How people describe their place: Approaches to interpreting and formalizing place descriptions

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I certify that I have properly acknowledged the contribution of other researchers to my thesis. I further certify that, with the above qualification, I have developed and written the enclosed thesis completely by myself, and have not used sources or means without declaration in the text.

Karlsruhe, 26 June 2013

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(**Daniela Richter**)

Abstract

Natural language expressions describing locations would provide a powerful interface to interact with geospatial services since queries such as ‘a hotel in downtown New York’ or ‘the library opposite the main station’ are a natural way for people to refer to geographic features they conceptualize as places. However, an automated interpretation of such expressions is still challenging, while at the same time the need for better automated interpretation becomes more urgent with the ever increasing availability of user-generated data containing place descriptions.

This cumulative thesis deals with human place descriptions and their interpretation. It poses four different research questions in particular: What are dominant types of place descriptions? Which different types of hierarchical structures do they use? What is the role of spatial relationships in defining the actual location? Can violations in form of flat structures or gaps in levels be related to the applied classification scheme?

To provide answers we investigate a corpus of georeferenced place descriptions, which were collected through a location-based mobile game. The first part of the thesis explores how people describe a place in natural language. Therefore, we develop a multidimensional classification and annotate the place descriptions according to different characteristic parameters, such as description type, description style, and spatial granularity. We then identify groups of different place descriptions by clustering the annotated place descriptions. In the second part, we investigate hierarchical structures of place descriptions using spatial granularity, which represents one parameter of the classifications. The third part determines the level of granularity to which the localization of a described place is possible. The focus is on integrating spatial relations into this process in particular. The feasibility of the procedure is evaluated in a comparison of place descriptions with people’s self-reported position on a map. In the last part, we investigate the identification of hierarchical structures in place descriptions, comparing different approaches to classify spatial granularity.

First, we found that there are certain clusters of place descriptions that represent prevalent ways of how people describe their place. Secondly, results show that most place descriptions are indeed hierarchical. However, a considerable number of deviations from hierarchical structures in form of flat or unordered structures occur. They are explained by principles other than spatial granularity, such as the presence of salient features and other construction principles. Results in the third part outline the importance of integrating spatial relationships into the resolution of place descriptions. Having found proof for the dominance of hierarchical structures (second part), results from the fourth part demonstrate that both hierarchical structures and deviations depend on the respective granularity classifications.

Research outcomes contribute to our general understanding of place descriptions and shed light on their particular structures. They show the need for and significance of more flexible models of hierarchies in the interpretation of place descriptions. This knowledge is important for developing formal methods for the automatic interpretation of place descriptions, and for their integration into location-based services. Identifying the finest possible level of granularity supports resolving place descriptions.

The interpretation of place descriptions is essential for the development of intelligent tools and location-based technologies as well as the interaction with users of location-based services or geographic information retrieval.

Kurzfassung

Ortsbeschreibungen stellen für Menschen eine gängige Methode dar, um Standorte oder Wege zu beschreiben sowie Dinge in ihrer Umgebung zu lokalisieren oder Informationen über eine Region zu erfragen. Während das Verstehen von Ortsbeschreibungen für Menschen eine triviale Aufgabe ist, haben Computer Schwierigkeiten bei der Erzeugung oder Interpretation von natürlich-sprachlichen Weg- oder Ortsbeschreibungen.

Die Bedeutung der Interpretation von Ortsbeschreibungen zeigt sich in vielen Bereichen, wie beispielsweise bei Navigationssystemen, bei der Mensch-Maschine-Interaktion und insbesondere auch im Katastrophenmanagement, welches eine schnelle Auswertung von natürlich-sprachlichen Berichten und die Bereitstellung von aktuellen Informationen erfordert. Darüber hinaus würden natürlich-sprachliche Ausdrücke zur Ortsbeschreibung eine leistungsfähige Schnittstelle zur Interaktion mit geo-räumlichen Diensten bieten und so beispielsweise Abfragen wie 'Hotels in der Nähe des Hauptbahnhofs' erlauben.

Die Anwendung hierarchischer Strukturen in Ortsbeschreibungen ist allgemein anerkannt und offensichtlich aus verschiedenen Studien. Hierarchische Strukturen dienen der Verankerung von Orten, einer Sache oder eines Ereignisses an bekannten Orten ('das Café gegenüber des Hauptbahnhofs') sowie zur Disambiguierung von Orten einer spezifischen Granularitätsebene. Beispielsweise dient in der Ortsbeschreibung 'Melbourne in Australien' die Referenz 'Australien' zur eindeutigen Unterscheidung des Ortes 'Melbourne' von anderen Orten gleichen Namens. Damit stellen die Gewinnung von räumlichen Informationen und die Klassifikation der räumlichen Granularität eine wesentliche Grundlage für die Interpretation von Ortsbeschreibungen dar. In dieser Hinsicht sind das Wissen über Sprachmuster und die Verwendung einer geeigneten Systematik zur Klassifikation der räumlichen Granularität unerlässlich.

Eine Hypothese dieser Arbeit ist, dass Menschen bei der Beschreibung ihrer Lage sowie von Orten oder Ereignissen in ihrer Umgebung häufig bestimmte Muster und überwiegend hierarchische Strukturen verwenden. Sie nutzen dabei räumliche Beziehungen, um bestimmte Orte an anderen, teils bekannteren, prominenteren Orten zu verankern oder bzw. und diese zu konkretisieren. Zur Bestimmung der feinsten Granularität des zu lokalisierenden Ortes ist es notwendig, neben der Granularität der Ortsnamen auch die beteiligten räumlichen Relationen zu berücksichtigen. Räumliche Relationen unterscheiden sich zum Beispiel in der Aussage 'Ich bin in der Nähe des Hauptbahnhofs' im Gegensatz zu der Aussage 'Ich stehe vor dem Hauptbahnhof'.

Eine weitere Hypothese der Arbeit ist, dass die Identifikation von hierarchischen Strukturen von dem angewandten Klassifikationssystem der räumlichen Granularität abhängig ist.

Folgende Fragestellungen werden in den verschiedenen Teilen der Dissertation untersucht: Welche dominanten Arten von Ortsbeschreibungen gibt es? Welche verschiedenen Arten von hierarchischen Strukturen verwenden sie? Können Abweichungen in Form von flachen Strukturen oder Lücken zwischen den Granularitätsebenen in Zusammenhang mit der angewandten Klassifikation der räumlichen Granularität gebracht werden? Und schließlich, welche Rolle spielen räumliche Relationen bei der Definition des tatsächlichen Standortes?

Zur Beantwortung dieser Forschungsfragen wurde im Rahmen der vorliegenden Arbeit eine systematische Studie von Ortsbeschreibungen durchgeführt, welche durch das Handy-Spiel *Tell-Us-Where* (Winter et al., 2011b) gesammelt wurden. Während Ortsbeschreibungen kontextspezifisch sind und sich auf alle Arten von Dingen im Raum beziehen können, liegt der Fokus hier auf menschlichen Standortbeschreibungen, die eine feinste Auflösungsgrenze in Bezug auf die Größe des menschlichen Körpers suggerieren. Die Teilnehmer des Spiels hatten die Frage "Beschreiben Sie, wo Sie sind" zu beantworten.

Der erste Teil der Arbeit (Artikel "Wie Menschen ihren Ort beschreiben") entwickelt ein Klassifikationsschema für charakteristische Parameter von Ortsbeschreibungen und nutzt dieses zur Annotation des gesammelten Korpus. Basierend darauf wurde ein agglomeratives Cluster-Verfahren durchgeführt, um dominierende Arten von Ortsbeschreibungen zu identifizieren.

Unter Verwendung des Klassifikationsmerkmals *räumliche Granularität* werden im zweiten Teil verschiedene hierarchische Strukturen (*flache*, *teilweise hierarchische*, *streng hierarchische*, *ungeordnete*) sowie die sequenzielle Abfolge der enthaltenen Granularitätsebenen (*heranzoomen* und *herauszoomen*) identifiziert. Einen weiteren Schwerpunkt bildet die Analyse des Einflusses markanter Referenzpunkte (Artikel "Heranzoomen – Herauszoomen: Hierarchien in Ortsbeschreibungen").

Im dritten Teil (Artikel "Granularität von Standorten, auf die sich Ortsbeschreibungen beziehen") wird die feinste Granularität der tatsächlichen Lage bestimmt, welche durch die Ortsbeschreibung referenziert wird. Hier werden Methoden zur Auflösung von Ortsbeschreibungen entwickelt, welche sowohl die Granularität der Orte als auch die beteiligten räumlichen Beziehungen zwischen ihnen berücksichtigen.

Abschließend werden im vierten Teil der Arbeit verschiedene Ansätze zur Klassifikation räumlicher Granularität untersucht, um Abweichungen von den allgemeinen hierarchischen Strukturen, wie Lücken oder flache Strukturen, zu erklären (Artikel "Der Einfluss von Klassifikationsansätzen für räumliche Granularität auf die Identifikation von Hierarchien in Ortsbeschreibungen").

Die erzielten Forschungsergebnisse tragen dazu bei, die Art und Weise zu verstehen, wie Menschen Orte beschreiben. Dieses Verständnis ist von wesentlicher Bedeutung für die Entwicklung von intelligenten Navigationssystemen und standortgebundenen Diensten. Sie zeigen ferner die Notwendigkeit und Wichtigkeit von flexibleren Modellen von Hierarchien in der Interaktion mit den Nutzern von standortgebundenen Diensten. Das Wissen um die feinste Granularität eines beschriebenen Ortes unterstützt die Auflösung von Ortsbeschreibungen, zum Beispiel in der geografischen Informationsgewinnung oder Lokalisierung.

Die Ergebnisse der prototypischen Implementierung zeigen, dass die entwickelten Verfahren in der Regel brauchbare Ergebnisse liefern. Sie unterstreichen jedoch auch die Notwendigkeit weiterer Forschungstätigkeiten in diesem Bereich.

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This thesis itself is closely linked to the project *'Talking about place: Tapping human knowledge to enrich national spatial data sets'* (`http://telluswhere.net/`), which is a joint research project comprising academics working in spatial information science, computational linguistics and linguistics at the University of Melbourne, the RMIT University, Melbourne, and the agencies PSMA Australia Ltd., the Committee for Geographic Names in Australia and ESTA, the emergency call-taking and dispatch service in Victoria.

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Contents

1. Introduction

1.1 Problem statement and motivation

Place descriptions, such as ‘I’m just opposite the hospital’ or ‘two minutes past the train station’, are a predominant means of human spatial communication. People use place descriptions to describe their locations, to give directions, to locate features in an environment, and to request information about an area. Verbal descriptions containing spatial information are also found in newspapers, directions, traffic reports, libraries and archives.

In recent years, there has been an increasing interest in creating web applications that assemble and disseminate geographic information provided by volunteers, a phenomenon commonly referred to as volunteered geographic information (Goodchild, 2007). OpenStreetMap[1], for instance, is an open-source map of the world based on the efforts of volunteers who collect or map geographic data for the project. Volunteered geographic information or crowdsourced data has also become an essential part of crisis-mapping projects, a fact clearly demonstrated, for example, after the Haiti earthquake in 2010 (e.g., Heinzelman and Waters, 2010).

Social media, in particular, are a major resource for sharing information on certain places or events. In crisis situations, they offer the opportunity to reach and to involve many people quickly, and via smartphones, information can be accessed almost anywhere, at any time, which is a great advantage for communicating information rapidly. One disadvantage, however, is the huge amount of data that decision-makers are faced with. Data that is relevant to a particular context is often scattered over various databases or throughout the internet. For example, approximately 20 million messages, or ‘tweets’, were sent about the impact of Hurricane Sandy from 29 October to 2 November in 2012. While various studies highlight the potential of identifying live news events in real time from such tweets, only a few of those tweets (in the case of Sandy, 3%) contain reliable georeferences (cf. Dittrich, 2013). These are based on the GNSS or WLAN signals of the senders’ smartphone. An analysis of messages relies on filtering by using certain event-related keywords. However, complex place descriptions or implicit location information are not yet considered when automatically geocoding tweets to produce crowdsourcing maps, such as by the web and mobile platform Ushahidi[2]. The growing availability of volunteered geographic information

[1] http://www.openstreetmap.org/
[2] http://www.ushahidi.com/

and user-generated geospatial content containing place descriptions thus provides a stimulus for the development of automated interpretation methods for place descriptions.

Interpreting verbal spatial and place descriptions is a topic of research in the areas of geographic information retrieval, the geospatial semantic web, and location based services. However, no suitable tools currently exist to automatically interpret place descriptions. Current web-mapping services only consider place names when resolving place descriptions (cf. Winter and Truelove, 2013). Nor are current information systems able to deal with the human concept of place or to handle the qualitative spatial information common to natural communication about place. What are lacking, in short, are data, semantics and reasoning techniques that can accurately represent how people conceptualize and communicate spatial information.

The automatic interpretation of place descriptions is relevant to a broad range of applications. Smarter tools that understand human spatial language could support the interactions between users and location-based services. This would, for instance, facilitate local search, support intelligent navigation systems or allow a person to talk to a machine in a natural way about geographic space (Winter and Wu, 2008). Moreover, such tools could help to better utilize the increasing amount of user-generated data containing place descriptions, for example, in emergency reports during crises or natural disasters. These applications would thus help people save time and money, and perhaps even lives.

The scientific core of this thesis is to better understand human spatial language and to support the development of intelligent spatial tools, in particular, the automatic interpretation of natural language descriptions of place. Therefore, it is necessary to assess the spatial information given in place descriptions and to understand how people communicate about places. The interpretation process will require knowledge about the structure and content of place descriptions and their relation to real-world locations. Various studies show that place descriptions are typically structured hierarchically. This reflects how the human mind organizes spatial knowledge. Hierarchical structures serve the purpose of anchoring less known references to better known ones and of resolving ambiguities between spatial references by using information on coarser levels to disambiguate information on finer levels. Distinct levels and spatial relations both matter in the process of defining the actual location referred to by a place description because the location differs in combination with, e.g., ‘in’, ‘opposite’ or ‘near’. Thus, prepositions indicating spatial relations between certain references also need to be considered in the interpretation process.

In summary, the automatic interpretation of place descriptions includes three steps: extracting relevant information by means of natural language processing, analyzing the content, and georeferencing the respective information in order to visualize or supply the requested information in form of maps or text output. In this thesis, we focus on human place descriptions and their structures and content. We develop a classification of place descriptions capable of assessing spatial information, such as the level of detail (granularity), hierarchical structures defined by spatial granularity, and vague spatial information in form of spatial relations in verbal descriptions. We show that research is needed both on how people describe places and on how to interpret the given spatial information in order to devise formal methods and algorithms that can support the automatic interpretation of natural language descriptions of place.

The following sections outline the overall research questions, as well as the contributions and structure of this thesis.

1.2 Research questions

Formal methods of how to interpret place descriptions have attracted much attention in various fields of research and there are several challenges that need to be considered. We aim to answer the following research questions in this thesis:

1. Are there certain structures of place descriptions that we can identify based on some characteristic place parameters?
2. What are the major building principles of hierarchical structures in place descriptions?
3. To which finest level of detail (or granularity) can place descriptions be resolved?
4. How are hierarchies of place descriptions related to the applied classification scheme and can deviations (in form of flat structures or gaps) be avoided by improving the classification?

These four questions address several issues in the interpretation process and directly relate to the current state-of-the-art and research needs we will elaborate on in more detail in Chapter 2. Considering earlier research and the outlined research questions our hypotheses are:

1. There are a few predominant ways of describing place.
2. Hierarchical structures, which dominate in human place descriptions, can be verified in a large corpus of place descriptions, and hierarchical structures are not organized purely by spatial granularity. Deviations from spatial hierarchies will show other hierarchical systems, for example, based on the cognitive principles of salience or prominence.
3. Looking at spatial relations is essential to find the finest level of granularity to which a place description can be resolved, and the noun phrase of the finest level of granularity used in the description is only the lower bound for the granularity of locating a place.
4. The identification of hierarchical structures in place descriptions in automated processes will depend on the applied classification of spatial granularity, and may cause the detection of gaps or flat structures. Alternatively, there may be other reasons for these deviations such as cognitive principles of salience and prominence that may explain these deviations.

1.3 Expected results and contributions

The findings of this thesis will improve the common understanding of how people describe places. They will validate previous theories on hierarchical structure and organization principles of spatial knowledge. Moreover, they will support the need for some flexibility in the implemented mechanisms to adapt the context of different place descriptions.

The relevance of this research is manifold. *Place* is an ubiquitous concept, and the interpretation of place descriptions is applicable in the field of artificial intelligence, for location and context-aware applications, supporting intelligent search queries or the automatic processing of short messages in social media. It can enhance representation and reasoning methods as well as the automatic understanding and generation of human spatial language.

