<td>36100</td>
<td>23.4</td>
</tr>
</tbody>
</table>
to compare the categories of the river system Reuss of swisstopo's Vector25 data for watercourses with the Atlas of Switzerland data and our representation. The topographic data set for rivers of swisstopo has 7 categories, yet there is only one category for lakes (Figure 4). Atlas of Switzerland has 3 categories for describing the rivers and lakes (Figure 5). In both datasets the first category contains the most important objects, the second some less important and so on.

![Image](image-url)  

**Fig. 3.** The 9 most important waterbodies of the river system Reuss according to the density of articles in German Wikipedia. Geometry of waterbodies: geodata @ swisstopo.

By comparing Figure 3, 4 and 5 it becomes obvious that there are some differences in the categorization of the waterbodies. Concerning rivers the categories of swisstopo and Atlas of Switzerland tend to be distributed uniformly. In our method the rivers in the center of the river system tend to be accentuated. Concerning lakes the swisstopo and the Atlas of Switzerland data categorize the objects by its size. In contrast in our method some small objects like lake Lauerz (Lauerzersee) are categorized as very relevant.

We can make a quantitative comparison of the datasets. This is done by adding up the integral value of each element that is shown in the generalized data set and divide it by the length of all elements. For Vector25 we use Category 1 and 2, for Atlas of Switzerland Category 1-3. Table 2 shows the name of the datasets, the number of elements selected and the relevance value according to our method.
Fig. 4. Lakes and category 1 (blue) and 2 (red) of rivers in the dataset Vector25 of swisstopo (geodata @ swisstopo).

Table 2. Comparing the categorization of several datasets. The relevance is calculated for the “number of elements” most important object.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Number of elements</th>
<th>Relevance value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Swissstopo Vector25 (only rivers)</td>
<td>4 elements</td>
<td>38.9</td>
</tr>
<tr>
<td>Our approach only rivers</td>
<td>4 elements</td>
<td>43.3</td>
</tr>
<tr>
<td>Atlas of Switzerland only rivers</td>
<td>5 elements</td>
<td>38.0</td>
</tr>
<tr>
<td>Our approach only rivers</td>
<td>5 elements</td>
<td>40.8</td>
</tr>
<tr>
<td>Atlas of Switzerland with rivers and lakes</td>
<td>9 elements</td>
<td>43.2</td>
</tr>
<tr>
<td>Our approach with rivers and lakes</td>
<td>9 elements</td>
<td>45.6</td>
</tr>
</tbody>
</table>
Fig. 5. Lakes and rivers according to the Atlas of Switzerland. Category 1: blue, category 2: orange, category 3: red.

In Table 2 the difference of the representation of the rivers are quantified. Of course, the objects selected according to our method have the higher relevance value than the other datasets under investigation. That’s obvious because we selected the elements in a manner to maximize this value. Anyhow it is not possible to conclude, that these datasets are categorized inappropriate.

The more elements are selected according to our method the more the relevance value should decrease. Looking at Table 2 this seems not to hold. But actually the relevance value for four and for five elements is calculated for the river system only. Per contra the relevance value for nine elements is calculated for rivers and lakes.

5 Summary and outlook on future work

The paper presented an approach to determine the importance of geographic features in order to use it for cartographic visualization and generalization. The underlying idea is the fact that geographic features that are mentioned in public knowledge repositories give an indication to their importance; the relative frequency determines the relative importance. In this way it was possible to identify different grades of importance which can be used for generalization and visualization.

Issues to consider are the following:
The frequency measures are not necessarily objective, as they will be higher in more populated areas; there might even be no web-articles for some spatial feature, although it is of importance in its local environment. In this way, the proposed measure reflects the usage of these features in the public awareness.

As described above, there are problems with the completeness of the knowledge repository. Non-existing links may indicate non-relevance. Here general quality measures should be derived that give hints to the completeness of a dataset. E.g., there are measures in OpenStreetMap that calculate an expected road density depending on the number of inhabitants in a city. If the actual number of roads is below this average value, it is an indication that some information is missing.

There is a dependency on the interpolation scheme, especially on the parameters of the density kernel. This leads to the problem that the combination of objects to object classes in combination with the density estimation is not necessarily distributive.

It may be difficult to compare the relative measures for different kinds of topographic features. E.g., a city area will probably be mentioned more often in web-repositories than a river system. So relative weights between different feature classes have to be investigated.

These issues will be addressed in future work.

References

Cartographic Aspects of Geoportals

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Abstract. Following the Inspire directive, several countries are now setting up geoportals. This paper focuses on the cartographic issues raised by view services in these geoportals. The problem with view services, from a cartographic perspective, is the absence of the traditional cartographer who optimizes the presentation of the cartographic data. In order to enhance the readability of the maps automatic methods should be used. The paper presents four types of methods for improving the readability: semantic, conflation generalization and symbolization methods, as well as some ideas of how the technical implementation of these methods could be performed.

1 Introduction

Several countries have built or are building portals for spatial information, so called geoportals. In Europe, this development is affected by the launch of the EC directive Inspire [15]. Inspire states, among other things, that each member state must have services for searching, viewing and downloading spatial information. This article focuses on cartographic aspects of view services (Figure 1).

A view service provides the users much flexibility. Users are able to choose what information (layers) to be displayed from which source (basic service) and to combine spatial information from several sources. To combine information is of course nothing new; the new thing is that what previously required a GIS program and efforts to acquire spatial information will now be possible to perform with a standard web browser.

The aim of this paper is to study the cartographic aspects of view services. It starts with a problem formulation where we discuss cartographic aspects of view services. The next section deals with methods that could be used to improve the cartographic quality. Section 4 contains a discussion of how the methods could be implemented. The paper ends with concluding remarks.
Fig. 1. A user requests a map from the view service of a geoportal. The request is redirected to the basic services at the server level.

2 Problem formulation

View services will provide us with more maps, which can be adapted for various purposes. This is of course positive. But will the maps be better from a cartographic perspective? No, as for many new technical inventions we will probably see an initial decrease in cartographic quality [5].

Cartographic quality is a wide term that could include artistic quality [18], usability (or functional quality; see, e.g., [25, 26, 29]) as well as descriptive quality of geographic data (e.g., specified using parameters in ISO 19138). In this paper we focus on the usability aspects of cartographic quality; the view services should provide maps that give the user quick and certain answers to relevant questions. However, as we cannot always predict for what purpose the user compiles the map in a view service, we cannot attain usability in its proper meaning; we have rather to strive for map readability. To conclude, what we mean by cartographic quality, in this paper, is to what degree the user visually can read the map.

Most current maps are made by a cartographer who selects an appropriate presentation for the entire map product including selection, generalization, integration and symbolisation of spatial information. Furthermore, the cartographer has optimized the presentation from an overall perspective in which he/she created visual hierarchies, selected suitable symbols for all object types, and so on. A view service lacks this cartographer who considers the entire map, which often results in maps similar the one in Figure 2. This is a typical example of a map from a combination of basic view services; three layers (geology, avalanche-prone zones and urban areas) are simultaneously displayed with their default legends that contain similar colours. The map has poor readability and there is a great risk for misinterpretations.

Most of us would agree that view services are good for the dissemination of maps; the question we should ask ourselves is what methods we could apply to improve the cartographic quality to increase the readability. This is the topic of the next section.
3 Methods to improve the cartographic quality in view services

In this section we describe some methods that could be used to enhance the cartographic quality in view services, but it should not be regarded as a complete list. The methods are categorized as semantic, conflation, generalization and symbolization methods.

3.1 Semantic methods

A view service often requires integration of data from several basic services. To integrate these data you have to consider both semantic and geometric aspects. In this section we only consider the semantic aspects of integration, which can be solved by e.g. semantic methods. Semantic methods are methods that relate to a greater understanding of the data; the basic idea of applying semantic methods is to annotate data with information about their intended meaning. It should be noted that we are here using semantic methods in a quite narrow sense. We are only interested in semantic methods to improve the cartographic quality (map readability). Semantic methods have a much broader interest when it comes to integration of geographic information.

The interpretation of data must be based on an ontology. Here we will restrict ourself to non-logical ontologies e.g. standards for geographic information [2]; these types of ontologies are necessary to create object catalogues. The ontologies support the integration of different information sources by providing a common basis for describing data in a meaningful way [17]. There are different types of non-logic based ontologies. They can be categorized as domain ontologies and top-level ontologies. Domain ontologies provide discipline-specific terminologies,
while top-level ontologies are very general and therefore can be applied to almost any discipline [2]. As the creation of a domain ontology for the geospatial world would be very complex, the creation of an upper-level and a number of sub-level ontologies are more feasible. This is also stated on the research agenda of UCGIS (American University Consortium for Geographic Information Science) [22].

If the view service only combines data based on the same ontology there will be no semantic problem (Figure 3 left). Unfortunately, in reality data sources often use different ontologies. In geoportals, for instance, it will frequently happen that view services are based on different object catalogues, thus disagreeing on the types assigned to objects and areas in different map layers. In this case, the different ontologies first have to be aligned to provide a basis for a shared intention about the meaning of data (Figure 4 right).

![Diagram showing (a) all the datasources share a common (global) ontology and (b) each datasource has its own (local) ontology which have to be aligned before integration of data.](image)

**Fig. 3.** Global vs. local ontologies.

The alignment of different ontologies is an active field of research in the area of semantic technologies [10, 7, 37]. Euzenat and Shvaiko [8] mention close to 50 different systems for integrating ontologies and related representations. These methods provide a basis for translating object type information from different sources into a common catalogue that provides the basis for providing an integrated view on the different sources in a geoportal. A method for translating data between different catalogues has been described by Stuckenschmidt and van Harmelen [36]. The translation of the data into a common ontology also provides a basis for identifying conflicts across different sources. If the unified view for example distinguishes between ‘buildings’ and ‘other structures’ and the representation of the same object from different sources is classified as ‘building’ by one and as ‘other structure’ by the other source it can be deduced that there is a potential conflict.

A problem not adequately addressed by current semantic methods are vagueness of concepts in the geographic domain. Recent work combining the web ontology language OWL [14] and fuzzy reasoning [35] addresses this problem to
some extent but so far, this extension is not an official language and there are so far (to the authors’ knowledge) no experiences with using Fuzzy OWL for modelling geographic concepts.

3.2 Conflation methods

In the previous section we discussed semantic aspects of integrating data from different sources. In this section we turn over to the geometric problem of integrating data, which can be solved using conflation methods. Conflation is defined as the process of merging two datasets into one in order to improve the quality of the representation of the objects [16]. The result of the conflation process is given as one dataset with the full coverage of the two original datasets. If no conflation is made when displaying related pieces of information from different sources, artificial inconsistencies can be seen. These inconsistencies are caused by the different precisions of the datasets (and geometric distortions) that introduce noise in maps and thus decrease readability. Figure 4 illustrates that with two datasets related to forested areas. One has a higher geometrical resolution, while the other splits the forests in several parts according to the type of trees. On the left, one may see that some borders of forests should be common but are artificially shifted; on the right, an (automated) conflation process removed those artificial shifts.

![Fig. 4. Visualization of forested areas before and after conflation.](image)

Conflation techniques require data matching techniques identifying homologous elements in various sources [39, 23, 33], and transformation techniques forcing the superimposition of homologous objects [13, 38]. However, most procedures and algorithms used for matching data from different data sources have been developed with specific datasets in mind. One approach, which could be
suitable for view services, is presented by Zhang and Meng [40]. Their algorithm is adaptive in order to function as a generic matching algorithm, and has some self-learning abilities in order to adjust itself to the particular datasets.

3.3 Generalization methods

Automatic cartographic generalization has been on the research agenda for decades (see [21] for an overview). Current research is mainly based on constraint-based modelling [11]. Constraints are properties that should be obtained in the generalization process. The constraints are of two major types: preservation and legibility [31]. The preservation constraints strive for maintaining important properties in the map while legibility constraints strive for map readability. Today there are several legibility constraints proposed (and used) for decreasing the geometric resolution in the map. This is an important task in cartographic generalization for map production where the main aim is to derive a small-scale map from a large-scale map.

In generalization for view services the problem is somewhat different from generalization for map production. The main trigger here is not the change of scale, but that we integrate data from different sources (assuming that the data are in correct scale from the basic services). This implies that the task is to decrease the amount of data, and adjust it to one another, to make the combined map readable. A typical example would be to simplify a base map (from one basic service) to make additional information (from another basic service) more clear. To perform this we need analytical descriptions, or constraints, that describes the readability of maps. Some recent studies [12, 33] have concentrated on establishing such readability constraints that could be used in view services. The basic idea was to develop a number of readability measures and then evaluate these measures in usability studies. These types of measures could, in the future, be used to control the generalization process in view services together with other constraints that mainly consider geometric resolution.

3.4 Symbolization methods

To get a good presentation of geographic data from different sources we have to consider the symbology. By proper choice of symbology we are able to create visual hierarchies (see e.g. Robinson, 1993), discern more detailed geometric information and discriminate different object types. One important aspect of symbolisation is colour. Proper use of the colour of the symbols, as well as the contrasts of them, can facilitate and improve the interpretation and reading of the presentation (see, e.g., [30, 4, 6, 3]). Cartographers have worked with colour contrasts for a very long time. What is new, in the light of view services, is the need for an automatic method that provides good contrast of data from different sources. The result of one such method is provided in Figure 5.
4 Implementation of a view service with good cartographic quality

In this section we describe an implementation of a view service with good cartographic quality. It should be noted that none of this is currently implemented; the aim is only to provide a discussion of how this could be done (as input ideas for future work).

The first issue we have to answer is the degree of user interaction that is wanted in the view services. When the user interaction is decided we can start defining a system architecture that supports this interaction. The third issue is which technical solution that could be used for the implementation of the methods (semantic, conflation generalization and symbolization) and how they can be integrated into a system architecture.

4.1 User interaction and requirements

The user should be able to access the view service only using a standard web browser and specify:

1. which data layers (from the basic services) that should be used,
2. which ontology (in this case object catalogue) that the data should be based on, and
3. which symbology that the final map should use.

If the user does not select an ontology and a symbolization the system must be able to make a proper automatic selection. Furthermore, the user will not be able to add own data (stored in a local computer) to the map.

The limitations above are justified with that a view service should be as simple as possible. If a user wants to use his own ontology he could download all the required data to his/her own computer (using a download service) and perform all the necessary operations himself. By doing so he/she could also integrate own local data.
4.2 System architecture

An important issue is to specify a system architecture to support the generalization, conflation and semantic methods [19]. Figure 6 contains a three layer architecture; the question is where we should implement the methods described above:

- Implementation at the server level is good for generalization of data from a single source. But since the view services really aim at integration of data from multiple sources implementation on the server level is not sufficient.
- Implementation of the methods on the portal level would better cope with the problems related to the integration of data from different sources.
- Implementation of the methods on user level requires that the user has a thick client, e.g., a GIS program, for using the view service.

Apparently, to support the user interactions and requirements in Section 4.1 above most of the methods have to be implemented in the portal level.

We could also use an external service for implementation of the methods. Open Geospatial Consortium (OGC) has defined a specification called WPS (Web Processing Service) for such calculation services [27]. WPS does not describe what specific processing services should look like (for example what inputs and outputs are used), but rather serves as a template for specific processing services. The use of processing services for the adaptation of cartographic data has been studied by, e.g., Neun et al. [24], Bergenheim et al. [1], Foerstner and Stoter [9] and Sarjakoski et al. [32].

A system architecture for view services that utilises a WPS could be as follows (Figure 6). (a) The client requests the geoportal about which ontologies and symbologies that are available (e.g., using a WMS getCapabilities command that also consider ontologies). The user then selects the ontology and symbology of his/her choice (if not the user let the system makes this choice). (b) In the next step, the client sends a new request to the portal layer, this time for requesting a map (for example using a WMS getMap request). (c) The portal service then requests data from the basic services (e.g., using download services such as Web Feature Service, WFS). When the data arrives at the portal layer there is an automated object catalogue transformation. (d) Then a request is then made to the WPS server. This request includes both processing instructions and the geographic data. The processing service include both conflation and generalization methods. (e) After processing the new geographic data are sent back to the portal. The geoportal then renders the geographic data into a map (vector or raster graphics). (f) and finally sends the map to the client.

A major problem with this approach is that it is slow. Spatial data—in the form of GML files—are sent between the basic services, the processing service and the portal. GML files are storage inefficient, which implies long transfer times; furthermore, the files must be parsed both in the processing service and in the geoportal. This makes the approach, in a near future, only acceptable for small data volumes. To improve the efficiency all the methods could be implemented in the geoportal rather than using a external processing service.
4.3 Implementations of some the methods

The aim of this section is to discuss the implementation of some of the methods in the system architecture given in Figure 6. The description concentrates on implementation of handling ontologies and symbologies in the geoportal.