The automatic classification of granularity and inferring locations based on granularity and spatial relations is an innovative solution. It is relevant for applications that need to process large volumes of data in real-time, for example, in crisis-mapping, for geographic information retrieval or location-based services, such as navigation systems.

The main contributions are:

- An analysis of types and structures people use in their place descriptions. This part develops a general classification capturing characteristic variables, that form the basis for further studies, and identifies some frequent types of place descriptions.
- Algorithms to analyze hierarchical structures based on a classification of granularity as well as an investigation into alternative organization principles. These algorithms analyze different organization principles and the order of levels (zooming in or zooming out).
- A method to infer the granularity of the most relevant location in place descriptions. This method uses the classification of granularity and furthermore develops a ranking order of spatial relationships in order to identify the most relevant spatial reference as well as whether a modification of the identified granularity applies. Moreover, it outlines the frequency of different prepositions indicating spatial relations between places.
- An investigation of several existent classification approaches for spatial granularity. This part compares, in particular, four different approaches how well they capture hierarchical structures and deviations in order to evaluate the classification of granularity developed in this thesis.

1.4 Thesis structure

Chapter 2 reviews related work and outlines, in particular, research challenges in the interpretation of place descriptions.

In Chapter 3, we give an overview of the general approach and the interrelation between the single parts of this thesis (Section 3.1), we describe the data we used in the experimental setup (Section 3.2), and summarize the developed methods and the achieved results (Section 3.3 – Section 3.6). Each of the latter four Sections relates to one scientific publication enclosed in this thesis.

Chapter 4 establishes the cumulative effect of these publications, the significance of the findings and the knowledge claim. It further gives an outlook on possible extensions.

Finally, Chapter 5 contains the published articles, and therein more information about the current state-of-research, design and implementation of the respective approaches.

2. Related work

2.1 Place and place descriptions

The concept of *place* captures how people perceive, memorize, reason and communicate about space. The central role of place for cognitive spatial representations, and their externalization in language or sketches, has been broadly recognized (e.g., Lynch, 1960; Hirtle and Jonides, 1985; Couclelis et al., 1987; Mark et al., 1999). People rarely use geometry or metric expressions, but refer to named and unnamed places and qualitative spatial relations between them (Landau and Jackendoff, 1993; Levinson, 2003; van der Zee and Slack, 2003). Human place descriptions are linguistic expressions and, hence, externalizations of what is in the minds of people. However, human concepts of places are hard to formalize due to their context-dependency and indeterminacy (Burrough and Frank, 1996; Bennett and Agarwal, 2007). Gazetteers or directories of points of interest collect place names and types, and they describe the spatial coverage of these names by a point (Hill, 2006).

Place descriptions are expressions that refer to places either by their names ('Southern Cross Station') or by the names of their category ('the train station'). They may be complex, linking different references by spatial relationships, either explicitly ('the hotel opposite the train station', 'the café near the city hall') or implicitly ('Carlton, Victoria', implying the Carlton in Victoria, in contrast to the other 23 Carltons world-wide, according to the Getty Thesaurus of Geographic Names). The structure of place descriptions has been studied in linguistics (e.g., Schegloff, 1972; Jarvella and Klein, 1982).

Place descriptions reflect the principle of relevance (Sperber and Wilson, 1986). A place description is selected to be as concise as possible, to save time, and as elaborate as necessary, to avoid disambiguities or uncertainties (Dale et al., 2005; Tomko and Winter, 2009). Many place descriptions apply a hierarchical structure by means of granularity (i.e., by part-of relationships) either by zooming in or by zooming out (Shanon, 1979; Plumert et al., 1995). Western postal addresses are an example of zooming out, although they are not particularly common in everyday language. An example in commonly used language would be 'at my desk in my office (in the Empire State Building)'. These hierarchical structures in language reflect hierarchical structures in cognitive spatial representations (Stevens and Coupe, 1978; Hirtle and Jonides, 1985). Another hierarchical structure of place descriptions is by salience, using more salient features as anchor points (Stevens and Coupe, 1978; Couclelis et al., 1987).

Various approaches study the characteristics of different types of place descriptions. There are approaches that capture the spatial meaning of place names (Hightower, 2003), for example, *personal* places, such as *home*, as well as *communal* places, i.e. places of shared meaning across larger communities. Approaches to automatically capture the meaning of place names have a spatial component and a labeling component. The spatial component identifies and locates a place, for example, by analyzing individual or multiple trajectories. Since place is characterized as a *location of rest* (Tuan, 1977), one can suppose to find places by detecting clusters in trajectories, or lack of movement. The located place then requires a label, which can be found, for instance, by interview-based methods (e.g., Ashbrook and Starner, 2003; Zhou et al., 2007). Alternatively, the spatial component identifies the locations of the use of a label, for example, by clustering (e.g., Grothe and Schaab, 2009). User-generated content from photo platforms has also been used to extract location-based emotions (cf. Hauthal and Burghardt, 2013). The authors, in particular, use photo titles or descriptions and tags of Flickr and Panoramio pictures to extract emotional information that, in sum, characterizes the respective places.

Descriptions typically arise within a particular context: they are produced according to the roles and relationships of the speaker and recipient, the assumed knowledge of the recipient, the location of the partners, the communication channel, and the purpose of the communication ('recipient design', Garfinkel, 1967). If the context changes, the description can change as well. For example, previous work has demonstrated different conceptualizations of indoor environments depending on tasks (Richter et al., 2011). Even types and relations can swap between contexts (Freksa and Barkowsky, 1996). Zhou et al. (2005) investigated different place descriptions and identified four factors, namely, *purpose*, *knows me*, *knows area*, and *privacy*, that influence how a person chooses to describe a place to different audiences.

The great variety and complexity of place descriptions makes it necessary to consider different styles, structures and the spatial and/or semantic context in order to understand the various types and characteristics. While some of the above-mentioned approaches focus on the relationship between a place name and the real world location, others consider certain aspects only. Approaches that specifically develop classifications to annotate spatial information in text sources (Cristani and Cohn, 2002; Mani et al., 2010; Bateman et al., 2010) show deficiencies in their classification of granularity or hierarchical structures.

2.2 Hierarchical organization

Various studies have provided evidence that people employ hierarchical structures in place descriptions (e.g., Paraboni and Deemter, 2002; Shanon, 1979, 1984; Plumert et al., 1995, 2001). These hierarchical organization principles are used to decrease the cognitive effort of storing and retrieving information, and to decrease ambiguity in spatial knowledge sharing (Taylor and Tversky, 1992). Hierarchical structures can be explained by the organization of spatial knowledge in the mind (Stevens and Coupe, 1978; Hirtle and Jonides, 1985). Siegel and White (1975) distinguish between 'landmarks' and 'routes' which form an essential part of this knowledge, and further cause distortions, i.e. asymmetric relationships by different salient or prominent features. Phenomena that impact cognitive salience may be visual, social and structural (Sorrows and Hirtle, 1999; Raubal and Winter, 2002; Elias, 2003; Duckham et al., 2010), but also individual or collective experiences. Measures for salience or prominence have been suggested, e.g., by Sorrows and Hirtle (1999) and by Raubal and Winter (2002).

Although place descriptions are broadly observed and accepted as being hierarchical, one can expect a high degree of variability in their construction from spatial knowledge. There is need for research to develop suitable interpretation methods to address this variability and to progress the automatic interpretation of place descriptions. Another deficiency of previous works is the lack of a comprehensive verification by means of experimental data. Moreover, the interplay between different hierarchical organization principles is still poorly understood.

2.3 Hierarchical structures by spatial granularity

Granularity describes varying levels of abstraction of a phenomenon, which form a hierarchy. Either the finer levels of a hierarchy contain representations that are more detailed than the coarser levels, as in cartographic generalizations, or the finer levels will contain smaller objects that are aggregated at coarser levels, as in partonomies (Timpf, 1998). Different understandings and (formal) definitions of granularity exist (e.g., Hobbs, 1985; Keet, 2006; Bittner and Smith, 2003). A hierarchy will necessarily contain at least two different levels of granularity.

Over the years, a number of classification schemes for spatial granularity have been proposed for various purposes. Whether a particular place description has a recognizable hierarchical structure often depends on which classification scheme is applied, and whether this structure is sequential or contains gaps. For example, using a typical address scheme of *street name*, *city* and *country*, the place description 'Grattan St, Australia' is hierarchical, but contains a gap between the *street name* (Grattan St') and the *country* level ('Australia'). Using a scheme inspired by embodied experience, say *personal space* (everything at arm's length) and *environmental space* instead, the same place description becomes flat, i.e. non-hierarchical. Since human place descriptions, for reasons of efficiency, usually follow Grice's maxims of conversation (Grice, 1975) they usually refer to relevant places. Then levels of granularity matter in order to characterize the resolution of a place description, and to identify the places of coarser resolution that disambiguate the ones of finer resolution (e.g., disambiguating Melbourne in Victoria from Melbourne in Florida).

Rosch et al. (1976) introduced the concept of *basic objects*, which relate to the preference of basic level categories in cognitive categorization from sub- or super-categories (e.g., the preference for using the word 'table' instead of 'kitchen table' or 'furniture', when asked 'where is the cup?'). Similarly, basic-level geographic categories exist (Smith and Mark, 2001) (e.g., 'country', or 'city', with their superordinate category 'place', or subordinate categories such as 'home country').

To select references for destination descriptions, Tomko and Winter (2009) developed a model based on three types of hierarchically structured data: a containment hierarchy of districts, the likelihood of using specific streets, and the visual and semantic salience of landmark buildings. Also *SpatialML* (Mani et al., 2010), a markup language for the annotation of natural language references to places, uses spatial granularity in form of tags for different feature types, such as *country*, *state* or *populated place*. Granularity was also applied for the study of place descriptions (Plumert et al., 2001; Richter et al., 2013b; Tenbrink and Winter, 2009).

In order to analyze or find hierarchical structures in place descriptions, a suitable classification for spatial granularity has to be applied. Different approaches have to be evaluated, whether and how they impact this identification, or respectively cause the detection of deviations from such.

2.4 Formalizing and interpreting of spatial information

Place descriptions commonly contain place names and spatial relations, which relate the location of one object to another. The semantics of spatial relations has been broadly studied in linguistics, psychology and cognitive science (Talmy, 1983; Landau and Jackendoff, 1993; Tenbrink, 2005). Qualitative relationships are typically preferred over quantitative relationships (Talmy, 1983; Levinson, 2003; van der Zee and Slack, 2003). They can be distinguished into topological relations (e.g., 'in'), distance relations (e.g., 'near'), and orientation relations (both projective and directional, e.g., 'left of' or 'behind').

Qualitative spatial relations have been formalized in computational models for distances and directions (Frank, 1992; Freksa, 1992; Cohn and Hazarika, 2001) as well as for topology (Egenhofer and Robert, 1991; Cui et al., 1993). These models laid the foundations for qualitative spatial and temporal reasoning (e.g., Bhatt et al., 2011), for geographic information retrieval (Jones et al., 2004), and for approaches to support qualitative spatial queries in spatial information systems (e.g., Yao and Thill, 2006). Furthermore, research concerning the semantics of place (Bennett and Agarwal, 2007) and semantics of linguistic spatial expressions (Bateman et al., 2010) is of relevance here, as semantics determines the applicability of specific relations.

In current information systems, place descriptions (or place names) are usually represented using coordinates or bounding box methods (Hill, 2006). Several studies suggest more elaborate methods addressing the uncertainty and shapes of the described locations, for example, using the point-radius method (Wieczorek et al., 2004), probabilistic methods (e.g., Liu et al., 2009; Guo et al., 2008), or fuzzy-set approaches (Zadeh, 1975).

The point-radius (Wieczorek et al., 2004), for instance, models locations as points and a circle with a radius calculated from measures of the precision and specificity of the locality description. In particular, these measures relate to the extent of the locality, imprecision in distance, direction, coordinate measurements, or the map scale. Probabilistic methods calculate an uncertainty field in order to represent the localities based on a set of assertions including positions, shapes, and uncertainties of its reference objects and their spatial relationships, considering areal, point, and linear features as well as offsets, headings and subdivisions (Liu et al., 2009; Guo et al., 2008). Doherty et al. (2011) implemented the point-radius and shape methods for the georeferencing of over one thousand incidents from search and rescue reports in a National Park. To analyze reports documenting landslide events Vorarlberg in Austria, Schuffert et al. (2010) also applied a fuzzy set approach that handles vagueness and uncertainty resulting from textual spatial references. This approach further used natural language processing techniques to automatically extract place names and spatial relationships of the described location that serve as an input for the model.

More recently, Gong et al. (2012) have presented a probabilistic method to generate locality descriptions. The approach is based on Voronoi neighbor relationships to compute candidate reference objects associated with given target objects. Probability functions are used to model the uncertainty in selecting reference objects. Additional constraints allow to build qualitative locality descriptions of a given target object that are more consistent with human spatial commonsense. Although the approach described uses constraints on the probability function to model human spatial commonsense, it lacks cognition experiments to validate and improve the model.

To progress the formal integration of verbal spatial information in geographic information systems, Lucas (2010, 2012) presented a methodology to translate such verbal description into a geographical representation. The author formalizes criteria to evaluate concrete spatial objects within the descriptions, and to calculate or identify from a set of possible objects the described one. The methodology is based on an empirical survey investigating how people conceptualize spatial relations. It establishes a functional model for processing fuzzy spatial references on the one hand, and accounts for the importance of the objects, the specific size and orientation as well as temporal and observation aspects on the other. The functional modeling of the spatial relations defines their semantics in the urban scale, based on the survey which includes mainly references such as streets, house numbers, and buildings.

As outlined above, various approaches and research on qualitative relations and locations contribute to the representation of places. Despite this progress, interpretations of spatial relations is still disregarded in most geospatial services or keyword-based retrieval methods of search engines. In particular, these services fail to deal with complex place descriptions or to capture and store qualitative information about place and spatial relations (Winter and Truelove, 2013). More research on structures and content of place descriptions and how spatial knowledge relates to the described location is needed in this regard.

2.5 Acquisition of place descriptions

User-contributed content or volunteered geographic information are a valuable source regarding active contributions to maintain projects such as OpenStreetMap. On the other hand they are also a great source to collect place descriptions, or to learn how people conceptualize or perceive space, including the vague or vernacular descriptions people typically use in their spatial communication.

Empirical data to acquire cognitive extents of vague places have been previously explored by interviews. For example, Montello et al. (2003) asked people to draw their perception of 'downtown Santa Barbara' on a map. An interview-based survey was also carried out at the Karlsruhe University Campus to investigate the perception of spatial relations (Lucas, 2010). In the survey students were asked, for example, whether they perceive certain buildings as being *nearby*, *slightly far*, or far away). Schuffert et al. (2010) studied people's spatial judgments in an rural area (the Black Forest) regarding quantitative distances (people were supposed to estimate the distance to a famous hut), or which area they assumed they were located at. Using a GNSS-tracking provided information on the actual locations or respective quality of peoples' estimations.

In contrast, *web-harvesting* techniques are used to acquire place names and their perceived extents from the web (e.g., Jones et al., 2008; Tezuka et al., 2001). Tezuka et al. (2001), for instance, proposed using inference rules in order to define the semantics of spatial relations by analyzing web pages that claim to be *near* a specific landmark to calculate popularity and co-occurrence rate. The approach assumes that similar to place descriptions (or user queries) web resources are created based on cognitive maps in contents creators' minds. A conceptual area asserted by 'near' is then calculated by looking at the importance value of other surrounding geographical objects, i.e. the area gets narrowed if there exists a more famous landmark close to the referred location. 'Path popularity based distortion' relates to a query to find 'hotels between Kyoto and Tokyo', which is more likely to refer to a narrow area along the major road ignoring local roads. Another issue is 'boundary based distortion' caused, for example, by rivers, railways or borders, that may refuse influences to cross. The authors outline the different usage of prepositions depending on its scale and its importance when applying the approach. However, scale is not addressed in the paper.

Furthermore, mobile location-based games that consider the location of the player during the game (e.g., tagging games, scavenger hunts, or role playing games) present an appropriate way for acquiring spatial knowledge in human place descriptions (Winter et al., 2011c). Location-based mobile games offer several advantages for spatial knowledge acquisition compared to other methods that have been proposed in literature (cf. Winter et al., 2011b). Players choose to play a game deliberately for their own pleasure or pastime, accepting certain efforts to advance the game, and due to the game character they are also less concerned about privacy issues than they would be, for example, when sharing their routes tracked by their navigation system. Moreover, location-based mobile games allow to specify the context by the game design. Certain activities can be interpreted or controlled on this basis.

In this thesis a corpus of crowd-sourced place descriptions from a location-based mobile game was studied, which asked players to submit a description of their location. The game gained attraction via the media and encouraged people to participate by the chance to win gift vouchers.

2.6 Summary and research challenges

Several issues need to be addressed in the process of automatically interpreting place descriptions. As outlined before, this thesis focuses on the understanding of human spatial language as one step of this interpretation. This chapter has provided some background on the current state-of-the-art and research challenges in this field.