**Ontologies.** The ontologies used in the proposed solution should preferably be based on the data available in the geoportal (i.e., the basic services). Ontologies of different levels (top-level as well as lower levels) should be available to enable the semantic integration. To obtain this we have to perform an ontology alignment.

The ontology alignment is performed when a dataset is first made available in the geoportal (Figure 6). The new dataset is classified according to the portal’s ontologies, with possible extension of the (lower level) ontologies to include the new dataset (cf. Fonseca et al. [10], and their work with Ontology-Driven Geographic Information Systems, ODGIS). After building ontologies and making classifications, this approach can also be used for finding out which information it is possible to integrate. When these integration rules are defined they could be stored in the geoportal to support integration of data from different basic services in real time. The integration rules could, e.g., control real-time transformations between object catalogues using XSLT (see, e.g., [20, 28]).

**Symbologies.** The symbologies could be stored in the geoportal using Styled Layer Descriptor (SLD). SLD is a standard that is complementary to the WMS (both specified by the OGC). WMS allows the user to determine several aspects
of the map such as layers, geographical area and file format. A limitation of WMS is that the user only can use predetermined presentations (as defined by the person creating the map service). This is where SLD is useful; using SLD, a user can specify which symbols to use for each object type and also let the attribute values affect the symbolization. The SLD specification can then be added to a WMS request (of type getMap) and thus the user can choose the map’s presentation. There are three possibilities of using SLD in this application:

1. The user uses a predefined SLD file on the geoportal (cf. Figure 6).
2. The user creates an own SLD file on the client and appends this file to the map request.
3. The system generates an SLD file that has good presentation properties.

There are standard methods to implement the two first methods. To implement the third method we could use semantic techniques (e.g., OWL) in conjunction with automatic symbolization methods (such as the one in Figure 5). If all data are annotated with extra information about meaning and normal presentation properties (e.g., if it is used as foreground/background data), then the system could select proper presentation for creating, e.g., visual hierarchies and good discrimination between object types (could be done in an external service denoted Symbolization optimization in Figure 6). This could be done in real-time or as a pre-process (where the symbologies are stored in the geoportal).

5 Concluding Remarks

The problem of bad quality and readability of maps in view services is caused by the lack of a cartographer controlling the compilation of cartographic information. To overcome this problem we have to use a wide range of methods. In this paper we have presented some semantic, conflation, generalization and symbolisation methods for this purpose. Some of these methods are well-known and well tested, while others need further studies. What is also required are studies of how these methods could be integrated in a system architecture and work together to replace the work of a cartographer.

Acknowledgment

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References


The Accuracy of Sketched Spatial Relations: How Cognitive Errors Affect Sketch Representation

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Abstract. Compared to verbal and textual language, sketch maps are an intuitive and effective way to communicate about spatial information. Untrained users can use sketch maps to easily interact with GISs, e.g., to query the spatial database by drawing freehand sketches. However, in these hand-drawn sketches, errors such as straightening, direction and shape distortions are inevitable and are a natural result of schematization, distortion and abstraction in perceptual and cognitive processes. These errors affect the accuracy of sketched spatial properties and spatial relations, e.g., topological relations or cardinal directions, which make sketch maps not as accurate as metric maps which is based on exact measurements. This paper analyzes typical cognitive errors in sketch maps and evaluates Egenhofer’s query-by-sketch approach for sketch map formalization with respect to these errors. We conduct an experiment that demonstrates how typical cognitive errors lead to false formalizations in the query-by-sketch approach and suggest how the formalization could be improved. We aim at developing an approach for sketch representation which is able to deal with cognitive errors, incomplete information, and capable of abstracting useful spatial relations at the right level of granularity for future spatial reasoning tasks.

1 Introduction and Motivation

Sketch map is a common way of human-human communication and is now widely applied in geospatial reasoning tasks for its direct representation of human spatial memories. It is a natural way to reflect how humans perceive the specific environment on a piece of paper. One challenging application of sketch maps is Spatial-Query-by-Sketch proposed by Egenhofer. It is a new interaction mechanism that allows a user to formulate a spatial query by drawing the desired spatial configuration with a pen on a touch-sensitive computer screen and get it translated into a symbolic representation to be processed against a geographic database [2]. However, during sketching, errors due to human spatial cognition may occur. They are neither random nor due solely to ignorance, but a result of cognitive processes [8]. Sketch maps typically contain only a few, relevant features of an area, misrepresent geometries and spatial relations among these features, and represent the information at a very general or abstract level. The
resulting sketch analysis must necessarily be wrong if it does not account for the fact that the cognitive errors lead to distorted or omitted spatial information.

If sketch maps are used to queried against a spatial database, it is necessary that the formalization approach can deal with incomplete and distorted information and represent it in a sketch map at the right level of granularity: Although people tend to simplify and abstract shapes of spatial objects on sketch maps, we can still get significant information. The approach has to include the relevant information in the query and ignore the irrelevant ones. This research investigates to what extent spatial relations between sketched objects can be used for spatial querying and what level of granularity is necessary to map spatial relations from the sketch map to its corresponding metric map. Moreover, the research addresses the question of how an existing computational model for sketch representation can be modified to account for inevitable cognitive errors.

The remainder of the paper is organized as follows: Section 2 gives an overview of the related work in the area of cognitive errors as well as sketch representations. Section 3 describes the empirical experiment where participants draw sketch maps of two familiar areas. We explain how to apply Egenhofers query-by-sketch to formalize sketch maps and identify which cognitive errors lead to a wrong formalization. In Section 4, we suggest modifications to the formalization approach, especially for directional relations. Section 5 concludes and gives directions of future work.

2 Related Work

In psychology, many researchers focus on how people think and communicate about the space they inhabit and create. It has already been documented that sketch maps reflect conceptions of reality, not reality itself [6]. It is inevitable that information will be omitted, regularized, exaggerated, fantasized and even added with smuggled messages, due to the inconsistent scales and perspectives used in sketch maps. These sketch representations of the real world thereby may never escape from errors. Some documented errors are reviewed as below: Direction get straightened in memory or people mentally rotate the directions of geographic entities around the axes created by themselves [8]; all sketch maps schematize and highlight the information relevant to their purposes, thus eliminate the irrelevant information [7]. This can be well exemplified by sketch maps representing spatial objects: People always conceive them as simple geometry shapes or just blobs. These sketched elements may well satisfy specific purposes but in fact they may severely distort the configuration of the reality.

Egenhofer [2] proposes a computational model to abstract away details of the sketches with an emphasis on the salient parts. A sketch map is represented symbolically by capturing qualitative spatial relations between each pair of spatial objects. Five types of spatial relations are distinguished: Coarse binary topological relations which is based on the 9-Intersection Model, detailed topological relations, metric refinements, coarse cardinal directions and detailed cardinal
directions. The spatial database is queried for the area where exactly the same spatial relations hold between pairs of spatial objects.

3 Experimental Exploration of Cognitive Errors in Sketch Maps

We conduct an experiment to explore the cognitive errors that people made in drawing sketch maps and analyze them to evaluate Egenhofers query-by-sketch. This study compares sketch maps drawn by participants to the two-dimensional metric maps of the same location. The sketch maps and the metric maps are formalized using query-by-sketch and qualitative methods are applied to analyze accuracy of sketch maps in the comparison to metric maps. Querying a database via sketches only succeeds, if the sketch map and the metric map of the same location have the same query-by-sketch formalization.

3.1 Experiment Settings

Many spatial properties cannot be described when being independent of scale. People present spatial information with different abstraction levels according to various spatial scales. We investigate three different spatial scales to determine a proper one for our study. Participants are asked to draw locations of three different spatial scales: The bounding box of the small area is \(0.01\text{km}^2\), the bounding box of the medium area (Figure 1) is \(0.2\text{km}^2\) and the bounding box of the large area is \(1\text{km}^2\). For the final experiment, two areas are discarded since the small area does not have sufficient spatial objects and complex street information, whereas the large area has excessive spatial objects and complex street information which is too difficult for participants to draw. Finally, two locations of medium size are selected for our experiment. Some basic spatial information of two locations are given in Table 1.