One issue is how to formalize human concepts of place. State-of-the-art natural language processing tools and techniques (e.g., Manning and Schütze, 1999; Cunningham, 2002; Jurafsky and Martin, 2008) are applicable to recognize, e.g., place names which may be linked to their coordinates by gazetteers (Hill, 2006). Representing places by primitives such as points, however, differs from the ways people perceive space. There is a lack of spatial semantics of place names including the extent and vagueness of the extent.

Ambiguities in natural language, or colloquial place names used in everyday language, as well as how to represent and reason on spatial relations between places, such as containment or nearness, also cause problems in the understanding of place descriptions. For the integration of place and place descriptions within formal computational systems reasoning techniques have to be developed using the structure and content of place descriptions.

In summary, more extensive research is needed to enable automatic interpretation of place descriptions. This calls for both data availability as well as the methods or formal approaches that could be implemented into practice. The next Chapter presents the approaches we have developed to investigate the research questions posed at the beginning of this thesis.

3. Overview of methods and results

3.1 General overview of the approach

As stated in the introduction, our objectives were to understand the different ways people describe their place, and to learn about typical construction patterns they apply as well as the relation to the locations referred to. Figure 1 shows the general workflow and therein the connections between the single parts of this thesis to address these research aims (cf. Section 1.4).

For our investigation we have used a corpus of georeferenced place descriptions from a location-based mobile game. Section 3.2 outlines the setup of the game.

In Section 3.3, we developed a classification scheme for different characteristics of place descriptions and applied it to the corpus. Based on the classified place descriptions, an agglomerative hierarchical clustering was performed to discover frequent patterns.

Spatial granularity as one classification criterion was then applied to study whether place descriptions are hierarchical by granularity, or whether other organizational principles are employed. Since hierarchical structures need at least two spatial references within a description, only such descriptions were analyzed in this work (Section 3.4).

The next approach (Section 3.5) used the classification of granularity levels to identify the finest level of granularity to which a place description can be resolved. In contrast to the previous part that focuses on the sequential order of granularity levels, this part determines the finest level of localization of place descriptions. A classification of spatial relationships among spatial references is incorporated in this reasoning. The aim of this integration is twofold: first, to find the most relevant (or specific) reference when multiple references exist in the finest level, and second, to determine whether a modification of this identified finest level applies. This is the case, for example, when spatial relationships of nearness are involved.

Lastly, we compared alternative approaches of classifying granularity with the previously employed classification and investigated the impact on the detection of hierarchies (Section 3.6).

3.2 Data collection

The location-based mobile game *Tell-Us-Where* (Winter et al., 2011b) was promoted in Melbourne and beyond via social networks, press and the local radio. It ran over a

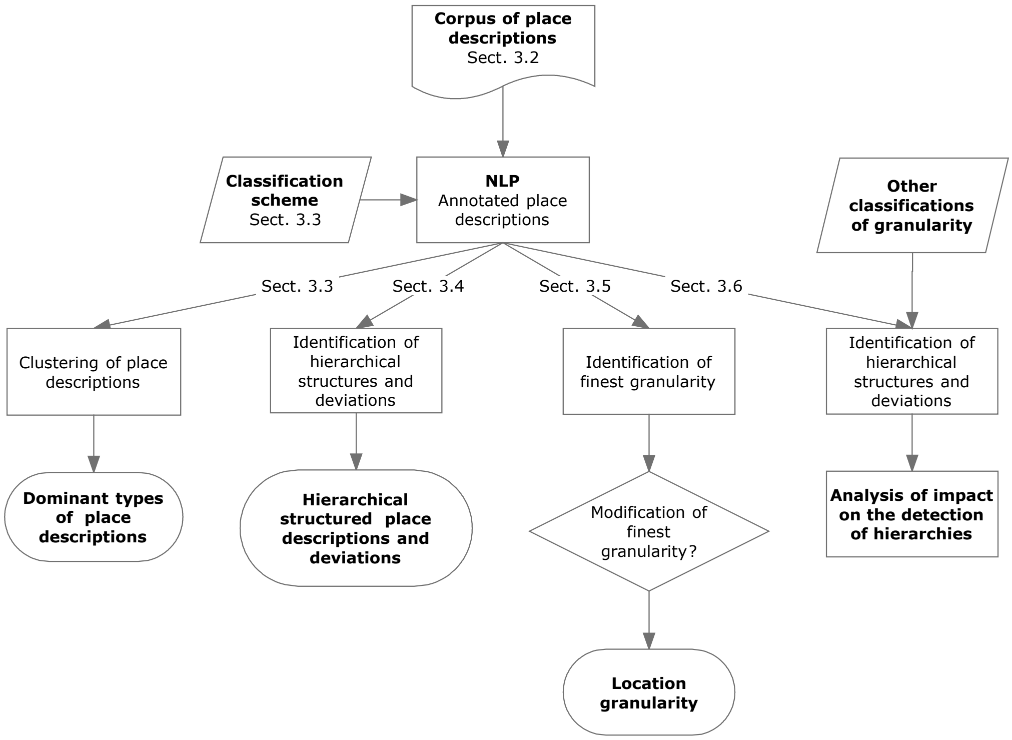

Figure 1: General overview of the approach.

period of six months. In the game, players were simply asked: 'Tell us where you are'. Since the players did not know to whom and for what purpose they were supposed to communicate, they chose a context intuitively, and submitted a large variety of place descriptions. Prior submitting a textual description of their location, players had to confirm their self-localization shown on a map (Figure 2). They were able to adjust this GPS-self-localization[1] and the respective zoom level of the map. Each submitted text message had the chance to win a gift voucher.

The game was implemented as a web-browser based application to run platform-independent on various current smartphone operating systems. All place descriptions were stored server-side with a record number, latitude/longitude and the map zoom level of the verified self-localization, date, and an indication whether the submitted place description actually won a prize. No data was acquired about the participants' age, gender or educational background, or the location and knowledge of the assumed recipients. The game intentionally avoided any filtering mechanisms to keep from restricting the input. Thus also informal or vernacular place descriptions, such as the commonly used 'mcg' (Melbourne Cricket Ground), which would not have been listed in a gazetteer of Victoria, were captured.

In total, 2221 place descriptions distributed all over Victoria and beyond were collected over the runtime of Tell-Us-Where. Figure 3 shows the general distribution of text messages within Australia. Most place descriptions are concentrated in Greater Melbourne—an effect caused by the population distribution, mobile internet coverage, and the social networks through which the game was promoted.

Because no real time filtering mechanisms were used, it is hardly surprising that some wrong records occur. In particular, 13% (310 data records) were sorted out due to empty strings, erroneous coordinates, single characters, or double entries, including also those

[1]We refer to GPS-self-localization in the following; given current technological advances in mobile phone sensors, other global navgation satellite systems (GNSS) such as Glonass could be used here as well.

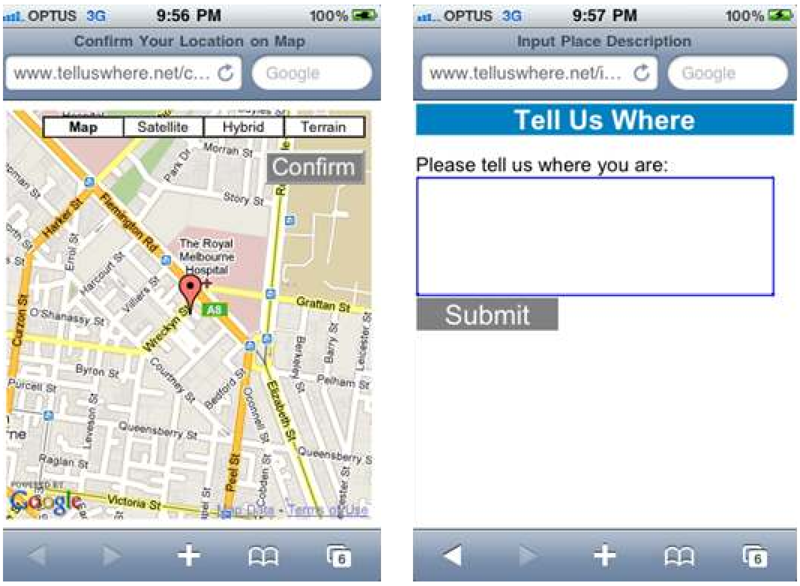

Figure 2: Tell-Us-Where starts with a self-localization of the players (left), and then asks for a verbal description of where the players are (right).

place descriptions, which used place in an abstract or non-literate way, such as 'I am lost'[2]), or 'on the moon'. In the following, we will only use the filtered corpus of 1911 place descriptions or respective subsets.

An important observation is the variety of submitted place descriptions including different types and styles, and the various game roles or purposes imagined by the players. People also did not only use static descriptions. They described their places while they were moving around ('walking to') or gave instructions how to find them ('turn right at the corner'). While common place descriptions answer a *where* question (Shanon, 1983), such descriptions may sometimes also focus on questions *where from* or *where to*, the type of movement (*how*), or certain activities carried out at described places such as 'I am jogging at hillside park', 'swimming in the yarra'). Descriptions range from rather specific ('Four houses past Nhill Hospital heading to Adelaide on Western Highway' to less specific ('on my way home'), including official but also personal place references. We will describe some more characteristics and examples of the collected data in the following sections.

3.3 Identification of predominant types of place descriptions

In our recent investigations (Richter et al., 2012, cf. Section 5.1), we focused on exploring patterns of place descriptions in the Tell-Us-Where corpus, and identifying some predominant types based on this data. At first, existing approaches to classify place descriptions were investigated. Because these displayed certain deficiencies in their classification of the various kinds of place descriptions (cf. Section 2.1), we developed our own classification and applied it for annotating the Tell-Us-Where corpus.

The classification scheme captures the following classes:

1. *Description type* distinguishes between place descriptions that describe a *position*, a *locomotion* (i.e. a movement towards or from a specific place), or a rather complex *route direction*.

2. *Description style* labels spatial and/or semantic information within the descriptions, such as *addresses* or *geofeatures* that incorporate official place names, or references

[2] All quoted examples are given in their original spelling.

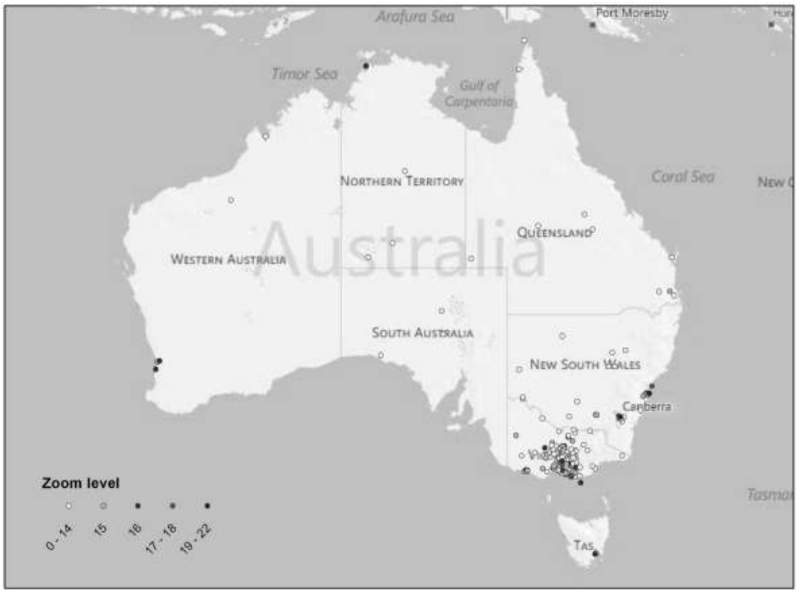

Figure 3: Map overview of Tell-Us-Where data illustrating a set of submitted place descriptions across Australia. The classes of zoom level show the recorded zoom level of the map display prior submission ((c) Esri, DeLorme, NAVTEQ, 2011).

related to *functions* of places ('school'), to *personal* context ('home', 'Jakes house'), or *names* of businesses and trademarks ('Apple store').

3. *Granularity* distinguishes between seven levels, namely, *country*, *city*, *suburb*, *street*, *building*, *room*, and *furniture*. Besides differentiating the levels, also the number of mentioned cues for each level are captured here. These levels reflect the scales of space as they were discussed by Montello (1993).

4. *Indoor/outdoor* labels place descriptions if they contain explicit and unambiguous statements referring to indoor or outdoor locations, e.g., 'in my office' (*indoor*) or 'in the park' (*outdoor*).

5. *Spatial relationship* concerns verbally expressed spatial relations between locations, which can be a) *topological* ('in Perth', 'Outside the restaurant'); b) a *qualitative distance* ('near', 'close to'); c) a *relative direction* ('in front of', 'opposite'); d) a *quantitative distance* ('4 houses past', '3 min far from'); e) an *absolute direction* that refers to cardinal directions ('north of'); or f) directional *towards* other place names ('going to broken hill').

Regarding the classification of spatial relationships, the preposition 'at' was labeled separately because of its ambiguous use in the English language. For example, 'I am at the supermarket' may refer to being inside the supermarket doing some shopping or being close to the supermarket waiting for someone. Only explicitly expressed information was classified, e.g., the description 'Lygon Street, Melbourne' was according to its references 'Lygon Street' and 'Melbourne' labelled with *description type 'position'*, *description style 'address'*, *granularity 'street'* and *'city'*. The classification is explained by examples in more detail in (Richter et al., 2012).

Based on the annotated corpus of place descriptions, a clustering approach was applied to identify groups, which represent dominant ways of describing a place. Among the traditional clustering approaches, *agglomerative clustering* (Kaufman and Rousseeuw, 1990) was chosen, because it works in a bottom-up manner merging iteratively the data items according to a distance measure without the need to pre-specify a number of clusters. In particular, Ward's method (Ward Jr, 1963, implemented in R; `http://www.r-project.org/`) was used in this

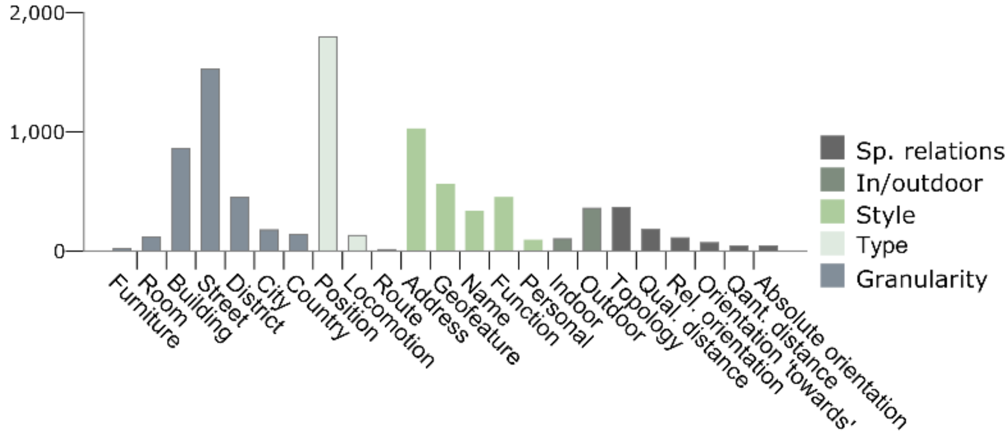

Figure 4: Annotation results based on data in (Richter et al., 2012).

study. From the dendrogram, which denotes the clustering sequence of place descriptions, large jumps in height between two successive combination steps may be identified to find an appropriate cut-off height and respective clusters of place descriptions (e.g., Halkidi et al., 2001). Following Salvador and Chan (2004), in this study a graph was used that plots the number of clusters against the merge distance between the single clusters. Selecting a cut-off height from the 'knee' region of the graph generates a balance between having clusters that are both homogeneous within themselves and dissimilar to each other.

The annotation results of 1911 place descriptions (cf. Figure 4) already show that specific annotated classes are more frequent than others (Richter et al., 2012). First, most place descriptions (93%) contained locational positions, while 7% described a locomotion, and 1% contained a rather complex route description. More than half of the place descriptions contained address information (55%) and 29% geographic features. 5% of the place descriptions contained personal, 23% functional, and 17% categorical information related to names of businesses or trademarks. The various levels of granularity show a high dominance of the street level granularity, which counts 46% of the spatial cues. 18% described topological relationships, 9% qualitative distances, 6% used relative orientation relations, 4% orientation relations towards other locations. Only 2% of the referenced place names use quantitative distances or absolute orientations. The relation 'at' was labeled separately for 11%. Within the classification overlapping categories will occur. Cross-checking 10% of all place descriptions achieved an inter-annotator agreement of 95% and confirmed that the scheme is stable.

Notably 23 individual clusters were obtained by the described clustering method, and a semantic label was assigned to each of them. A further combination of these clusters into larger clusters ends up with particularly five clusters before clusters become semantically meaningless. These five clusters are 1) outliers; 2) location descriptions/place names; 3) locomotion descriptions; 4) complex place descriptions containing spatial relations; and 5) route directions.

In summary, most of the people gave a description of their actual location according to the task of the game. The majority of descriptions were submitted in the 'Greater Melbourne' urban area, which explains the high amount of address information on street or building level. A considerable part of descriptions also contained rather personal information such as described purposes and imagined recipients. These descriptions may address friends or locals using colloquial expression or abbreviated place names. Several place descriptions comprise subjective observations ('its a beauty park'), local knowledge ('Malvern golf course - 18 holes, one of best in melb') or some advice associated with the individual place ('on the side of this road are speed cameras'). Place descriptions that report certain forms of locomotion may be attributed to the data collection method. Being able to participate at the game in various situations (via smartphone) might have encouraged people to participate as a pastime while sitting in a tram or train, for example.

In summary, the devised analysis confirmed that there exist some prevalent types of place descriptions in human communication. A detailed presentation of the annotation categories that cluster together and the typical correlations between parameters were beyond the scope of the paper, but should be investigated in the future. Future work should also address how the actual location of a person determines the way a place is described or whether certain clusters of place descriptions can be related to certain environments. Locomotion descriptions could be exploited to study how people describe places while they are moving or whether the movement speed or activities affect the perception or cognition of place, and therefore the way it is described (cf. Jordan et al., 1998). The classification of granularity provides the starting point to investigate hierarchical structures, and/or spatial cues per level (cf. Section 3.4), as well as an estimate of the described location (cf. Section 3.5). Moreover, the identified characteristic parameters could eventually lead to a representation of place descriptions in a (multi-dimensional) space (cf. Gärdenfors' conceptual spaces model, Gärdenfors, 2000), which was also applied by Raubal (2004) for modeling context in a way-finding service.

3.4 Identification of hierarchies in place descriptions

For the analysis of hierarchical structures, a subset of 722 place descriptions was extracted from Tell-Us-Where, which contained descriptions with at least two spatial cues. While hierarchical structures in place descriptions are evident from various studies (cf. Plumert et al., 1995, 2001; Shanon, 1984; Taylor and Tversky, 1992), the objective was to verify their dominance in a large corpus of human place descriptions, and to study further organization principles apart from the broadly observed ones. The previous section already pointed out the different types of place descriptions, involving egocentric locomotion (*heading to*), or listener-centric route descriptions (*to find me, you ...*). These types may also cause deviations from the expected hierarchies.

Figure 5 shows the general workflow of the methodology comprising three algorithms to extract hierarchical structures, whereby spatial granularity as part of the above-mentioned classification represents a substantial component. The first algorithm identifies hierarchical structures based on the annotated corpus. Based on the order of level of granularity, these structures are differentiated between:

a) *strictly hierarchical*, showing a strictly monotonically increasing or decreasing behavior towards the spatial hierarchy;

b) *partially hierarchical*, showing a monotonically increasing or decreasing behavior, but here also duplicates of the same levels occur;

c) *flat*, showing a constant behavior towards the spatial hierarchy; and

d) *unordered*, non-monotonic place descriptions (cf. Richter et al., 2013b).

Strict and partial hierarchical place descriptions were additionally classified to be either *zooming-in* (a coarser element is followed by a finer element, as for example, 'little lonsdale street near the parliament house') or *zooming-out* (zooming out from the finer element to the coarser element, as in 'Bourke Street, Melbourne').

After this detection of hierarchical structures, a second algorithm investigates the number of flat and unordered descriptions for hierarchical structures ordered by salience or prominence

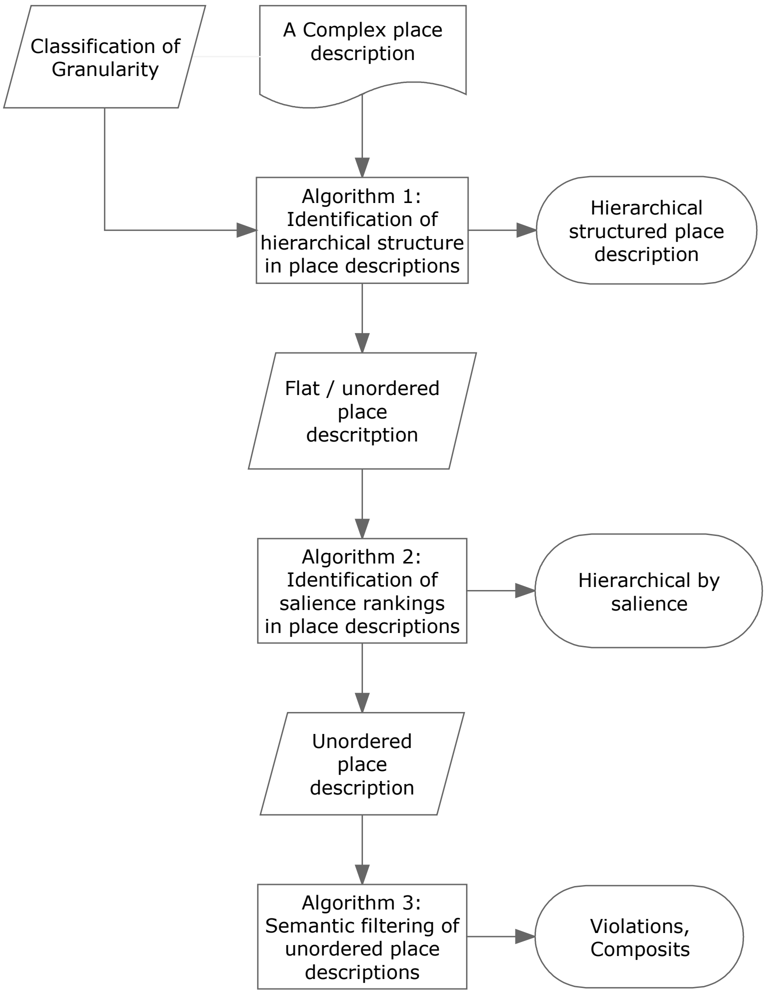

Figure 5: Identification of hierarchies in place descriptions according to the approach described in (Richter et al., 2013b).

rankings. A typical hierarchical structure based on salience shows the description 'tram stop near Myer' where the more salient reference 'Myer' anchors the less salient 'tram stop'. For the detection of hierarchies based on salience different strategies can be used: A more salient reference in a place description may be signalized by a locative preposition, or indicated, for example, by visual cues 'the red building'. This is done based on a semantic, context-aware interpretation.

It will be tested whether a place description classified as unordered is semantically rather a flat or even hierarchical one using a third algorithm. For instance, a place description 'I'm in the cafè across the street from the library' is primarily identified as unordered, switching from a building level to a street level and back to a building level. However, the prepositional phrase 'across the street' belongs in this case to 'from the library', and is therefore not an independent reference to a geographic feature. In such cases, the algorithm will eliminate spatial granularity levels from respective sequences. In the given example, this will result in a flat structure, consequently, re-examined for the presence of salience hierarchies (Algortihm 2).

The results obtained show that the majority (86%) of the analyzed place descriptions of the Tell-Us-Where corpus refer to two or more geographic features on different levels of spatial granularity. More than 70% of them display either a strictly or partially hierarchical structure (cf. Figure 6). These results confirm the assumption from the outset of the study

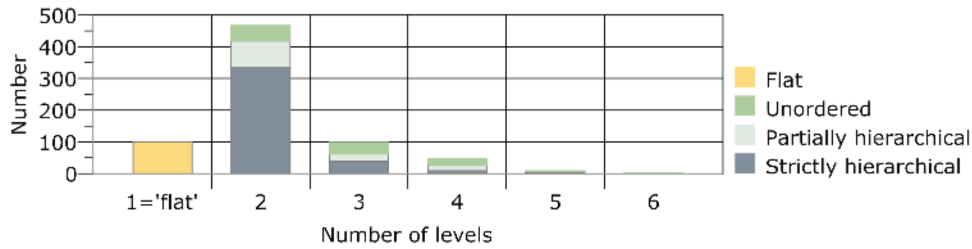

Figure 6: Frequency distribution of the number of different granularity levels within place descriptions, grouped by the different types of hierarchical order based on data shown in (Richter et al., 2013b).

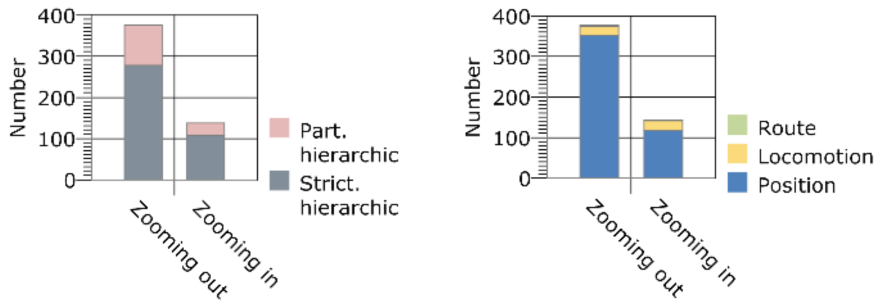

Figure 7: Frequency distribution of hierarchical place descriptions according to the different directions of order based on data shown in (Richter et al., 2013b).

and align well with previously reported findings from literature (Plumert et al., 2001). Moreover, people preferred to order spatial information in a hierarchy of increasing size of spatial references (*zooming-out*) when describing locations (cf. Figure 7).

However, our results also indicate that apart from differences in spatial granularity deviations from the common zooming-in or zooming-out structures occur. In particular, nearly one third (29%) was observed to be flat and unordered structures. They are an evidence that further mechanisms are involved when people describe their place.

A considerable number of the flat or unordered place descriptions were found to be hierarchical based on salience of features or on spatial relationships. In many of them, the use of locative prepositions (e.g., 'in front of', 'behind', 'next to', 'near') defines a semantic or salience hierarchy, and anchors a place relative to other features in an environment. For instance, within a flat description 'In Gopal's restaurant, diagonally opposite of Melbourne City Hall', 'Melbourne City Hall' is the prominent landmark that defines an anchoring region for 'Gopal's restaurant' that defines a more exact location. Some of the prepositions (e.g., 'near') may also be used to refine the location with respect to a larger region, as in 'frawley road near tennis courts'.

The relatively large portion of unordered descriptions (15%) has been investigated more closely with respect to their grammatical, semantic and referential structure as well as whether potential ordering patterns such as salience of locations motivate the apparent switching between granularity levels. Many of those descriptions turned out to have a two-part structure. In particular, three kinds of patterns were observed: 1. General location (overall place, usually building or institution) + more specific location within it; or 2. Location + salient reference point to help further identification; or 3. Apposed location + alternative description of the same location (e.g., street address + name of the building).

An example of the first pattern is represented by 'In the University of Melbourne in the building number 174 near to Grattan street from south'. This description goes from street level (‘University of Melbourne’ as institution) to building level (‘in the building 174’) to street level again (‘near Grattan street from south’). If semantically interpreted, the description can be decomposed into two locational descriptions and classified as hierarchical, going from the first general location (‘In the University of Melbourne’) to the more specific location within it (‘in the building number 174 near to Grattan street from south’). The description ‘483 swanston st. opposite public city bath’ is an example for the second pattern, going from building level to street level to building level again. Semantically, the first spatial reference provides a location (the address ‘483 swanston st.’, classified as building plus street level), followed by a prepositional phrase that uses a more salient feature (‘public city bath’) to support identifying the location. In this case, the description can be considered as flat, comprising two locational descriptions of the same (building) level. An example of the third pattern is ‘570 Bourke Street, DSE building’ that goes from building, to street, to building level. It can be considered as the composition of two alternative descriptions of the same place (address and building name) resulting in a conceptually flat description.

Some limitations might have influenced the obtained results: First, the chosen processing order (Algorithms 1-3) identifies hierarchies based on spatial granularity in the first place. Hierarchies based on salience are solely investigated in descriptions that were not yet classified as hierarchical. This way, the possible interplay between the two hierarchies is disregarded.

Second, deviations appear to be caused by place descriptions during movements. The identified locomotion descriptions and route directions present further deviations from static hierarchical place descriptions. Their detailed analysis is part of future work. Since the producers of locomotion descriptions are moving, an exact localization of their current place is not helpful. Rather, their final destination or the geographical feature they are traveling on is of interest, often expressed at coarser levels of granularity (city level, or highways classified as country level). If such a description also contains the mode of transportation (‘in my car’ classified as room level), descriptions become hierarchical with references to very different granularity levels.

Third, some deviations are artifacts resulting from how the classification scheme defines granularity levels. To this end, the detection of hierarchies will essentially depend on the respective classification of granularity which impacts how well certain structures are picked up. This aspect will be investigated in Section 3.6. Furthermore, the present study only assumes certain relations between real world objects. Since natural objects vary in their extend, a strict classification may not always be appropriate, or the classification of objects in certain levels will impact the correctness of the detected hierarchies with respect to the respective real world situation. For example, an island located on a lake within a city would need to be classified differently than an island that contains other cities. Such knowledge, however, can be retrieved only from context. Integration of spatial data to assure consistency may be one solution to address this issue.

3.5 Determination of granularity of locations referred to by place descriptions

Our work presented in (Richter et al., 2013c, cf. Section 5.3) identifies the level of granularity to which a localization of a described place is possible. This approach proposes that specifically granularity in combination with spatial relations can be utilized for interpreting place descriptions. Still, its purpose is solely the identification of the finest level of granularity; the approach is not concerned with a functional evaluation respectively the real location or its uncertainty and shape.

The approach first identifies references on the finest level of granularity by applying the classification (cf. Richter et al., 2013b). While this scheme was used for the particular study, basically any other classification could be used as well. The procedure consists of the following steps:

- Compiling a set of all locative nouns and compounds in place descriptions.
- Determining the level of granularity for each of these nouns according to a granularity classification.
- Identification of the finest element(s) from the set of classified nouns.

To illustrate the described procedure with an example, consider the description 'I am on Lygon Street, in front of Readings'. First, both of the locative nouns 'Lygon Street' and 'Readings', which is a book store, will be identified and classified on street as well as on building level. Assuming a nested hierarchy of granularity in which a building is on a finer level than a street the procedure would deliver the reference 'Readings' and its granularity level *building*. Having identified flat or partially hierarchical descriptions that contain multiple reference of one single level of granularity, it is necessary to identify those references being most relevant in the context of the described place. For this purpose respective spatial relationships attached to those references will be considered. Moreover, spatial relationships imply whether the finest level of granularity needs to be modified to determine the actual level of granularity to which a place description is localizable. We distinguish five classes of spatial relationships:

1. *Topological* relations, including all nouns or compounds with *no* preposition (for which a default containment relationship is assumed), do not change the level of granularity found in the primary reference. As an example consider 'I am in the house'.
2. *Relative orientation* relations such as *in front of*, *behind*, or *left of*, do not change the level of granularity found in the primary reference. As an example consider 'in front of the house'.
3. *Absolute orientation* relations such as *north of* demarcate vaguely an acceptance region of one level coarser than the primary feature. In this category also place descriptions that contain references to directed movements, such as '[I am walking] to the train station' are considered.
4. *Qualitative distance* relations, especially *near* (other ones are rarely used), do coarsen the granularity found in the primary reference. Consider, for example, 'near the house'.
5. *Quantitative distance* relations, such as '75 meters from Meville Road', 'two minutes past the train station' will be examined individually.

In our approach these classes of spatial relations (or locative prepositions) form an ordered set, namely, 1–*none*, 2–*topology*, 3–*relative orientation*, 4–*qualitative distance*, 5–*absolute orientation* (with $none <_{RO} \ldots <_{RO}$ *absolute orientation*). The class *none* refers to primary features that occur without a locative preposition. This order corresponds to a preference ranking of relations in determining the most relevant reference (or primary feature).

The following steps are applied to identify this reference, and to determine whether a modification of the finest granularity applies:

- Identification of all spatial relations that refer to features on finest granularity level.
- For cases with multiple references on finest granularity, determination of the most relevant spatial reference and relation(s), i.e. the relation(s) that are first in the ordered set of spatial relation classes (as specified above).

- Adjustment of the finest granularity level depending on the used spatial relationships. In more detail, this step will result in a coarsening by one granularity level if relations of qualitative distance or absolute orientation is used in combination with the finest reference feature.

As an example, consider the place description 'near the train station, opposite McDonald's'. Both noun phrases are of finest granularity (building). With respect to the categorization of spatial relations, the relative orientation relation 'near the train station' is higher (later) in the order than the qualitative distance relation 'opposite McDonald's'. Thus, 'opposite' or 'McDonald's' will be selected, and no coarsening of the finest level of granularity on building level will be applied.