<table>
<thead>
<tr>
<th>Table 1. Basic spatial information of the two locations with medium spatial scales.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location A (the castle to IFGI)</td>
</tr>
<tr>
<td>Bounding Box 0.21 km(^2) (0.86°x0.24)</td>
</tr>
<tr>
<td>Route Length 0.8 km</td>
</tr>
<tr>
<td>Main Streets</td>
</tr>
<tr>
<td>1 main curved street (Hüffer street) with 4 main branches</td>
</tr>
<tr>
<td>3 turns</td>
</tr>
<tr>
<td>Intersections T shape, cross shape, L shape</td>
</tr>
</tbody>
</table>

The participants are provided with a sample map of a comparable area with a similar scale, a route with similar geographic and non-geographic features and the similar route complexity.
3.2 Experiment Method

The empirical experiment is carried out in the context of the use case, which determines the scale, size and type of area we discussed before.

Participants. All participants are familiar with the locations the experimenters have chosen. As a result, errors that come from participant ignorance of areas can be eliminated. Ten participants (six males and four females, with average age of 27.5) from University of Muenster take part in the experiment individually and do the testing voluntarily. Though all of them are with GI1 experience, it does not mean that they have any exceptionally good understanding of sketching spatial areas or any better spatial intelligence. The participants are familiar with GI terminology such as feature, geographic/non-geographic object and sketch map.

Stimuli and Design. Each participant is given instructions about the two locations and a sample map showing a finished sketch map. Here is the example for location A, the instruction reads “Please draw a sketch map describing the spatial area when you walk from the castle to IFGI (Robert-Koch Str, 26). Please delineate in the map the salient fixed features along the path you take as accurately as possible”.

3.3 Sketch Map Analysis

The examinations of the sketch maps in our study focus on elementary components, such as sketched objects and binary spatial relations between objects. All valid sketched objects of each participant are analyzed one after another and object-by-object. The assessment of each sketch map is done manually.

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1 GI is the acronym of Geographic Information.
Completeness Assessment. Of all 20 sketch maps for both areas, only 14 are kept for the following analysis. The remaining 6 are discarded, for the reason that they are too simple to sustain an analysis: The discarded maps contain only starting and ending points (some also a third landmark) with one connecting street. We require more than 4 sketched objects to do a reasonable analysis. In this study, sketched objects are the logical entities in a sketch and treated like virtual objects without strokes [1]. They possess a spatial location and have spatial relations with other sketched objects. The knowledge about the types and numbers of sketched objects reveal a portion of a sketch map’s meaning and imply the intended purpose when people perceive the environment in a sketch. Table 2 and Table 3 show the salient sketched objects found in sketch maps. The criterion for salient objects is adopted by 10 participants: there are no less than 50% of people who draw such objects.

<table>
<thead>
<tr>
<th>Participants</th>
<th>Geographic</th>
<th>Non-geographic</th>
<th>FH building</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Ditch</td>
<td>Castle IFGI</td>
<td>Bakery</td>
</tr>
<tr>
<td>B</td>
<td>O</td>
<td>O</td>
<td>O</td>
</tr>
<tr>
<td>C</td>
<td>O Trees</td>
<td>O O O</td>
<td>O</td>
</tr>
<tr>
<td>D</td>
<td>O Grassland</td>
<td>O O O</td>
<td>O</td>
</tr>
<tr>
<td>E</td>
<td>O Trees</td>
<td>O O O</td>
<td>O</td>
</tr>
<tr>
<td>F</td>
<td>O X</td>
<td>O O O</td>
<td>X</td>
</tr>
<tr>
<td>G</td>
<td>X X</td>
<td>O O X</td>
<td>X</td>
</tr>
<tr>
<td>H</td>
<td>X X</td>
<td>O O X</td>
<td>O</td>
</tr>
<tr>
<td>I</td>
<td>O</td>
<td>O O O</td>
<td>O</td>
</tr>
<tr>
<td>J</td>
<td>O Trees</td>
<td>O O O</td>
<td>O</td>
</tr>
</tbody>
</table>

(O stands for sketched objects, whereas X refers to non-sketched objects)

From the results, we observe that the most frequently used sketched objects (100% sketched by participants) are the starting and ending points in both two areas: The castle and IFGI in location A, and Mensa and IFGI in location B. Other sketched objects which are relevant to the wayfinding task are drawn frequently as well, e.g., in location B, lake Aa and the grassland are depicted by almost all the participants because they are adjacent to the short-cut when walking from Mensa to IFGI. Completeness in a sketch map is impossible to ensure because people tend to ignore the irrelevant objects, e.g., in this experiment, natural objects, such as vegetation (trees and grasses) which cover a large area,
Table 3. Salient sketched objects of location B.

<table>
<thead>
<tr>
<th>Participants</th>
<th>Geographic</th>
<th>Non-geographic</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Lake</td>
<td>Grassland</td>
</tr>
<tr>
<td>B</td>
<td>O</td>
<td>O</td>
</tr>
<tr>
<td>C</td>
<td>O</td>
<td>O</td>
</tr>
<tr>
<td>D</td>
<td>O</td>
<td>O</td>
</tr>
<tr>
<td>E</td>
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<td>G</td>
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<td>O</td>
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<tr>
<td>J</td>
<td>O</td>
<td>O</td>
</tr>
</tbody>
</table>

(O stands for sketched objects, whereas X refers to non-sketched objects)

make up only a small part of the entire set of sketched objects whereas artificial objects related to wayfinding task, such as buildings or streets which cover only a small area occur much more frequently.

**Accuracy Assessment.** By comparison with metric maps, accuracy assessment is processed along two directions: One is the accuracy of properties of sketched objects, such as size and shape; the other is the accuracy of spatial relations abstracted from sketches. The latter is achieved through Egenhofer’s sketch representation for query-by-sketch. One sketch map of location A is taken as an example and analyzed as below.

**Sketched Objects.** In reality (Figure 2), the route from the castle to IFGI is the west-east direction Hüffer street intersected by Himmelreich street, Robert-Koch street and a trail behind the castle. The segment of the main street called Hüffer is a curved one with 6 straight branches that are not parallel to each other. Some branches intersect with Hüffer street with obtuse angles, so that, when turning from Hüffer street to Robert-Koch street, the angle is bigger than 90 degrees; and some intersect Hüffer street with a right angle. Salient spatial objects in location A are with complex shapes whose representations are not simply based on a pure symbolic representation.

However, in sketch maps (Figure 2), sketched street information is unfortunately reduced by simplification, distortion and omission: Junctions with non-orthogonal angles are simplified to 90 degrees; all the streets are straightened, despite of those existing curvatures; small street branches are totally ignored
by people. Other sketched objects are represented by simple shape forms, such as circles, squares and ovals. These symbolic and distorted representations have nothing in common with the visual appearance of the object in reality. They have the origins from cognitive errors as schematization and systematic errors during human perception processes.

![Fig. 2. An example illustrating the differences between a metric map (left) and a sketch map (right).](image)

**Spatial Relations.** Almost all the sketched objects are scattered buildings in reality, and located along Hüffer street. Therefore when mapping the sketched spatial relations onto 9-Intersection Model, we only get one topological relation of 'disjoint'. According to Egenhofer's approach, among five types of spatial relations, detailed topological relations and metric refinements, which are based on non-empty intersections are not applicable in this study. Figure 3 shows analysis results for the metric map in Figure 2. Firstly, all sketched objects except streets are extracted and identified as A, B, C, D and E, which represent IFGI, FH building, the castle, ditch and bakery respectively. In the second step, the spatial relations between all objects are computed. Figure 3 shows the spatial relations exemplarily for object A to all other objects. Figure 3(a) depicts the coarse topological relations that are derived from the 9-Intersection Model. Figure 3(b) shows the coarse cardinal directions of object A to all other objects. The objects E, D, and C all fall into one single partition, while B spans of 5 partitions. Figure 3(c) shows the detailed cardinal directions of object A to all other objects. It captures the details of the distribution over multiple partitions, recording by how much an object extends over multiple partitions.

The same as Figure 3, Figure 4 speaks up for the analytical results of sketched spatial relations of location A from a sketch map. From the result, no participants make mistake of topological relations. Among all possible binary relations of cardinal directions between five spatial objects, the number of correctly sketched relations from seven valid sketch maps is 14, 14, 13, 12, 8, 12 respectively, and the average accuracy rate of cardinal directions is 61%. The same situation is found in location B as well: The average accuracy rate of cardinal directions
Fig. 3. Analytical results of (a) topological relations, (b) cardinal directions, and (c) detailed cardinal directions of location A from a metric map.

Fig. 4. Analytical results of (a) topological relations, (b) cardinal directions, and (c) detailed cardinal directions of location A from a sketch map.
is 60%. The low accuracy rate of cardinal directions is caused by the omission, distortion and schematization of sketched objects we discussed before. Therefore we suggest to modify the sketch maps, e.g., keep the spatial configuration the same except for the distorted main street, and replace it with its real shape. The cardinal directions are computed based on the modified sketch map again. Figure 5 shows the modification by replacing with real shapes of Hüber street and the ditch on a sketch map. With this methodology, we could increase the accuracy rate of cardinal directions by 33%. This confirms clearly how important it is to include typical cognitive errors in sketch representation.

![Fig. 5. Modified sketch map with curved Hüber street and the ditch (the left map is the original one with straightened Hüber street and the ditch).](image)

3.4 Summary

The experiment outcomes show that human knowledge about space is typically qualitative: Instead of absolute locations and their exact geometries, participants cognize only a few but significant relationships of spatial objects at a level of granularity which is important to solve tasks, e.g., wayfinding in this case. Moreover, as stated before, sketch maps are drawn from observation and affected by human memories. Therefore, the set of relationships and properties used to describe a spatial area in a sketch map differs substantially from it in a corresponding metric map which is based on exact and complete metric measurements. Special attention must be paid to various types of properties of spatial objects, their relevance and the relations among them. Based on the experiment results, a set of underlying principles of cognitive errors is suggested as below.

Size and shape, e.g., curvature of streets, angle of intersections and footprint of buildings. Sizes of objects are often expressed relatively to each other; however, it is significantly influenced by many other aspects, such as the importance of a landmark, the significance of a decision point, or the information density. The experiment results show that people have a strong tendency to draw geographic features at the starting point and at the ending point larger than features on the route. With respect to the abstraction level of realism, almost all the sketched
spatial objects from the experiment are based on a symbolic representation and have nothing in common with actual look of the objects in reality. Region objects are depicted as square, circle, oval, cross or the combination of simple geometries. Although shapes of spatial objects are simplified, participants try to capture reality with the expression of unique or distinguishable shape of an object [1] in those cases where the object is remarkable or important for solving the task, e.g., wayfinding in this study.

Approximate topological relations, particularly relations between disjointed, meeting and connected features. Participants tend to use preliminary topology to describe a specific area. In the case of this study, only one topological relation ‘disjoint’ is captured from the sketches even though the sketchers know some of the spatial objects are connected or meet with each other.

Relative metric relations and the ordinal alignment as landmarks along the streets. The exact metric relations or even the relative ones captured from sketch maps are not reliable. However, the experiment output shows that participants seldom make mistakes when drawing order of spatial objects along the streets or path-extent objects, e.g., river or green belt.

Directional relations and different reference frames. The precision of directional or orientation relations between objects in a sketch map are affected strongly by human schematization, particularly from the tendency to straighten streets, distort angles and stylize street networks, e.g., street branches are either parallel or orthogonal to each other.

Number and types of features contained or left out. From the survey of object class (Table 2), Non-geographic features, especially artificial objects as buildings occur frequently. Especially the ones near the starting and the ending point are the most frequently sketched objects. However, natural objects, such as body of water or vegetation make up only a small part of the entire set of objects found in sketch maps.

4 Sketch Map Representation Accounting for Cognitive Errors

Based on observations from the experiment, we suggest to modified Egenhofer’s approach for sketch representation by accounting for cognitive errors. In this study, we focus on the calculation of cardinal directions. We address the question whether the combination of metric and directional relations such as ordinal relations might lead to more suitable sketch representation. Besides, we proposed a new approach to choose reference objects, which is taking main streets or path-extent spatial objects as reference objects. A simplified reference frame is developed for directional calculation, and ‘object order’ is proposed as a refinement of directional calculation based on the new reference frame.

4.1 Cardinal directions in 4 half-plane

Cardinal directions based on projections have two kinds of systems of directions. One is $D_4 = \{N, E, S, W\}$ and the other is extensive $D_8 = \{N, E, S, W,$
NE, NW, SE, SW. Egenhofer’s approach for representing cardinal directions in sketch maps is based on \( D_8 \) with additional direction 0 representing identical position. However, complexity in calculations may cause more inaccuracies because people do not perceive directions as detailed as \( D_8 \), i.e. they can not distinguish 9 partitions during sketching. To the contrary, simplicity works better in directional calculations since it can relax constraints and consider not only exact matches but also similar ones between reality and people’s sketches. As a result, cardinal directions based on \( D_4 \) are imported as a simplified way for directional calculations in sketch maps. In \( D_4 \), the four directions are pair wise opposites and each pair divides the plane into two half-planes. The direction operation assigns for each pair of objects a composition of two directions, e.g., South and East for a total of four different directions [4].

4.2 New Reference Frame with Streets as Reference Objects

In our experiment, both areas that needed to be sketched contain regions and routes\(^2\), and almost all the prominent spatial objects are adjacent to the street network, especially located along the main streets. Considering the situation that people always make errors of straightening streets and they can not distinguish 9 partitions during drawing, it is more proper to talk about one object being above (or to the North), below (or to the South), right (or to the East), left (or to the West) or at the same location (0) along with the street. In this case, a new reference frame can be built for directional calculations, i.e. We only assign main streets as reference objects and calculate cardinal directions of others with relative to references objects, but not calculate cardinal directions of all pairs of sketched objects. Because of the arbitrarily depicted streets from sketch maps, the assigned directions are relative to straight street segments or the minimum bounding box of curved ones which are both considered as enclosing polygons in this study.

As the following, all possibilities to define ‘above’, ‘below’ and ‘at the same location’ (Figure 6) are discussed.

Let \( Y_{\text{min}}, Y_{\text{max}} \) be the minimum \( Y \) value and maximum \( Y \) value respectively. \( A, B \) represent the minimum bounding boxes of spatial objects, and \( B \) is the reference object.

\[
\begin{align*}
\text{Above} & : & Y_{\text{max}(A)} & > Y_{\text{max}(B)} \\
\text{At the same location} & : & (Y_{\text{max}(A)} & \leq Y_{\text{max}(B)}) & \wedge & (Y_{\text{min}(A)} & \geq Y_{\text{min}(B)}) \\
\text{Below} & : & Y_{\text{min}(A)} & < Y_{\text{min}(B)}
\end{align*}
\]

In Figure 7, we discussed the possible situations to define ‘right’, ‘left’ and ‘at the same location’ in 4 half-planes.

Let \( X_{\text{min}}, X_{\text{max}} \) be the minimum \( X \) value and maximum \( X \) value respectively. \( A, B \) represent the minimum bounding boxes of spatial objects, and \( B \) is the

\(^2\) There are two broad classes of maps: those that convey regions and those that convey routes [7].
Fig. 6. Directional relations of object A with respect to reference object B.

Fig. 7. Directional relations of object A with respect to reference object B.
reference object.

\[
\text{Right : } X_{\text{max}(A)} > X_{\text{max}(B)} \\
\text{At the same location : } (X_{\text{max}(A)} \leq X_{\text{max}(B)}) \land (X_{\text{min}(A)} \geq X_{\text{min}(B)}) \\
\text{Left : } X_{\text{min}(A)} < X_{\text{min}(B)}
\]

All the metric measurement are processed in 2-D Cartesian coordinate systems and where to set the origin and how to build up the datum of the reference system are dependent with the shape of reference object (in this case, street segment). Figure 8 shows some examples to calculate directional relations with different street shapes of horizontal, vertical and inclined.

![Figure 8](image_url)

**Fig. 8.** Build up a datum for qualitative metric measurement.

### 4.3 Refinement of Modified Approach using Object Order

The same as the most formalizations or implementations of spatial reasoning, the modified qualitative directional relations rely on the Euclidean geometry and the Cartesian coordinate system, and there is a clear need for a fully qualitative system of directional relation reasoning, combing topological and metric relations [3]. In this case, metric properties such as relative distances to reference objects are indispensable for positional relations reasoning. Although the granularity level for directional relations is already decreased from $D_8$ to $D_4$, the simplified method is still insufficient to characterize directional relations without ambiguities. We propose object order as a refinement of cardinal directions
based on 4 half-planes. Object order is calculated by recording the sequences of objects with relative to the reference object. Compared with exact distances to reference object, humans make much less errors on representing object orders.