Evaluating the results of the procedure relied on manually checking the georeferences that had been collected with the Tell-Us-Where place descriptions. In more detail, the recorded coordinates were visualized in Google Maps and it was checked whether they matched with the respective finest granularity level obtained by the algorithms. Rules to define a match distinguish between different granularity levels on one side, and whether a modification was applied or not on the other (cf. Richter et al., 2013c). Figure 8 illustrates how this evaluation was basically carried out for reference objects on building and room level, whereas the referenced location is marked in red and the respective admissible bound in gray.

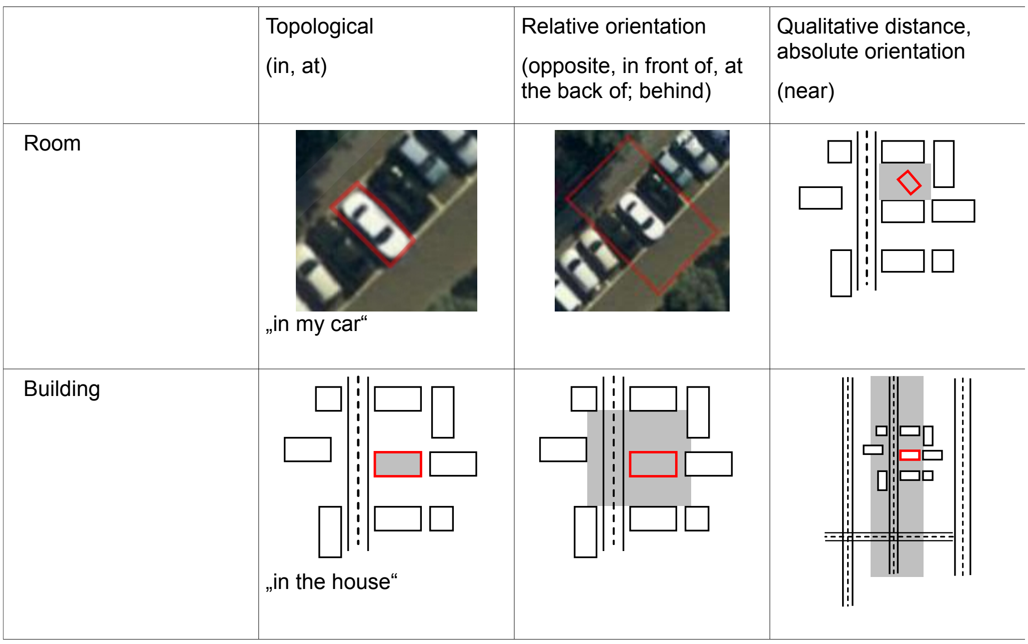

Figure 8: Evaluation of granularity classification and coordinates according to the approach described in (Richter et al., 2013c).

The described procedure is in principle applicable to all kinds of place descriptions. However, in this case, descriptions referring explicitly to indoor-places have been excluded because the self-localization would have been too unreliable here. Overall, the results of the evaluation show that the developed procedure generally delivers good results in good agreement with the corresponding map locations. For 85% of the 287 place descriptions, the user-submitted coordinate position is within the bounds of the admissible geographic region that is determined based on the given place description. In place descriptions with multiple features of finest granularity an equally high percentage of matches (85%) supports the suggested preference order of spatial relationships for selecting the most relevant reference feature and relation. For those cases where no relationship was attached to the identified relevant feature a topological relation of containment was assumed.

Clearly, the results from the discussion above support the developed procedure to determine the granularity of a described location based on the finest granular noun phrases and their spatial relationships. However, there are various limitations, which need to be considered in future work. The main issues will be summarized in the following.

First, in the above discussion, a good evaluation for the modified cases was outlined. However, this is also related to the fact that a coarsening consequently enlarges the admissible region for the coordinate position. Refinements of granularity, which may apply, for example, in descriptions such as 'I am near the pub, near the bank, and near the post office' are not considered by the approach. In this example, the person may be located somewhere in the intersection of the 'nearness' regions of all referenced buildings, which would require georeferenced data to be calculated. A geometric interpretation of spatial relations is one of the long-term goals of this research, which involves being able to handle several context factors that require more and different data than available for this study.

In some cases, references are classified on coarser granularity levels than they would need to be. To this point, for example, highways are in general classified on country level granularity. If a person describes a part of highway that runs through a city, a classification on city level would be more appropriate than on country level because the person can be located in the city. Similar to the previous limitation, this can only be detected by georeferencing features.

Third, some mismatches are caused by ambiguities in the structure of complex place descriptions. Because the proposed mechanistic procedure only accounts for information contained in a given place description, i.e. noun phrases and spatial relations, it ignores any contextual information (such as available from discourse history) or potentially available geographic data which might help to resolve such ambiguities. To illustrate this issue consider the example 'just near the cemetery on lee street' that contains two spatial references on the same level of granularity, 'near the cemetery' and 'on lee street', which are both on street level. If the specified selection order is applied here, no coarsening would occur because 'on' would be selected prior 'near'. On the other hand, it can also be assumed that Lee Street serves to disambiguate the cemetery, thus the person is 'near the cemetery' that is 'on Lee Street'. Incorporating more knowledge into the procedure would help to resolve such cases.

Another limitation is related to the evaluation methodology, which assumes that the participants submitted a correct self-localization as they where asked to confirm their location on a map, and finally, mismatches were also observed in examples that described locations while a person was in motion and thus probably already passed the described places at the time of submission.

Currently, the proposed algorithms treat all relations of a given type equally. For example, the relations *next to*, *close to* and *just off* are all treated as qualitative distance relations and, thus, the same as the relation *near*; they are seen to be synonymous. However, there might be differences in their semantics that may alter the admissible geographic area for these relations and, consequently, potentially change their effect on determining the finest level of granularity. An analysis of these effects is one step in future work. Applicability and meaning of different relations may also change depending on the granularity of the reference objects. For example, we did not observe any relative orientation relations on district, city, or country level. The analysis in this paper excluded quantitative distances and absolute orientation relations (e.g., 'north of'). This is not a principled decision, but was based on the lack of sufficient samples. Further data collection, possibly encouraging such descriptions, may allow for their analysis as well, but it seems like such relations are not a preferred option in producing place descriptions.

Also, in order to validate the categorization of spatial relationships proposed in the approach, well-designed cognitive experiments are needed. These experiments would likely either have a large number of participants describe various spatial scenes, or have them (dis-)agree to such descriptions, in order to collect a statistically relevant sample of how spatial relationships are used. Further, prominence of features may result in increased size of the area defined by the *near* relation, or conversely the area may be narrowed if a more prominent landmark exists close to the referred location (cf. Tezuka et al., 2001). Accounting for such effects—if they exist—requires a measure of a feature's prominence, which is ongoing research in geographic information science.

Extending the algorithms to also account for geographic data in determining the level of finest granularity seems like a logical next step. Among others, this would allow us to also consider those parts of a place description that serve for disambiguating a place. As mentioned above, currently the proposed procedure only takes into account information explicitly contained in the place descriptions. Therefore, it is safe to ignore disambiguating expressions. However, if the procedure is extended to exploit geographic data, these expressions would support a localization of the described place. Such references may further partition the region identified by the algorithms, restricting possible locations. Consider the example 'in front of melbourne central station at swanston street'. Here, 'at swanston street' is a disambiguating expression that would restrict the location of the participant (to being on the side of Melbourne Central Station where Swanston Street is), thus, partitioning the area defined by the 'in front of' relation. The 'front' of Melbourne Central Station is not unambiguous as the station is within a large shopping center that has at least four entrances on four different streets, and the main entrance (most likely defining the front) may be assumed to be on either Swanston Street or Elisabeth Street on the opposite side of the station.

Although the application of the proposed algorithms has been carried out manually, their implementation can be realized by natural language processing frameworks and gazetteers to extract references to locations. A natural language processing component would have to identify locative nouns and compounds as well as respective locative prepositions indicating a spatial relation. Then, an automated evaluation of the algorithms using the applied rules is basically possible given georeferenced (vector) data, their appropriate allocation to different levels of granularity, and basic functionalities such as point-in-polygon tests or buffers.

Finally, the classification scheme may be revisited to include further levels of granularity, which may result in a better approximation of the respective location. For example, Google's Geocoding API distinguishes accuracy of geocoded addresses in levels of *country*, *region* (state, province, prefecture, etc.), *sub-region* (county, municipality, etc.), *town* (city, village), *post code* (zip code), *street*, *intersection*, *address*, and *premises* (building name, property name, shopping center, etc.). This is similar to the classification used in this paper, but introduces some intermediate levels not used so far. The effects of these additional levels may be tested in a follow-up study using the same evaluation method (cf. also Richter et al., 2013a).

3.6 Classification of spatial granularity for the detection of hierarchies in place descriptions

The findings from the previously described approaches indicate that the obtained results highly depend on the applied classification of spatial granularity (Richter et al., 2013b,c, 2012; Vasardani et al., 2012). The presented methodology in this final section investigates the impact of different classification approaches on the detection of hierarchies (Richter et al., 2013a, cf. Section 5.4).

At first, existing classifications of spatial granularity (e.g., Kuipers, 1978; Lynch, 1960; Zubin, 1989; Montello, 1993; Couclelis and Gale, 1986; Kolars et al., 1975) were investigated and evaluated for their suitability to capture spatial granularity. This comparison builds on a study of Freundschuh and Egenhofer (1997) that reviewed a number of classifications of spatial granularity with a focus on scales of *human conceptions of space*. While different classifications cover varying numbers of distinguishing levels, with regard to (Rosch et al., 1976) the focus was on models of at least four different levels of granularity. The investigation revealed that a number of approaches are not well-suited for classifying hierarchical structures in human place descriptions, or appeared to be ambiguous and unstable in their classification of objects (e.g., Couclelis and Gale, 1986; Zubin, 1989).

Four classification approaches have been chosen for this study: A classification by Kolars et al. (1975), by Montello (1993), by Richter et al. (2013b), and the geocoding scheme of the Google Geocoding API Version 2.0, which also provides a geocoding accuracy value (cf. Figure 9). In the following these classifications will be referred to as *Montello*, *Kolars*, *Richter*, and *Google*, respectively. For details on the different classification see (Richter et al., 2013a).

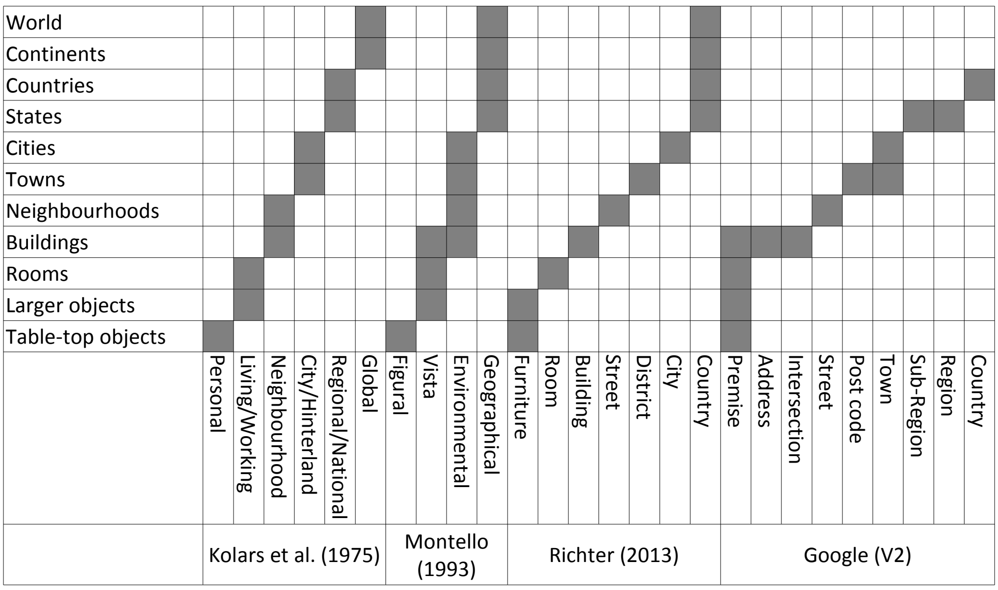

Figure 9: Models of spatial granularity (Richter et al., 2013a)

To test the different models, the subset from the Tell-Us-Where corpus, which consists of place descriptions of at least two spatial cues, was used again. Each classification was applied to each place description and the different hierarchical structures were determined as described in Section 3.4 (cf. Richter et al., 2013b). In addition, this approach identifies *gaps* of levels within these structures. For example, 'I am at Union House, located in the University of Melbourne in Parkville, Melbourne' would result in a flat structure when applying Montello's classification, because all four references would be classified on an *environmental space* granularity level. Using Kolar's classification, the same description would be partially hierarchical (without gaps), classifying the Union House and the University of Melbourne as *houses and neighborhood space*, and Parkville and Melbourne as *city-hinterland space* granularity. The classification of Richter would identify a strictly hierarchical structure with a sequential order of the four levels *building* (Union House), *street* (the University of Melbourne), *district* (Parkville), and *city* (Melbourne). Likewise, Google's scheme results in three levels of granularity: *premise* (Union House), *street* (the University of Melbourne), and *town* (Parkville and Melbourne). With more than one cue on the same level of granularity, the latter structure is partially hierarchical.

In the classification, all spatial relationships were ignored. A single exception to this has been made in classifying references at building level for Montello's vista and environmental space. References at building level are classified as *environmental space* if the person is inside, taken either from prepositions such as *in*, *inside*, *at* (cf. Vasardani et al., 2012), or from the lack of prepositions (e.g., addresses). It is also classified *environmental space* if the person is outside, but uses a preposition synonymous to *near*. In all other cases, for example, in presence of prepositions such as *in front of* or *opposite*, a reference at building level will be classified as *vista space*.

Generally, references to multitudes of objects (e.g., apartments) are classified at their next coarser granularity level. For instance, in some classification scheme 'apartment' may be classified as room level, but 'apartments' as building level. The finest and the coarsest granularity level in each classification schema are collectives of everything at and below, or everything at and beyond this level of granularity. For example, Google's classification scheme does not provide a granularity level below *premises*, so in this scheme everything smaller than a premise (e.g., an apartment) will be classified on this level.

The devised approach forms a basis to study different classification schemes and their potential to pick up hierarchical structures in place descriptions as well as deviations from regular, sequential hierarchical structures. Testing the different approaches with the Tell-Us-Where subset showed that Montello's or Kolars' classifications, which distinguish fewer classes, tend to produce more *flat* structures than those by Richter or Google. However, the latter two result in many more gaps that appear in the hierarchical structures (cf. classification results in Figure 10 and resulting hierarchical structures in Figure 11).

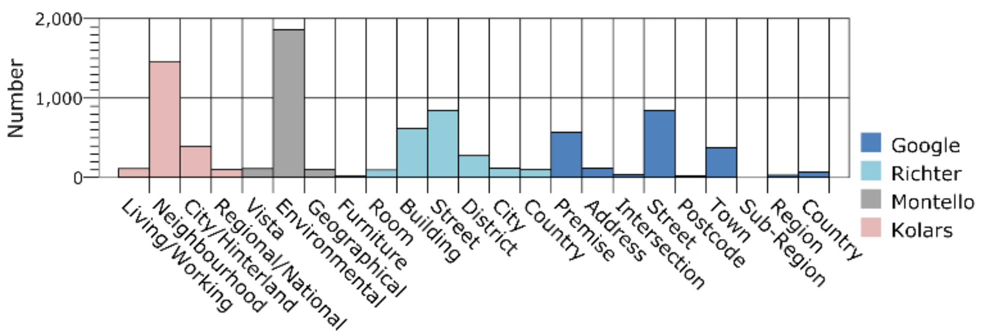

Figure 10: Frequency distribution of single space categories of the four classifications *Montello*, *Kolars*, *Richter*, and *Google* based on data presented and compared in (Richter et al., 2013a).

In some more detail, the results show an interplay between the number of categories used in a classification scheme, the distinctions they can pick up, and the deviations that appear. Some of the gaps in one scheme disappear by applying another. For example, applying Richter's classification scheme to 'Under the tree at marinda park' would skip *room* and *building* levels (trees are classified on *furniture* level, while parks are on *street* level), whereas applying Montello's classification scheme would result in only two granularity levels without a gap (classifying a tree on *vista space* and a park on *environmental space*). Some descriptions that are considered flat in other classification schemes, are classified as hierarchical in Montello's classification due to the special consideration of buildings

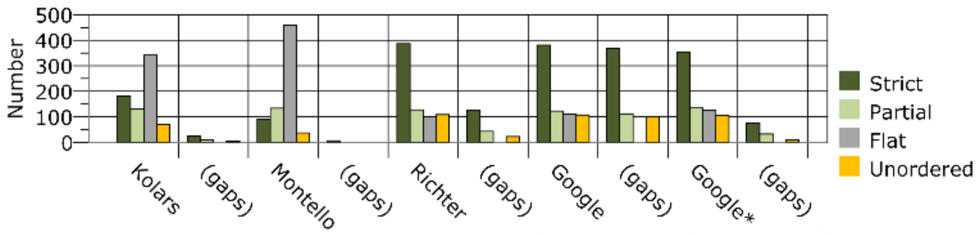

Figure 11: Comparison of hierarchical structures in different models based on data presented in (Richter et al., 2013a). (* merges the classes premise, intersection, address to one class, and post code and town to another, and further excludes the class sub-region for counties and municipalities.)

regarding their categorization into *vista* or *environmental space* granularity. For example, 'tram stop near myer', 'i'm in front of ella bache near the foodcourt', or 'In Gopal's restaurant, diagonally opposite of Melbourne City Hall' would contain both references on *vista* ('tram stop', 'in front of ella bache', 'opposite or Melbourne City Hall') and also *environmental space* ('myer', 'near the footcourt', 'in Gopal's restaurant'), whereas Richter's scheme would consider all these references to be on *building* level.