Here we show one example of using modified approach for directional calculation. The basic principle to choose reference object is to find the streets which have at least two objects along either side of them and only trend towards one direction. The next step is to mark them with different calculation resolutions. For example, as Figure 9 shows, the Hüffer street is marked as ‘1’, which means in the most coarse level of calculation, this street is taken as the reference object. Two branches marked with 2a and 2b are the reference objects which will make further partitions of directions with more details. For instance, street segment ‘2a’ is a partition of space above street segment ‘1’, which will be assigned for directions of left (or west) and right (or east). Spatial objects above street segment ‘1’ can be further distinguished by their positional relations with relative to reference object ‘2a’.

![Fig. 9. Taking streets as reference object for calculating directional relations.](image)

As below is the resulting table (Table 4) of directional calculations of a sketch map with new reference frame and object order. Using the modified approach we proposed, the differences for directional relations between metric maps and sketch maps are decreased to 0, which means an exact match between sketched directional relations and the directional relations recorded in a metric map.

Table 4. Results of directional relations in a sketch map using modified approach.

<table>
<thead>
<tr>
<th>Sketched object</th>
<th>Directional relations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Castle</td>
<td>(above “1”) &amp; (right to “2a”)</td>
</tr>
<tr>
<td>Ditch</td>
<td>(above “1”) &amp; (left to “2a”)</td>
</tr>
<tr>
<td>Bakery</td>
<td>(below “1”) &amp; (right to “2b”)</td>
</tr>
<tr>
<td>IFGI</td>
<td>(below “1”) &amp; (left to “2b”)  &amp; (O)</td>
</tr>
<tr>
<td>FH building</td>
<td>(below “1”) &amp; (left to “2b”)  &amp; (O)</td>
</tr>
</tbody>
</table>

(O, O₁ are object order of IFGI and FH building with respect to reference object “2b”)
5 Conclusions and Future Work

The outcomes show that sketches drawn from memories about spatial representations of the environment are inaccurate and erroneous [5]. Therefore, compared with metric maps which are from exact measurements, sketch maps contain only a few, relevant spatial objects of an area and they contain inaccurate geometries and spatial relations among these spatial objects. With respect to relevance, the empirical findings show that sketches including information important to sketchers' purposes while eliminating the irrelevant ones. Sketch maps represent information at an abstract level, meaning that people generalized details which are irrelevant for sketch tasks. With respect to inaccuracy caused by cognitive errors, the empirical investigations show that the typically inaccurate information on sketch maps such as distortions of size and shape, incompleteness of types of features, incorrectness of relative metric relations and topological relations is a natural consequence of schematization and distortion in normal perceptual and cognitive processes.

The incompleteness or inaccuracy of sketch maps, i.e., capturing only the relevant or significant information, and the representation at an abstract level, e.g., ignoring the exact metric details, but representing them qualitatively with a low granularity instead do not pose a problem in way-finding, but do pose a problem when these sketch maps are compared with metric maps: a large amount of differences will be found and sketch maps will be considered as metrically incorrect. As a result, sketches can only be used for querying spatial databases if the sketch representation captures the information at the necessary abstract level. Although the Spatial-Query-by-Sketch from Egenhofer represents sketches qualitatively, i.e. already at an abstract and rather general level, it is obviously far beyond being fine-granular: in our case, the resulting formalization of sketch maps using Egenhofer's approach still reflects many of the typical human distortion and schematization errors and cannot be directly mapped into the corresponding metric maps. Thus in future research, a revised formalization approach needs to be developed by focusing on the adequate qualitative formalization taking typical human cognitive errors into account.

Acknowledgement

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References


Appendix

As below are the scanned version of sketch maps from one participant which we used as examples in this paper.

Fig. 10. Location A: from the castle to IFGI
Fig. 11. Location B: from Mensa to IFGI
Invoking a Sense of Orientation in Digital Libraries

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Abstract. In our contribution, we will discuss how understanding of visualization and interaction with the information discovery system DiLiA (Digital Library Assistant) \cite{1} can be improved by recurring to properties and principles of human spatial problem solving and navigation in real world environments. We will outline the properties that these two problem domains have in common and also highlight the differences between them. In the end, we will propose a visualization of a data space that is inspired by the discussed principles and also makes use of principles of faceted search. This visualization should invoke in users a \textit{sense of orientation} in scientific literature that is created by intelligently presenting digital libraries’ content.

1 Introduction

In our contribution, we will discuss how principles of structuring real world environments may support invoking a sense of orientation in users of digital libraries. Quoting Franzius et al. \cite{2}: “To orient ourselves, we mainly need two pieces of information: where am I and in which direction am I heading?” These two questions need to be answered with respect to exploring digital libraries.

To this end, we will discuss structural properties of spatial environments and compare them to the properties of data spaces that encompass scientific publications. We will outline possible actions that allow a person to efficiently solve information seeking tasks and compare them to problem solving steps and strategies that come into operation in physical environments. Finally, we will conclude with a discussion about how the identified principles can be transported into a visualization of scientific literature to provide the desired sense of orientation in a digital library.

In general, the structure of an environment surrounding you gives cues about where you are and what possible actions can be performed next. However, with respect to digital libraries this structure is dynamic, since the topics and the
search goals evolve during the information seeking process [3]. Hence, a visualization has to cover this dynamic structure of the information space and to explain how moving through it is possible (in the very moment and in principle). We believe that presenting information on different levels of granularity in a single display will result in the required sense of orientation. That way, users can well understand granularity shifts and abstraction becomes possible. Such information display integrates relevant multi-granular information, very much in the way that schematization may be employed for creating visualizations for spatial assistance [4].

The paper is structured as follows: in the next two sections, we discuss the structure of spatial environments and digital libraries, and their mental representation, respectively. Section 4 then highlights commonalities and differences between both structures with respect to navigating through them. In Section 5, we present current trends in information visualization for digital libraries in light of the previous discussions, while Section 6 then details our approach to information visualization. The paper ends with some conclusions and an outlook on future work in Section 7.

2 The Structure of Environments and Their Mental Representation

The structure of an environment, i.e., its layout, has great influence on people’s mental representation. Likewise, people’s experience and expectations influence how they mentally represent an environment and how they interact with an environment.

2.1 Environmental Structure

In his seminal book “the image of the city” Kevin Lynch [5] laid the foundations for analyzing environmental structure from the perspective of how humans cognize it. He identified five fundamental elements that structure our image of a city: 1) paths; 2) edges; 3) districts; 4) nodes; 5) landmarks. People travel through an environment along paths; these paths may meet at nodes, which generally describe important strategic places, such as intersections or breaks in transportation. Travel may be restricted by edges, which are perceived as boundaries between areas, either only perceptually or as actual physical objects. Districts are regions that are perceived as containing common features that their elements share. Landmarks, finally, are outstanding features of an environment that gain their significance through physical or social concepts (cf. also [6]).

2.2 Spatial Mental Models

The complexity of an environment strongly influences people’s mental models of that environment. In complex environments, people have more difficulty building up a useful mental model [7]. In built environments, which are predominantly
under consideration in cognitive science, the complexity of an environment depends on architectural differentiation, the degree of visual access, and the complexity of its layout [8, 9]. In general, mental models of spatial environments are hierarchical [10]. This hierarchization is formed either based on explicit region information provided by the environment, or by building spatial clusters around landmarks (e.g., [11]). Such mental models may contain unrelated contradicting knowledge in different formats (e.g., propositional and pictorial) [12]. Unlike the metaphor “cognitive map” may imply, these models are rather not like 2D survey maps.

2.3 Wayfinding Strategies

Based on how they perceive the structure of an environment, human wayfinding seldom relies on geometrically shortest distance or shortest travel time, as automatic assistance systems (e.g., internet route planners or car navigation systems) usually calculate their paths. Instead, a number of factors determine path choice [13]: next to distance and time these include number of turns, shortest or longest leg first, many curves or turns, first noticed and most scenic route. Further, the deviation angle of how the direction of current movement differs from the direction to the destination may have an influence on path choice [14]. In environments with a perceivable region structure (e.g., districts as defined above or regions formed around landmarks), people rely on this region structure and employ hierarchical wayfinding strategies [15]. In general, paths are not fully planned ahead in every detail, but some options can only be verified and, thus, chosen in situ [16].

3 The Structure of Digital Libraries and Their Mental Representation

Digital libraries are not bounded in their structure by the limitations of physical space, for example, gravity and metrics. However, just as with physical space, interaction and mental representation of their structure depends on people’s experience and expectations.