In general, the application of classification schemes to place descriptions (or any spatial description) requires to assign geographic entities to specific granularity levels. This may introduce some biases and may lead to results that are not always correct. For example, 'Melbourne' may be categorized to be on *city* level, however, the term 'Melbourne' is ambiguous, as it may refer to the suburb Melbourne, the 'City of Melbourne', which is the local government area incorporating the city center and a number of inner-city suburbs, or the region 'Greater Melbourne', which comprises of all suburbs that form the metropolitan area 'Melbourne'.

Other terms, such as 'home', are underspecified regarding the geographic area they refer to. It was classified on *building* level in Richter's classification scheme, but it could also refer to a city or country, depending on the context. And there are types of geographic entities, which may be of significantly different scales, such as islands, rivers or highways. These would require a more flexible, case-based categorization. The same holds for businesses, such as cafes or restaurants, which sometimes may be part of a larger building (being on granularity level *room*), and sometimes occupying a whole building. Implementing such flexible categorization would avoid some of the gaps that emerged in the presented experiments.

Still, in the end there are deviations that cannot be explained just by the particularities of the respective classification schemes. There are place descriptions that exhibit a flat structure regardless of the chosen classification scheme. These include locomotion descriptions (e.g., 'walking down greeves street to spring street'), and descriptions that just mention multiple references on the same granularity level (referring to several geographic entities of the same type), such as 'between melville rd and reynolds pde'. Furthermore, a few place descriptions contain gaps regardless of the classification approach. Descriptions such as 'a loud street intersection, just before crossing the yarra', 'traveling down the napean highway in the car', 'yarra river sitting on the docks', 'whale rock, tidal river' all contain a gap in Montello's *environmental space*, and thus, as well when applying the other schemes.

4. Discussion and future research

In the following, the achieved results will be evaluated regarding the research objectives outlined in the introduction of this thesis, and considering the scientific relevance of the work as well as the potential operationalization of the developed methods. Moreover, conclusions for future research will be drawn.

The mobile game Tell-Us-Where allowed to collect a large corpus of georeferenced natural-language place descriptions through user-generated content, encouraging informal natural place descriptions. The great potential of such crowdsourced data could be demonstrated by the various tasks of this thesis.

The contributions of the work studying *dominant types* of place descriptions lie in the exploratory data analysis, the study of existing methods for the classification of place descriptions, and the development of a new classification method, and here especially in the integration of spatial granularity. In a systematic study of the corpus using the developed classification scheme and an agglomerative clustering approach, dominant types of place description have been identified. The results show that the major groups among them are location descriptions using place names, locomotion descriptions, and route directions (plus a group of outliers). The applied methodology provided further evidence into characteristic construction principles of place descriptions. These results contribute to the understanding how people describe places to support advances in the development of intelligent tools and location-based technologies. The implication of this work is underlined by the peer-reviewed publication which was presented at the *First ACM SIGSPATIAL International Workshop on Crowdsourced and Volunteered Geographic Information* 2012 (Richter et al., 2012).

The approach to analyze certain building principles in place descriptions, namely, *hierarchical structures*, confirmed that most of the place descriptions have a spatially hierarchical structure of either *zooming-in* to or *zooming-out* from the place of 'where people are.' Moreover, the approach identified and explained deviations from such hierarchies. In particular, results also illustrate that people employ hierarchies of salience besides hierarchies of spatial granularity. The approach comprises a sequence of three (high-level) algorithms for the interpretation of place descriptions. Implementing these algorithms would allow for automatically interpreting most of the collected place descriptions. However, several descriptions have been found to be context-dependent and requiring careful semantic analysis, which has implications for the inclusion of place descriptions in location-based services. Results have to be interpreted with care because the proposed algorithms are based on place descriptions given in English only. A general application of the algorithms will need further investigations of certain similarities in structures of place descriptions with respect to other languages and cultures. This work was published and presented at the *9th Symposium on Location Based Services (LBS 2012) (Richter et al., 2013b).*

The approach to define the *granularity of location* referred to by place descriptions also utilizes the proposed classification of spatial granularity. The scientific progress of the work presented here lies in the use of granularity for classifying and identifying the finest element, and further, in the integration of spatial relations to decide whether this finest element should be modified in its level. The described algorithms are capable of handling complex place descriptions containing several references and spatial relations. Results from validating the approach show that the procedure generally delivers reliable results that match with the described locations in most of the cases. Further improvements could be achieved by integrating georeferenced data and contextual knowledge. This would allow to eliminate mismatches caused by ambiguity in the structure of complex place descriptions, or artifacts by the classification of spatial granularity. A further extension is the refinement of granularity levels in combined place descriptions with multiple references. The approach has been published in a full-paper refereed journal article (Richter et al., 2013c) that highlights the significance of the work.

Finally, several *classification schemes for spatial granularity* in place descriptions were investigated, and applied to the Tell-Us-Where place descriptions in order to investigate their impact on the detection of hierarchical structures. The results show that the detection of hierarchies and their deviations strongly depends on the applied classification, so that, for example, hierarchical structures with some classifications can be identified better than using others. Also, most of the deviations from hierarchical structures can be related to the respective classification. However, a remaining amount of 10% can not be explained by the applied schemes, such as flat structures where people seem to employ hierarchies of salience, or locomotion descriptions. We claimed that too few categories in a scheme prevent from making relevant distinctions, and too many categories could deteriorate cognitive representation and reasoning. Applied to place descriptions, a balance between enough granularity levels to pick up these structures, and few enough levels to avoid artificial gaps is desirable. In this respect, the developed classification scheme (cf. Richter et al., 2013b, 2012), but also the geocoding accuracy classification by Google showed better results regarding, in particular, place descriptions at human scale. This paper has been presented at the *16th AGILE Conference on Geographic Information Science* in May 2013 and was published in another *Springer* book (Richter et al., 2013a).

Continuing work on the interpretation of spatial relations was carried out by Vasardani et al. (2012). In detail, the authors utilized place descriptions from Tell-Us-Where as well as the granularity classification (Richter et al., 2013b) to develop a model for the interpretation of the preposition *'at'*. The preposition 'at' in place descriptions results in highly underspecified locations, because 'at' may be used in the sense of different spatial prepositions similar to 'in', 'on', or 'by'. The suggested approach enables the interpretation of 'at' according to the granularity level and classification type of the spatial feature it refers to. This means knowing the granularity and the type of the spatial feature 'at' refers to (e.g., building, bounded outdoor area, or surface), a more location-specific preposition is recommended as a substitute for 'at'. Findings from this work support the integration of verbal spatial queries in search engines. Moreover, they provide knowledge for the approach (Richter et al., 2013c), which so far excluded the preposition 'at'.

The results of this thesis have raised some important questions requiring further investigations: It would be interesting to investigate whether the actual position influences the place description, or how the structure of the environment influences the content and organization of place descriptions (Plumert et al., 1995). For such an analysis, further parameters need to be controlled in future data acquisition in order to capture people's spatial context and circumstances, or the communication task.

Variations among languages concerning how locations are typically referred to in linguistic descriptions (cf. Burenhult and Levinson, 2008; Levinson, 2003) may affect the devised methodologies. Tell-Us-Where collected place descriptions within Victoria, Australia only. To make the algorithms applicable for place descriptions in different languages, additional testing is required regarding the variable semantics of terms as well as how different spatial relations are conceptualized in other languages (cf. Burenhult and Levinson, 2008; Levinson, 2003).

Research on how people acquire spatial knowledge suggests that maps and direct environmental learning produce qualitatively different spatial representations (e.g., Thorndyke and Hayes-Roth, 1982), which may also be reflected in spatial judgments of place descriptions. Future studies are needed to test whether and how the displayed map in the game impacts the construction of place descriptions.

An integration of geospatial data could improve the classification and devised algorithms. Georeferencing would also be required to establish a location of the described places. The localization or geographic information retrieval based on place descriptions is an important field of current research with many open research challenges, for example, regarding uncertainties of the position and the vagueness of the extent (Vasardani et al., 2013).

In this thesis, we have presented algorithms that were developed for human place descriptions, in particular, descriptions of people's locations. Similar structures can also be observed in other kinds of linguistic spatial descriptions, which occur, for example, in internet blogs or news articles. Evaluating the applicability of the proposed approaches in such contexts seems therefore worthwhile. For this purpose, we could consider place descriptions in emergency calls such as '[...] there is black smoke coming out of an apartment building at Elberstraße, at the tram station Elberstraße next to the hotel.'[1] (cf. Lucas, 2012) or local information in social networks and Twitter blogs. The messages 'sandy floods 63rd street', 'Flooding on Pitney Rd is just from a storm drain', for instance, illustrate examples provided by eyewitnesses in flooding emergencies (Dittrich, 2013; Kunz et al., 2013). Alternatively, a corpus of historical verbal descriptions of landslide events in Vorarlberg, Austria, which has been previously investigated in the context of early warning systems, would provide a starting point for such an investigation (Breunig et al., 2008; Schuffert et al., 2010).

The developed algorithms were applied manually in this thesis. An automation of the developed approaches may be achieved by means of natural language processing (e.g., using an open-source framework such as GATE (Cunningham, 2002)) together with gazetteers for place name detection. An implementation of salience rankings and semantic filtering of unordered place descriptions in (Richter et al., 2013b) would require to set up further parsing rules in order to interpret complex descriptions and to integrate measures for salience based on context knowledge.

As mentioned earlier, this research was carried out in the context of the project *'Talking about place'*, aiming at the development of novel methods to facilitate the automatic interpretation of place descriptions. Despite some limitations and open issues for further research, the results from this research contribute to the understanding of place descriptions, and the developed approaches present some valuable steps to support their automatic interpretation. The work focused on basic research questions. An integration into practice

[1] Original text example in (Lucas, 2012): '[...] in der Elberstraße raucht es ganz schwarz aus einem Mehrfamilienhaus, und zwar Haltestelle Elberstraße direkt neben dem Hotel.'

requires more work in this area, and future developments will show to what extent this is possible.

5. Publications

The methods and results summarized in Chapter 3 have been accepted for publication in four articles. These concern the research topics described in Section 3.3 – Section 3.6 and represent the essential part of this thesis. Each of them has been *peer-reviewed* by at least three different reviewers from an international scientific committee (full paper, mainly double-blind review).

- Three of the articles have been presented in the context of international conferences: The *First ACM SIGSPATIAL International Workshop on Crowdsourced and Volunteered Geographic Information 2012*, the *9th Symposium on Location Based Services (LBS 2012)*, and the *16th AGILE Conference on Geographic Information Science*. They were further published in the printed proceedings of these conferences, *ACM Press* (Richter et al., 2012) and *Springer Series Lecture Notes in Geoinformation and Cartography* (Richter et al., 2013b,a). The acceptance rate of these conferences is about 30%.
- One article has been published in the journal *Computers, Environment and Urban Systems* (Richter et al., 2013c). According to the Thomson Reuters' Journal Citation Reports 2013 the journal's impact factor in 2012 was 1.674.

The following paragraph states the original contribution of the author of this thesis to each publication and by every co-author to each paper/manuscript that is included in the thesis. Section 5.1 – Section 5.4 contain the four articles in the order they were listed above.

Contributions of Author and Co-authors

The author of this thesis acts as the first author of the four publications, and did the major part of the research and writing. The research shown in this thesis is embedded in the group of the project *'Talking about place'*. Within this team, the author was responsible for designing the scientific concepts, analyses and realization of the described approaches and experiments.

Prof. Winter and Dr. Kai-Florian Richter were involved in all stages of the different research lines leading to the final papers of this thesis (Richter et al., 2012, 2013b,a,c). They contributed to the design of research proposals, experiments and validation methodologies, and to the writing and revision of the papers.

Prof. Stirling was involved in the discussion and revision of three papers (Richter et al., 2012, 2013b,c). Dr. Maria Vasardani significantly contributed the paper (Richter et al., 2013b).

The data was collected by means of the game Tell-Us-Where implemented by Hairuo Xie. Another student was involved in the cross-checking of annotations of the place descriptions to evaluate the robustness of the applied classification scheme (Richter et al., 2012). Visual Priming on the place descriptions was analyzed in a master thesis by Robert Pearson (Pearson, 2012).

Apart from the mentioned publications, the author of this thesis has contributed to (Winter et al., 2011a) on preliminary results at an earlier stage of this study. The developed classification of spatial granularity (Richter et al., 2013b) was furthermore used to study the preposition ‘at’ in (Vasardani et al., 2012) and was also applied to study the identifiability of spatial references with respect to different levels of granularity (Tytyk and Baldwin, 2012).

5.1 Paper “How People Describe their Place”

Richter, D., Winter, S., Richter, K.-F., and Stirling, L. (2012). How people describe their place: identifying predominant types of place descriptions. In *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Crowdsourced and Volunteered Geographic Information*, GEOCROWD '12, pages 30–37, New York, NY, USA. ACM

How People Describe their Place: Identifying Predominant Types of Place Descriptions

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ABSTRACT

People communicate about locations using place descriptions. Despite the growth of mobile location- and context-aware applications, the automatic interpretation of place descriptions remains a challenge. Currently no software tools exist that are capable of understanding complex verbal spatial language. This paper explores a corpus of place descriptions collected through crowdsourcing mechanisms within a mobile game. It introduces a general classification scheme to annotate place descriptions according to different characteristic parameters and uses this scheme to demonstrate the existence of certain clusters of prevalent types of place descriptions in human communication. Research outcomes contribute to the common understanding of the way people refer to places, which is essential to support the development of intelligent tools and location based technologies.

Categories and Subject Descriptors

I.5.3 [**Computer-Communication Networks**]: Clustering; H.1.2 [**Information Systems**]: User/Machine Systems—*Human Information Processing*

General Terms

Human Factors, Experimentation

Keywords

Place descriptions, volunteered geographic information, data collection, data extraction, tagging schemes

1. INTRODUCTION

People communicate about locations using descriptions of places and their relationship to each other. The automated interpretation of such place descriptions remains a challenge. Currently no software tools exist that are capable of understanding complex verbal spatial language or answering *where* questions.

People in different situations or contexts form different descriptions of their location. In their speech construction they focalize for a particular communication purpose [31]. Focalization shows in people's choices of particular references, different levels of granularity, and different construction principles. The task of identifying a location by a place description inherits the need to interpret this flexibility.

The flexibility of place descriptions can be made evident from examples (e.g., 'I am in my office' vs. 'Engineering Block D, Room 412A'). And research supports these claims of flexibility (e.g., [37]). People aim to meet the local needs of the communication in an efficient way by providing a description which is both relevant to its purposes and just informative enough [11].

This paper is interested in whether we can identify, in the space of possible place descriptions, specific construction patterns that are more frequent, and whether we can describe them with some characteristic parameters. Thus, the objective of this paper is to understand the types of place descriptions humans use. The paper aims to answer the following research question: *Are there certain structures of place descriptions that can be identified based on some characteristic place parameters?* In particular, we expect to discover a larger variety in the types of place descriptions than only the previously studied hierarchical ones [23, 24].

To study this research question, we focus on a corpus of georeferenced place descriptions, which was collected through a location-based mobile game. Players were asked: 'Tell us where you are'. Since the players did not know to whom and for what purpose they were supposed to communicate they chose a context intuitively, and submitted a large variety of kinds of place descriptions.

For the collected place descriptions a classification scheme was developed. The scheme is based on different characteristics, differentiating, for example, whether the place description is hierarchical, categorical, or linear. The scheme was tested for inter-annotator reliability, and proved to be stable. Based on this scheme this paper will apply an agglomerative hierarchic clustering on the classified place descriptions, and explore common patterns and their frequency distribution. Some predominant types of place descriptions will be identified on this basis.

Findings from the presented study contribute to a better understanding of how people describe places. Such knowledge is relevant for artificial intelligence since place descriptions are omnipresent, from search queries to short messages in social media. Thus this knowledge can facilitate more meaningful interpretations for machines, and further enhance representation and reasoning methods for location- and context-aware applications.