3.1 The Structure of Scientific Literature

A scientific article is characterized by the meta-data that makes it unique: title, author(s), editor(s), year, publishing source (e.g., the name of the journal, or conference proceedings, volume, issuer), abstract, and its text. Some digital libraries (e.g., ACM digital library³, CiteSeer⁴) provide further information such as keywords, categories, and links to the referenced articles. Using this information, a data space can be constructed as a network consisting of articles connected to

³ http://portal.acm.org/
⁴ http://citeseerx.ist.psu.edu/
their references, or articles and co-author relations. Such a network introduces topological relations between information items.

Modern digital libraries make this data space accessible to the user via a graphical user interface that usually consists of a search panel and a hit list. The search panel allows for stating a search query that involves a combination of terms and optional Boolean AND, OR, and NOT operators. The hit list includes the results of a query. Each hit list item presents the metadata that belongs to each retrieved document. The user examines the items in a hit list and accesses their relevance. If a document is considered to be relevant, it is usually downloaded (according to the copyright conditions) for further inspection.

3.2 Information Seeking

It is surprisingly easy today to find a specific book, a journal, or an article if the search goal is known. Yet, if the information seeker is not familiar with the targeted topic, search queries are underspecified and most often lead to a huge amount of resulting hits.

Marchionini [17] defines information seeking as “a special case of problem solving. It includes recognizing and interpreting the information problem, establishing a plan of search, conducting the search, evaluating the results, and, if necessary, iterating through the process again.”

Bates [3] describes information seeking as a process that starts with either a definition of a broader topic or a single relevant reference. People move through the data space and discover new pieces of information by tracing the references, running through the relevant sources (e.g., journals, conference proceedings), or examining works of selected authors. These actions contribute to new ideas and directions to follow, and consequently new conceptions of search queries as well as better understanding of the search problem. She called this process evolving search and compared the integration of newly acquired knowledge fragments to “berrypicking.” In doing so, the relevant items are distributed over the data space so that the information seeker has to pick them up from different sources using the strategies described above (e.g., journal runs, citation tracing, etc.).

Obviously, information seeking has a close relation to learning. When searching for information about unfamiliar topic, people try to connect previous knowledge with the newly acquired information. In doing so, people economically reuse the available knowledge structures that involve concepts and relations identified and learned before or directly during a search session [18]. Learning is particularly efficient when the structure which is learned corresponds to the structure of the previous knowledge [19].

3.3 Mental Knowledge of Scientific Literature

Traditionally, information seeking behavior has been studied in connection with some information retrieval (IR) system. Such studies focus on the analysis of the actions performed by users when solving an information seeking problem. For
example, Vakkari [20] analyzed the keywords used by students while accomplishing a research proposal for a masters thesis. The traces of keywords indicated the evolving conceptualization of the studied topic. The insights gained from these studies, however, are restricted to the operations (such as the definition of keywords in combinations with Boolean operators) supported by an IR system and do not provide information on how mental representations are actually structured and how people employ them to find relevant information.

In information seeking, people are usually involved in some larger task context, since “search is a means towards some other end, rather than a goal in itself” [21]. For example in academia, scientists search for relevant information when writing an application for a grant, a scientific paper, or preparing a lecture for a university course. Although information seeking is a long studied area, investigations into people’s interaction with scientific literature in context of their everyday scientific work are rare.

In the scope of this paper, we will refer to one particular study, conducted by Anderson [22], which is focused on information choices of expert scientists over a long period of time in the context of academic work, especially, how expert scientists establish the relevance criteria that guide their search for appropriate literature in large data collections, such as digital libraries. The study describes the relevance criteria that lead to information selection decisions made during search. These criteria are derived from think-aloud protocols collected during multiple interviews and search sessions. The protocols show that experts rely not solely on the so called topicality of a scientific document, but rather rely on subjective judgments that involve various multidimensional aspects, for example:

1. a personal connection to the author of an article, or familiarity with an author’s work (so called key-authors who coined a research area or a topic),
2. popularity and the impact factor of journals or conference proceedings, i.e., the source of an article where it was published,
3. author’s affiliation to a specific organization or institution.

These criteria come into operation simultaneously. Therefore, even an article that fits well in a search query can be discarded in case its authors or its source have a bad reputation. On top of that, personal interaction and communication about scientific topics with other researchers at different conferences or symposia turns out to be a crucial source of information about who works on which topics.

In that, information seeking is fundamentally different from another important process in scientific work, namely double-blind reviewing where authors and affiliations are intentionally blended out. In information seeking, scientists eagerly use this information for judging the relevance of others’ work and for guiding their search.

4 Finding Your Way in the Real World and in Digital Libraries

Structurally, spatial environments and digital libraries do not have much in common at a first (and maybe second) glance: a spatial environment is structured
through physical reality; it is a metric space, which affords physical effort to get from a spot A to a spot B. Movement is restricted by obstacles (either man-made or natural). In a digital library (browser) no such restrictions apply. No physical movement that would be crucial for getting from one state to another needs to be performed. The structure is not metric to begin with; physical properties, such as gravity, do not play a role.

Still, when navigating such spaces, some important commonalities occur (cf. also [23]). In both worlds, those navigating the space reach specific points where decisions about the further way to take are due. In real-world navigation, these points are referred to as decision points. Usually, these points correspond to intersections in a street network where there are several possibilities to continue one’s travel. In Lynch’s terminology (see above), the sequence of decision points and segments between them form a path, the movement pattern of traveling along that path describes a route [24]. The ease of navigating decision points depends on their structure (e.g., number of meeting segments) on the one hand. On the other hand, visual or structural cues help to identify decision points and to indicate the further way to take [6, 25]. Such cues might be signage or landmarks, for example. They provide a sense of orientation along a route. As discussed in Section 2, to orient themselves with respect to the larger environment surrounding the route, people also make use of regions.

In digital libraries, no a priori network exists that movement through the content may be performed on. But the sequence of interaction steps while exploring a digital library corresponds to some kind of movement pattern that forms a path where each new state is topologically connected to its predecessor. This way, a path emerges that describes a user’s movement through the library—it might also become a branching network, when backtracking to previous states and continuation with a different interaction from there is added to the interaction history. Information seekers may remember these states as the origin of several interaction paths and, thus, as the nucleus of a specific part of the data space. That is, conceptual regions may emerge from the branching in interaction history.

Such interaction paths allow for answering the crucial questions for having a sense of orientation as defined in the introduction: 1) “where am I” (in my interaction sequence)? 2) “where can I go to” (which are useful options at this state)? Just as with paths in the real world, each state in the exploration of the digital library corresponds to a decision point. And just as with real world navigation, visual and structural cues help in identifying the state, answering the “where am I?” question, and in indicating further ways to takes, answering the “where can I go to?” question. Thus, an interface to a digital library is called for that clearly presents the current state in its exploration context and, likewise, clearly indicates which interactions, i.e., which operations using which items, are sensible for further exploration from this state.

Furthermore, background knowledge plays a crucial role in navigation in both worlds. In the real world, background knowledge allows for assistance-free navigation in well known environments, i.e., people just know the way to take.
But such knowledge also helps navigating unknown environments by recurring to knowledge gained in similar environments. For example, knowing how a city is structured, one may infer that buses often run along major streets and that shopping facilities are often located near the main station.

Differences in background knowledge is even more important for navigating digital libraries. As discussed in Section 3.3, scientists rely a lot on information that they have gained through social interaction and as part of their work experience. This knowledge is largely acquired outside a digital library and then used to explore its content. It drives interaction with the presented content, particularly which further “paths” are taken from the choice of possible next steps. Thus, making this additional information available, such as the country or institute the publication has been written at or the journal / conference it has been published in, is an important aspect of supporting navigation in a digital library, especially for the “where can I go to?” question. For experienced scientists, this allows for being quickly able to judge particular publications, for novices it supports gaining the required background knowledge for the research field under inspection.

5 Trends in Interface Design of Digital Libraries

Different metaphors have been used in the context of explaining and strengthening the visual experience of a digital library’s structure. The approaches taken so far range from classical simple form-based search panels and hit list components (e.g., google search) to animated three-dimensional hierarchical cone-tree structures that allow for interactive exploration of a data space.

5.1 Spatialization

Fabrikant [27] proposed a visualization of different topics as a geographical map; she terms this technique spatialization. Related topics are positioned near each other, whereas topics that have nothing in common are far away. Spatial distance between topics enables users to get an overview about relations between various scientific areas at a single glance. By rendering height information in the third dimension, a spatialized data space may show the number of documents contained in a topic, for example. A similar spatial distance metaphor has been used to visualize concept spaces.