2. PLACE AND PLACE DESCRIPTIONS

The concept of *place* is the way people perceive, memorize, reason and communicate about space. The central role of place for cognitive spatial representations, and their externalization in language or sketches, has been broadly recognized (e.g., [20, 15, 5]). People rarely use geometry (or metric expressions), but refer to named and unnamed places and qualitative spatial relations between them [18, 19]. Human place descriptions are linguistic expressions, and hence externalisations of what is in the minds of people.

2.1 Spatial Semantics of Place

Human concepts of places are hard to formalize due to their context-dependency and their indeterminacy [4, 3]. Gazetteers or directories of points of interest collect placenames and types, and they describe the spatial coverage of these names by a point [14].

Approaches to automatically capturing the meaning of placenames have a spatial component and a labelling component. The spatial component identifies and locates a place, for example by analysing individual or multiple trajectories. Since place is characterized as a *location of rest* [33], one can suppose to find places by detecting clusters in trajectories, or lack of movement. The located place then requires a label, which can be found, for example, by interview-based methods (e.g., [1, 37]). Alternatively, the spatial component identifies the locations of the use of a label, for example by clustering (e.g., [12]).

In this paper, we are interested in the structure of place descriptions, instead of the relation between a placename and the location of the place referred to in the real world. The place descriptions studied here have a structure that potentially consists of more than one label, which are linked by explicit or implicit spatial relationships.

2.2 Complex Descriptions

Place descriptions are expressions referring to places either by names of places ('Southern Cross Station') or by the names of their category ('the train station'). They may be complex, linking different references by spatial relationships, either explicitly ('the hotel opposite the train station', 'the café near the city hall') or implicitly ('Carlton, Victoria' implying the Carlton in Victoria, in contrast to the other 23 Carltons world-wide according to the Getty Thesaurus of Geographic Names).

Place descriptions reflect the principle of relevance [30]. A place description is selective to be as efficient as possible, and as elaborate as necessary to avoid disambiguities or uncertainties [7, 32].

Many place descriptions apply a hierarchical structure through granularity—i.e., by part_of relationships—either by zooming in or by zooming out [29, 24]. Western postal addresses are an example of zooming out, although they are not particularly common in every-day language. An example in commonly used language would be 'at my desk in my office'. These hierarchical structures in language reflect hierarchical structures in cognitive spatial representations [15].

Another hierarchical structure of place descriptions is by salience, using more salient features as anchor points [5].

2.3 Focalization

Descriptions focalize on a particular context: they are produced according to the roles and relationships of the speaker and recipient, the assumed knowledge of the recipient, the location of the partners, the communication channel and the purpose of the communication ('recipient design', [10]). If the context changes the description can change as well. For example, previous work has demonstrated different conceptualizations of indoor environments depending on tasks [27]. Even types and relations can swap between contexts [8].

Regarding place descriptions in different contexts, Zhou et al. [38] investigated different place descriptions and identified factors, namely *purpose*, *knows me*, *knows area*, and *privacy*, that influence what description a person chooses regarding different audiences of social applications.

2.4 Representing Characteristic Parameters of Place Descriptions

Place descriptions reflect people's conceptualization of their environment in general, and the described place in particular. Such cognitive aspects are hard to specify exhaustively, but it is often possible to identify characteristic differences between two (or more) conceptualizations, based on differences in their externalization, which may be described by specific parameters. If these characteristic parameters are independent of each other, they may be described as a (multi-dimensional) space, borrowing ideas and concepts from *conceptual spaces* [9].

Gärdenfors' conceptual spaces model [9] is a framework for representing information on the conceptual level based on human cognitive abilities. A conceptual space S consists of classes $D_1, \dots D_n$ of quality dimensions. A point in S is represented by a vector $v = < d_1, \dots, d_n >$ with one index for each dimension. Concepts are represented as regions in such a space, allowing for similarity measurements based on semantic distance. Raubal [25], for example, presented a case study applying conceptual spaces to a wayfinding service. Different contexts were modeled by assigning different weights to the identified quality dimensions.

3. PREDOMINANT TYPES OF PLACE DESCRIPTIONS

The previous section established that *place* is a ubiquitous, prevailing concept in human understanding of and communication about space. In this paper, we focus on the communication of place descriptions. In general, context determines which geographic features are conceptualized as being a (relevant) place, and how they are referred to. Multiple factors contribute to the context: spatial factors include the location of the speaker and the location of the addressee; discourse-pragmatic factors include the task (or *purpose*) and the assumed knowledge of the addressee (*knows me, knows area*). In the specific setup used for this research, however, the communication context is severely underspecified, which, in principle, forces participants to establish their own context. Still, our hypothesis is that:

> Despite the underspecified communication context, there is a small number of predominant ways of describing place.

The research further aims to provide some answers to the following questions:

- What level of detail do people choose in their place descriptions?
- Are there common patterns in structure and content between place descriptions?

The required data can be collected employing methods of user-generated content [17]. Using such methods has the potential for large-scale automated acquisition of spatial knowledge. One realization of these methods is by mobile location-based gaming. Such games offer an engaging, playful setting that users get into voluntarily for their leisure, which has the potential to attract a large number of players [36]. Thus, games typically provide a context for the interaction of the players, and players immerse themselves in this context. However, games can also underspecify the context of communication or interaction. A simple question: "Tell us where you are" for the chance to win a prize does leave the players in the dark about the communication partner, their location, their knowledge, or the purpose of communicating their place other than the need to provide a place description to win a price.

With such a repository of user-contributed content at hand it becomes possible to address the hypothesis and questions listed above. A large corpus of place descriptions allows for an analysis using statistical methods, having enough individual descriptions to compensate for outliers and noise in the data.

4. APPROACH

This research applies a classification scheme (Section 4.2) to a corpus of place descriptions collected through a mobile game (Section 4.1). Clustering is then used to analyze the classified place descriptions (Section 4.3).

4.1 Corpus Collection

The corpus of place descriptions was collected through the mobile location-based game *Tell-Us-Where* [36]. Tell-Us-Where was promoted in Melbourne and beyond via social networks, press and the local radio, and ran over a period of six months. It was implemented as a web-browser based application to run platform-independent on various current smartphone operating systems. The task of the game was relatively simple. Participants had first to confirm their GPS self-localization shown on a map (Figure 1, left), and then to submit a textual description of their location (Figure 1, right). Participants were able to adjust this self-localization and also the respective zoom level of the map. The question 'Tell us where you are' did not provide any further context, and thus the corpus shows a large variety of place description styles or assumed communication contexts. Motivated by the chance to win a gift voucher players submitted in total 2221 geocoded place descriptions. All place descriptions were stored server-side. Records were directly attributed with a record number, the latitude and longitude of the self-localization, the map zoom level of the self-localization confirmation, the date, and an indication whether the submitted place description actually won a voucher.

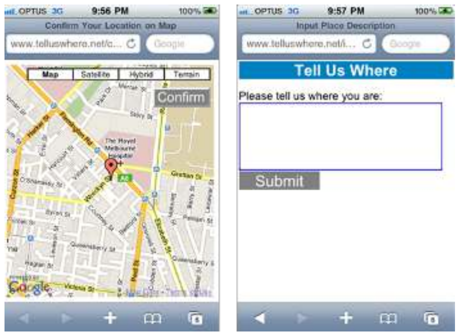

Figure 1: Tell-Us-Where started with a self-localization of the players (*left*), and then asked for a verbal description of where the players are (*right*).

The game did not require any player registration. Players were able to participate anytime and anywhere; neither did they receive any cues asking for submission, nor where there any restrictions implemented that prevented submission. There were no data acquired about the participants' age, gender or educational background. We also did not collect information about location and knowledge of the assumed recipients.

4.2 Classification Scheme

Given the large variety of collected place descriptions, a classification scheme was developed to label characteristic parameters. The classification aims to capture specific parameters including description type, spatial and/or semantic context, levels of granularity, as well as complexity and construction principles of the collected place descriptions. While there are a number of approaches that specifically develop classifications for spatial descriptions [6, 21, 2], none of these sufficiently covers aspects of spatial granularity, which is a primary focus of our research. Table 1 lists the specified variables used to annotate the Tell-Us-Where corpus. Capturing various dimensions results in a classification of overlapping categories. The place descriptions were manually annotated. To test the robustness of the specification of the classification scheme, a random sample of 10% of the corpus was independently annotated a second time.

The classification scheme can be structured into five larger groups (Table 1): type of description, style of description, granularity of elements in the description, in- or outdoor, and use of verbal spatial relations.

Type of description.
A first type of place description reports a location (or position) by means of addresses or landmarks, for example, 'i am at hope st'[1], or 'near flinders street station'. The second type of submitted descriptions indicate current movement towards or from a specific place, e.g., 'heading to emerald off road'. A third type comprises rather complex route descriptions of either how people have reached a respective location and/or how they will proceed to their destination, or they try to give detailed instructions allowing other people to find a particular place. The fourth type (*undefined*) collects all those descriptions that use place in an uninterpretable, abstract or nonliteral way, such as 'i am lost', or 'on the moon'. Although filter mechanisms of the game would have been capable to reject such descriptions, the use of filter mechanisms has been deliberately omitted, in order to not accidentally reject any valid place descriptions.

Style of description.
Place descriptions included a variety of expressed knowledge about the environment of the location. Types of knowledge include *Addresses* and *Geofeatures* that incorporate official place names as found either in the gazetteer of the State Government of Victoria, Google Maps or Microsoft Bing. Other types of knowledge required local knowledge of the annotator, especially regarding colloquial or abbreviated place names, which are normally not included in gazetteer services. Apart from specific official or colloquial place names, place descriptions involved further semantic information normally related to functions of places ('school', 'bar'), to personal context ('at work', 'Jakes house'), or business names and trademarks ('ANZ Bank', 'Apple store').

Granularity of elements.
We distinguish between seven levels of granularity, namely country, city, suburb, street, building, room, and furniture. These levels reflect the scales of space as they were discussed by Montello [22] in that they distinguish differences in size and accessibility as experienced by humans in their everyday lives. Furthermore, the classification takes into account the different levels on the one hand, and on the other hand the number of mentioned cues. For example, considering 'i'm at the bp which is right next to hungry jacks and is also near the sofas restaurant' in contrast to 'In a nice wine bar in little Bourke st, just after china town', both descriptions contain three cues, but the first uses only one level of granularity, whereas the second description contains different levels of granularity. Granularity as part of this classification is in detail described in [26], where it was applied to study hierarchical structures in place descriptions.

Indoor/outdoor.
The labels *Indoor* and *Outdoor* concern place descriptions that contain explicit statements referring to in- or outdoor locations, for example, 'in my office' (indoor) or 'in the park' (outdoor). Some place descriptions could not be labeled because explicit statements were missing and an inference was not unambiguous.

Verbal spatial relationships.
A last type of label is attributed to verbally expressed spatial relationships between locations. It takes into account utterances such as '4 houses past', '3 min far from' (quantitative distance relationships), 'near', 'close to', 'just off' (qualitative distance relationships), 'in front of', 'opposite', 'left of'(relative directional relationships), 'north of' (directional relationships, referring to cardinal directions), 'going to broken hill' (directional relationships by means of landmarks, where the term landmark could be in our classification any place name), and utterances explicitly indicating topological relationships such as 'in perth', 'on lexton ave', 'heading through craigie', 'Outside the restaurant'. The relation 'at' was excluded from classification and labeled separately because of its ambiguous use in the English language (e.g., 'I am at the supermarket' may refer to being inside the supermarket doing some shopping or being close to the supermarket waiting for someone; see [34] for a detailed analysis of the relation 'at').

[1] All citations of collected place descriptions are shown here in their original spelling.

4.3 Cluster Analysis

Clustering is the unsupervised classification of patterns (observations, data items, or feature vectors) into groups (clusters). It is applied in this study to identify groups in the annotated place descriptions, which correspond to preferred ways of describing a place. Agglomerative hierarchical clustering was used, as it is deterministic and does not require pre-specifying the number of clusters. It starts with $n-1$ pairwise joins between the n items in the data set, and produces a hierarchical structure as output by considering the distance between the classified place descriptions according to a range of specified (or coded) features. Specifically, Ward's method was used [35].

5. RESULTS

5.1 Collected Corpus of Place Descriptions

A corpus of 2221 place descriptions has been collected over seven months of running the Tell-Us-Where game. These place descriptions are distributed all over Victoria and beyond. Because of the population distribution, mobile internet coverage, and the social networks through which the game was promoted, the majority is concentrated in Greater Melbourne. More detailed analysis of the player population is impossible since no data has been collected on them. An important observation is the variety of submitted place descriptions, with various game roles or purposes imagined by the players.

5.2 Classification Results

As a consequence of not using any automated filtering mechanisms 310 data sets were sorted out manually prior to classification. These were erroneous records (empty strings, erroneous coordinates, single characters, or double entries), and those descriptions that are listed as type 'undefined' in the classification. As mentioned before, we intentionally did not restrict the possible inputs, to allow also abbreviated or colloquial place names, such as the commonly used 'mcg' (Melbourne Cricket Ground). The text length of a place description after the filtering varies between two and 586 characters, and is 30 characters on average.

Table 1: Classified Attributes.

Attribute	Comment
Type	
Position	Place descriptions of a location/position
Locomotion	Indication of movement towards a goal
Route	Place descriptions of route directions
Undefined	Information that cannot be physically localized
Style	
Address	Address information
Geofeatures	Geographic names, landscape features
Name	Categorical place names referring to businesses
Functional	Categorical place names that refer to functions of a place
Personal	Place names that describe personal places
Granularity	
Furniture	Location within a room, referring to furniture
Room	Specified location within a building, or within parts belonging to it
Building	Specified location of a building e.g. street nr., street cnr, building name
Street	Institution, public space or street level
District	Suburb, rural district or locality, post code areas
City	Town or city level, metropolitan areas
Country	Everything beyond city level
In-/Outdoor	
Indoor	Explicit statement
Outdoor	Unambiguously outdoor
Spatial Relations	
Distance quantitative	Quantitative distance relationships
Distance qualitative	Qualitative distance relationships
Orientation relative	Directional relationships
Orientation absolute	Directional relationships, referring to compass directions
Orientation landmark	Directional relationships, referring to an orientation towards other features
Topology	Indication of topological relationships

An annotation of the remaining 1911 place descriptions according to the proposed classification scheme (Table 1) led to the following results. The majority (93% of the descriptions) contained locational positions, by means of spatial or semantic information, such as addresses, landmarks or spatial relations, for example, 'i am at home'. 7% of the descriptions included locomotion information, i.e. people indicated that they were actually moving to or around somewhere, for example, 'walking down Collins street', 'heading to emerald off road', and 1% contained a rather complex route description. Also, approximately 1% of all place descriptions were classified in more than one type category, for example, if participants describe where they are, and also how to find them. 55% of all place descriptions contained address information, 29% geographic features, and 5% personal, 23% functional, and 17% categorical information related to names of businesses or trademarks (again, an individual description may cover multiples of these categories). Looking at the sum of cues in the various levels of granularity, the street level shows the most cues overall (1503 cues, or 46% of all cues), followed by 854 cues (26%) on the building level, 459 cues (14 %) on suburb level, 172 cues (5%) on city level, and 139 cues (4%) on country level. 118 cues (4%) were counted on the room level, and only 21 cues (1%) on the furniture level. The number of spatial cues per place descriptions varies between one and 20 cues, with an average of 1.47 cues. In total 108 place descriptions (6%) were labeled as explicitly describing indoor locations, whereas 246 place descriptions (13%) were interpreted as being outdoor.

344 place descriptions (18%) described topological relationships and 176 (9%) qualitative distances. 109 (6%) used relative orientation relations, and 70 descriptions (4%) indicated orientation relations towards other locations. Only a small portion of 42 (2%) referenced place names using quantitative distances, and only 39 (2%) absolute orientations.

An inter-annotator agreement of 95%, established through cross-checking 10% of all place descriptions, illustrates that the classification scheme is appropriate. Given that participants had to confirm their location on a displayed map prior to submitting their descriptions, there might be priming effects with respect to the map content. Preliminary results of a study investigating such priming effects do not confirm such an effect.

5.3 Clustering Results

In order to get at clusters of place descriptions, the dendrogram resulting from the hierarchical clustering is cut at specific heights—a method agreed on in the literature (e.g., [13]). Every top-level branch resulting from these cuts represents a single cluster.

74% of all place descriptions already form groups at a clustering height of 0. Place descriptions that have exactly the same attributes according to the classification group on this level; they have the highest possible similarity. The distribution of these clusters with highest similarity, containing at least 12 place descriptions, is shown in Table 2. Some of the groups with highest similarity are, for example, simple street names (9.3% of all place descriptions), geo-features on street level granularity (8.2%), suburbs (7.6%), or place descriptions including names on the street level (5.7%).

While there are some relatively large clusters on this level already, cutting the dendrogram at height 0 results in 636 individual clusters. Increasing the height at which a cut

Table 2: Cluster of place descriptions at clustering height 0 (highest similarity).