5.2 Citation and Co-Author Networks

Citation networks visualize references between articles. Co-author networks display relations between researchers who cooperate with each other by co-authoring scientific publications. This type of visualization is useful in identifying citation clusters or groups of closely cooperating researchers. The citation or cooperation

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5 www.google.com
density may indicate interesting emerging topics in a scientific community. The major problem in using network-graphs for information visualization is the potentially high connectivity of nodes. Therefore, it is often very hard to perceive the boundaries between such clusters.

Although spatialization, and citation and co-author networks may seem to be different at first glance, these methods share one thing in common. They reduce the dimensionality of the data space by focusing on selected aspects: topics, citations, or authors. Due to this information reduction important connections between researchers, institutions, and topics are lost.

5.3 Faceted search

Faceted search is a recent approach in interface design that turns back to classical form-based data presentations. In order to facilitate the exploration of data, faceted search interfaces include not only hierarchically organized categories or topics but also offer facets to navigate through the data space. Facets reflect the structural properties of the underlying documents including meta-data, year of publication, research institutions, and also specific characteristics of a document, for example, its format [29]. Information seekers can explore the data space by incrementally selecting and adding different facets in order to interactively refine the resulting hit list.

Digital libraries, such as gopubmed hosted by Transinsight GmbH or AuthorMapper hosted by Springer, implement a combination of the currently proposed visualization techniques described above. Mainly, these digital libraries have a facets-based interface that integrates tools for further analysis of resulting hits. Such tools include bar charts that allow for examining how a research topic is developing over time filtered by different facets (e.g., articles per year according to a selected topic, country, author, keywords, journals, or institutions). Additional tools, such as co-author networks or locations of the corresponding institutions depicted on geographic maps, provide further perspectives on the data space.

Figure 1 illustrates the interface of the gopumed digital library. The facets, including categories, keywords, and technical terms, are on the left side of the screen. The resulting hits are to the right. Users now have the possibility to filter various dimensions to refine the resulting hit list. Users explore the literature contained in the digital library by interactively adding or removing proposed facets.

Faceted search is a promising method for integration and visualization of multiple dimensions relevant for exploring and understanding digital libraries. It forms the basis for our approach of information visualization that goes one step further by providing a compact, relational, and interactive visualization.

6 http://flamenco.berkeley.edu/index.html
7 http://www.gopubmed.com/
8 http://www.authormapper.com/
6 Multidimensional Query Visualization Approach

The main idea behind the approach pursued in DiLiA [1] is to establish relations among multiple dimensions of a data space and to make them visually accessible to the user. In addition to the current trends and visual features discussed so far, a relational query visualization offers a number of interactive operations that allow for stating new queries, modifying old queries using Boolean operators, and retrieving new relations.

DiLiA integrates different levels of granularity in its visualization. A first step to achieve this is a division of the main panel into two parts (see Figure 2). On the right side, consistent with the digital libraries described above, it contains a search panel and a hit list. The left side of the screen displays relations between search queries formulated by the user during the search.

6.1 Interactive Hit List

The hit list displays traditional meta data that characterizes a scientific publication, such as title, author names, source, abstract, a publishing year, and keywords. Beyond that, the hit list is augmented with technical terms, which are automatically extracted from the abstracts (see [30] for details). One hit is displayed in detail, while additional hits can be accessed by pressing their title bar.

Users have different possibilities for stating a search query. The search panel allows for a free selection of search terms. Authors, titles, keywords, and technical
terms are implemented as hyperlinks that enable users to seamlessly invoke new search queries. Each query is visualized as a blob on the left side of the main panel.

6.2 Query View

Each query blob displayed in the query view corresponds to a state in the exploration history (cf. Section 4). Query blobs represent different metadata types, for example authors, keywords, search terms, or organizations. Query blobs are connected with each other via edges that symbolize query intersections. The edge thickness shows how many documents are shared between the queries. This gives users an immediate impression about which Boolean operator can be applied to a pair of query blobs. It supports the “where can I go to?” question as it offers clear hints of what next steps are possible. Users can perform Boolean operations by dragging and dropping the blobs surrounding the central query to the corresponding AND, OR, and NOT panels (see Figure 3). The system suppresses AND and NOT operations if query blobs have no intersections. In doing so, the system helps the user to avoid frustrating “no hits” situations.

Information seekers can browse the content of the query blobs by clicking on them. This operation moves the clicked query blob into the center by an animation and displays the documents contained in it in the hit list. Keeping the currently selected blob in the middle of the display puts it in visual focus and clearly indicates a user’s location within the exploration process. It answers the “where am I?” question.

Users can examine the results of performed operations at different levels of granularity: as updated relations between queries (the left side of the screen) or as a hit list of articles (the right side of the screen). Users further may remove a
query blob from the view in case it is not needed any more. This allows avoiding information overload and keeping the query view compact and clear. Removed query blobs can be restored from a trash box which is situated under the search panel. The “MORE” button, finally, invokes an online clustering procedure that proposes semantic labels extracted from the documents contained in the query (see Figure 4).

Information seekers incrementally construct a relational query visualization during their individual exploration of the data space. By applying the AND operator, they refine the search goal. The OR operator allows for broadening the search. The NOT operator can be explicitly applied, for example, to search for articles that are written by less prominent authors. If researchers always only read those authors whom they know, they would easily miss new interesting ideas stemming from young scientists or other scientific communities.

The relational query view integrates information on different levels of granularity. First of all, metadata may be on different levels of granularity, for example, a research field, such as “visualization,” compared to a single author or even paper in that field. Even more, applying Boolean operators results in hierarchical relationships between the newly emerging query blob as a parent of the topics combined with the Boolean operator. To add to this, the AND operator narrows results, i.e., moves to a finer level of granularity, while the OR operator does the opposite. In DiLiA, all these different granularity levels are integrated and connected in a single view without the need for moving up or down hierarchical list or tree views. Thus, information seekers always have an overview of where they are in their exploration as well as easily gain insight in the structure of and relationships in the research field under inspection.
This way, the relational query view maintains the search steps made by the user, or in other words the traversed decision points, by maintaining query blobs and spanning a network between them showing their relationships, both with respect to the content of the library and the exploration history. Having such a multidimensional representation of query results at hand, users can incrementally construct their individual picture of the scientific literature being under investigation. Combining different dimensions in a single visualization provides a better understanding of research activities and connections between topics, authors, or institutions. One can see how many articles a particular author has published to a specific topic. By retrieving additional semantic labels, users may explore additional topics the author has been working on. Such operations provide an overview and at the same time propose new directions for exploration. To sum up, query blobs show the paths taken so far, the relations between them show further steps that can be followed without running into a dead end, i.e., frustrating “no hits” situations.

7 Conclusions and Outlook

This contribution discusses how users may be supported in information seeking in digital libraries. We have argued for commonalities in the structure of real world environments and the structure of a library’s data space, and in navigating in both that allow for employing concepts from real world orientation also in the digital world. This enables the creation of information displays that invoke a sense of orientation in the users, which in turn fosters gaining an overview over a scientific field and detecting novel research ideas from related fields or less well-known authors. We have exemplified the discussed principles by presenting DiLiA (Digital Library Assistant) a novel interface for exploring information stored in a digital library.

Future work first and foremost comprises user studies to elicit whether the claims made in this paper, while plausible from existing research, indeed hold. We
are currently setting up a first experiment that will shed light on usability issues of the system. First, we will test basic usability issues (learnability, efficiency, memorability, errors, and satisfaction) using the IsoMetrics questionnaire [31]. Second, we will conduct a study exploring more specific aspects of interacting with DiLiA, for example, which Boolean operators may be used more intensively than others, which kind of queries may be preferred, and which dimensions are explored. This will provide important feedback for further system design.

In general, surveying and mapping of scientific data has just really started. Commercial online digital libraries hosted by established publishers (e.g., Springer, ACM) provide very good information quality. Yet, the content of such libraries is limited to the articles issued by these publishers, there is still a lot of room for improving exploration of content, and the access to their content is restricted to the organizations who have a subscription. Openly accessible digital libraries, such as DBLP or CiteSeer, are limited to metadata acquired through crawling the web, often without access to the full texts. Unfortunately, the quality of this metadata is poor, important information, like organization or even source, is missing. In light of the large effect social information and interaction has on browsing digital libraries, reliable metadata supporting this social interaction can be expected to increase the quality of information drastically. Since it is to a considerable extend a social venture, technologies developed in connection to web 2.0 may help to collect and exchange the required data on a larger scale.

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