Count	Cluster name (example)
177 (9.3%)	Street name ('Bourke st')
157 (8.2%)	Geo-feature on street level ('carlton gardens')
146 (7.6%)	Suburb name ('Fitzroy')
108 (5.7%)	Name on street level ('at thomas embling hospital')
103 (5.4%)	Geo-feature on building level ('flinders street station')
56 (2.9%)	Geo-feature outdoor ('at price park feeding the ducks')
50 (2.6%)	Address no + street ('360 collins street')
38 (2%)	Name on building level ('Repco','Kmart', 'Hallam hotel')
32 (1.7%)	Functional place name on street level ('park', 'uni', 'hospital')
29 (1.5%)	City name ('melbourne')
28 (1.5%)	Personal names on building level ('at home', 'my house', 'at work')
25 (1.3%)	on + Street name ('on bourke st')
23 (1.2%)	Functional name on building level ('library', 'at the movies')
17 (0.9%)	Address no + street + suburb ('6 Oliver Road Templestowe')
14 (0.7%)	Building in area ('Old Engineering Building University of Melbourne')
12 (0.6%)	Address street + suburb ('McKean Street, Fitzroy North')
12 (0.6%)	Functional name on street level, outdoor ('at the reserve kicking a footy')

is made reduces the number of clusters, as more and more clusters get combined to ever larger clusters. Finding a good cut-off height can be based either on a predefined level of similarity or on identifying large jumps in height between two successive combination steps in the dendrogram. In this study, a similar method as in [28] is used. The cut-off height is selected by identifying the 'knee' in the graph that plots the number of clusters against the similarity (merge distance) between the respective clusters. Figure 2 shows such a graph for the clustering of the place descriptions. Selecting a cut-off height from the 'knee' region of the graph results in a balance between having clusters that are both homogeneous within themselves and dissimilar to each other.

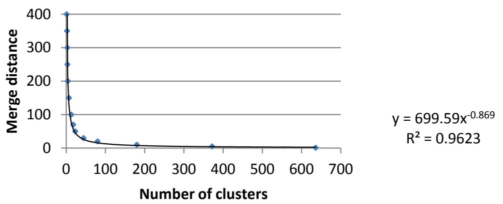

Figure 2: Merge distance (height) vs. number of clusters.

A cut-off height of 50 was selected, resulting in 23 individual clusters. For each of these clusters, a semantic label was identified based on which parameters were most common in the selected sub-group, but rare in the rest of the data. Figure 3 is a generalized dendrogram, representing the 23 clusters above cut-off height 50. A complete dendrogram of the whole cluster would be too large to visualize here. In Figure 3 the further combination of the 23 clusters into larger clusters is indicated by the numbers below the respective cluster names. In particular, beyond a cut-off height of 150, the resulting clusters become meaningless, i.e., a semantic interpretation of the similarity among the contained place descriptions is not possible anymore. Thus, the five clusters at cut-off height 150 represent prevalent kinds of place descriptions in the collected data: 1) outliers; 2) location descriptions/place names; 3) locomotion descriptions; 4) complex place descriptions containing spatial relations; 5) route directions. Space restrictions prevent a more detailed presentation of the clusters' setup.

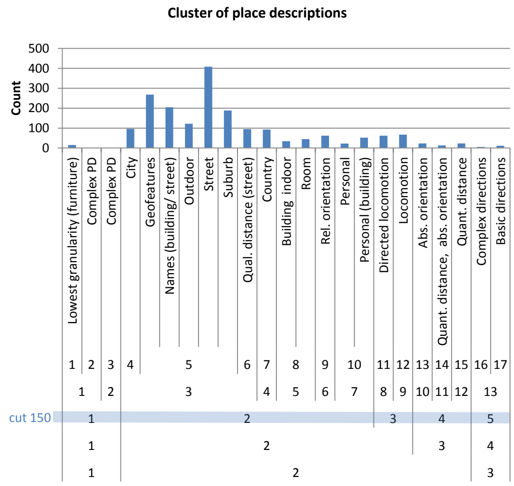

Figure 3: Clusters of place descriptions at a cut-off height of 50 and beyond. At cut-off heights greater than 150, clusters become meaningless.

6. DISCUSSION OF RESULTS

The classification scheme developed for annotating place descriptions proves to be reliable and, thus, forms a valid basis for the clustering analysis. This analysis in turn reveals that there are prevalent types of place descriptions in human communication.

Overall, most people intended to describe their actual location, as asked for by the game. Many also tried to make these descriptions informative, i.e., allow others to understand where they are. Many contain (street or building level) address information, which usually is clearly identifiable and useful in an urban context. However, various descriptions seem to be meant for different purposes and are targeted at imagined addressees, such as friends or other locals, that share vernacular references and certain commonly used abbreviations. Moreover, several users provide additional information beyond simple placenames, highlighting subjective comments about a place ('its a beauty park; Malvern golf course - 18 holes, one of best in melb!; Suzuki auto centre where they sell crap cars on Narre cranny road'), or report relevant local knowledge on an objective level ('it used to be called bunyip crt'). Some descriptions intend to give recommendations related to the respective locations ('on the side of this road is speed cameras'; 'Vert ave is the easiest way to the park!'). All these additions clearly demonstrate that the people providing the descriptions assume that they are meant to be used in some useful way to assist others.

A considerable part of the place descriptions contain forms of locomotion (e.g., 'going along the coast to get to perth'). Since the descriptions were collected in a mobile setting, this reflects the characteristics of such a use case where people are not necessarily static. Still, place is usually described as an area of rest, or as the origin or destination of some movement. Accordingly, these descriptions contain a significantly higher level of uncertainty with respect to being able to localize the provider of the description. The supplementary information mentioned above often is provided in this context, referring to traffic or road conditions. These types of place description may best reflect the game-like character of the collection method; while sitting in a tram or the passenger seat of a car people may use the Tell-Us-Where game to distract themselves.

Many of the descriptions are complex, combining various levels of granularity and showing hierarchical as well as categorical structures. Within these descriptions there is a preference for place names on the street level, which has the maximum number of cues for all three identified types of place descriptions. There are slight differences in the distribution of cues; locomotion descriptions seem to have less cues on room and building level than route directions and location descriptions. On the other hand, route descriptions contain a higher number of references on room and building level, and less on city and country level. Still, the dominance of cues on the street level likely reflects the predominant use of mobile devices in an urban environment where the street level seems to provide a useful level of granularity for disambiguation of one's location.

We assumed that there is a small number of prevalent ways in which people describe place. The obtained results support this hypothesis. Before clustering ends up with semantically meaningless clusters, only three types of descriptions remain: location descriptions using place names of various kinds including complex relational descriptions, locomotion descriptions and route descriptions.

7. CONCLUSION

A corpus of place descriptions was collected using methods of user-generated content. This corpus was subsequently investigated regarding the way people provide these place descriptions. To this end, a classification scheme was developed that accounts for different characteristic parameters, such as style or granularity. Agglomerative clustering identified three prevalent types of place descriptions: location descriptions using place names; locomotion descriptions, and route directions (plus a group of outliers). These prevalent types and the employed analysis method allowed gaining insight into construction principles of place descriptions.

Overall, the presented study is another step towards better understanding the way people refer to places in order to support advances in the development of intelligent tools and location-based technologies. The study also illustrates that methods of user-generated content are a powerful tool to collect large amounts of data in unconstrained ('natural') settings.

An important next step is to see how the actual location of a person determines the way a place is described, and if different cluster of place descriptions can be related to different environments. Ongoing and future research will investigate how to model the uncertainty of the described location and how to describe its spatial extent. Besides these goals, future research should also investigate if there is a variation in the place description techniques people use depending on their cultural, geographic or language background. The findings also seem to indicate that movement speed may affect the perception or cognition of place, and consequently the way it is described. This can be seen in the differences of chosen granularity level depending on the kind of activity users were involved in (see also [16]). This is as well an aspect to be further investigated in future work—it requires more data than currently available.

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5.2 Paper "Zooming In – Zooming Out: Hierarchies in Place Descriptions"

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Zooming In–Zooming Out Hierarchies in Place Descriptions

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Abstract Hierarchical place descriptions are a common means for people to communicate about place. Within them hierarchically ordered elements are linked by explicit or implicit relationships. This study analyses place descriptions collected in a mobile game, investigating hierarchies based on a classification of spatial granularity. The main findings show a dominance of hierarchical structures in place descriptions, but also a considerable number of deviations. Deviations are explained by principles other than spatial granularity, such as the presence of salient features and other construction principles. We conclude the need for and significance of more flexible models of hierarchies in the interaction with users of location-based services.

Keywords Place descriptions · Hierarchies · Granularity · Salience

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1 Introduction

Verbal place descriptions—descriptions answering a where question about a thing or event—typically have a hierarchical structure (Shanon 1979). The hierarchical structure can appear as zooming in (e.g., 'in the park, at the pond') or as zooming out (e.g., 'in Parkville, Victoria') (Plumert et al. 2001). A hierarchical structure of verbal descriptions reflects the hierarchic organization of spatial knowledge in the mind (Hirtle and Jonides 1985), which, in turn, is based on the individual's acquisition of this knowledge through direct and indirect interaction with the environment. Thus, while place descriptions are broadly observed and accepted as being hierarchical, one can expect a high degree of variability in their construction from spatial knowledge. This variability requires flexible interpretation mechanisms in location-based services.

This chapter focuses on human place descriptions. It will identify the major building principles of hierarchical structures in these place descriptions, which will progress their automatic interpretation. Our hypothesis is that:

1. The dominance of hierarchical structures in human place descriptions can be verified in a large corpus of place descriptions.
2. Hierarchical structures are not organized purely by spatial granularity; deviations from spatial hierarchies will reveal other hierarchical systems, for example, based on the cognitive principles of salience or prominence.[1]

The chapter will systematically study a large corpus of human place descriptions collected in a mobile game called *Tell-Us-Where* (Winter et al. 2011). The corpus can be analyzed to learn about the general classification principles of place descriptions. Spatial granularity is one of the classification criteria. Applying it in the present study, we will identify whether such descriptions are hierarchical by granularity, or whether other organizational principles were used. Hierarchical structures can only emerge if at least two spatial references are present. Thus, in this chapter only such place descriptions will be considered. It will be interesting to see how the hierarchical systems of spatial granularity and salience are linked, whether there are preferences for one of them, and whether they can occur independently.

[1] *Salience* refers to outstanding perceptual or semantic properties of a feature, while *prominence* refers to the degree of shared knowledge about a feature in a community. While the two terms are not synonymous it can be expected that salient features over time also become prominent. In this chapter no strict distinction is needed; mostly, the term salience will be used. For example, the Eiffel Tower is a salient feature because of its unique pyramid-shaped, metal skeleton construction that is very different from the rest of the buildings in Paris. However, it has also become one of France's most prominent (or well-known) features, and certainly a feature that is associated with Paris. Therefore, it can be used as an anchor point of place descriptions in the city of Paris. However, it has also become one of France's most prominent (or well-known) features, and certainly a feature that is associated with Paris. Therefore, it can be used as an anchor-point of place descriptions in the city of Paris.

Hierarchical structures (on whatever principle) have mainly two roles: one is anchoring the location of a thing or event to known places or anchor points ('[I'm in] a café near the library'), and the other is disambiguating the places referred to ('[I'm in] the café near the library'). Anchor point locations are presumed to be cognitively salient cues in the environment referring to a person's individual cognitive map, and thus are known at least by one single person (Couclelis et al. 1987).

The functions of anchoring and disambiguating place are critical for communication success, and this motivates the strong expectation expressed in the hypothesis. However, we also detect different structures, especially answers involving egocentric locomotion ('heading to…'), or listener-centric route descriptions ('to find me, you…'). We will also discuss these deviations from the expressed expectation. We expect to shed some light on the current perceptions of the hierarchical structure of spatial knowledge and to confirm the need for some flexibility in the implemented mechanisms, rather than adherence to absolute rules that may not be able to accommodate the context of different place descriptions. The results will be relevant for understanding and generating human spatial language, facilitating human computer interaction and the creation of intelligent systems.

The remainder of the chapter is as follows: Sect. 2 introduces prior work; Sect. 3 discusses the theoretical framework for the analysis. Section 4 details the analyzed corpus and the classification schema. Sections 5 and 6 present and discuss the results of the analysis.

2 Literature Review

Spatial mental representations are acquired through direct and indirect interaction with the environment (Ishikawa and Montello 2006; Siegel and White 1975) and help people communicate about space. Verbal place descriptions, as one such communication means, reflect cognitive organization principles of spatial knowledge. From a linguistic perspective, place descriptions are referring expressions (Dale et al. 2005) to locations of objects. Gestalt theory suggests that with a focus on the object they form the figure, and references to (the locations of) other features are taken from the ground (the environment). Talmy (1983) specifies that the figure object typically is more movable, is smaller, is conceived as geometrically simpler, is more salient, or is more recent on the scene. The ground object acts as a reference object with known spatial characteristics, is more permanently located, is larger, has greater geometric complexity, is less salient, or is earlier on the scene. Some of these observations directly correlate with the expectation that place descriptions must be hierarchically structured (e.g., smaller–larger), but not all of them (e.g., salience).

Schegloff (1972) points out the large variety of a place's 'correct' location formulations (place descriptions in the sense of this chapter). In a given context, references are selected using the principles of relevance and appropriateness. A more developed model of relevance in conversation is provided by Grice: conversational participants behave in accordance with an assumed in principle agreement to be co-operative (Grice 1975). In particular, they adhere to a relevance principle, which claims that the recipient in a specific communication context will interpret the expression according to this context, in order to maximize the efficiency of actions. Usually, people select the most relevant referents from a possible set of referents. These conversation principles are relevant to the rest of the chapter. They are, for example, cited in the context of generating hierarchically organized place descriptions (Kelleher and Kruijff 2006; Tomko and Winter 2009) to select first, intermediate and final place references in an incremental manner.

The mental organization of spatial knowledge is based on an individual's acquisition of this knowledge. It is formed by landmarks and routes (Siegel and White 1975), and distorted by preferential reasoning through anchor points (Couclelis et al. 1987; Sadalla et al. 1980), i.e., asymmetric relationships caused by differences in salience, and hierarchical structures defined by partonomies (Hirtle and Jonides 1985; Stevens and Coupe 1978). If salience causes asymmetric relationships, it imposes an order, which is independent from partonomies. Measures for salience have been suggested (e.g. Raubal and Winter 2002; Sorrows and Hirtle 1999), but they are local measures, providing an order only in a given context. They do not lend themselves to building a global hierarchy.

Place descriptions inherit the hierarchical organization of spatial knowledge (Plumert et al. 2001; Shanon 1979). These hierarchical structures are employed to decrease the cognitive effort of storing and retrieving information, and to decrease ambiguity in spatial knowledge sharing (Taylor and Tversky 1992). However, dealing with (at least) two independent hierarchical organization principles it is not clear from the outset how these two principles harmonize or are applied together. Finally, while our hypothesis expects a monotonic zooming in or zooming out behaviour, route directions, for example, have been shown to vary in their hierarchic structures with trips that involve various modes of transport (Tenbrink and Winter 2009) or various levels of a hierarchical transportation network (Timpf et al. 1992).

3 Hierarchies in Place Descriptions

3.1 Defining Place Descriptions

A place description is a verbal description answering a where question. Language provides great flexibility in construction principles, to a large extent related to the communication context. A typical form to describe the location of X is:

[[(opt) subject verb] (opt) prepostition] NP

We expect the noun phrase (NP) to refer to a location, as in: 'Where are you?'—'[[I'm] in] Brunswick'. The locative noun phrase can be a simple noun (as in the example), a compound ('Melbourne Central Station'), or complex. If we agree that anchoring one's place to a known place, as in the simple place description, is not hierarchical as such, only complex forms can expose a hierarchical structure. Complex forms can be nested (as in postal addresses) or independent sequences (as in ternary relationships). Prepositions may be explicit (as in the example) or implicit (as in postal addresses).

Research has provided formal models for qualitative spatial relations, distinguishing topological relations, absolute and relative direction relations, and distance relations. However, prepositional phrases (PPs) in language may be ambiguous in their classification. For example, 'at' can appear as a topological descriptor of *in* ('I am at school'), *touching* ('arriving at the school'), or a distance descriptor of *near* ('at the intersection'). These and more ambiguities can often be resolved only from context.

3.2 Identifying Hierarchical Structures in Place Descriptions

Studies identifying a zooming in or zooming out hierarchical behaviour of place descriptions focus solely on an organization by spatial granularity. Many of these hierarchies exist and all are formed by part of relationships. These spatial hierarchies are reflected in cognitive representations and reasoning (Stevens and Coupe 1978); it is reasonable to expect them to be reflected in language as well. An example is postal addresses: a street is part of a city, which is part of a state, which is part of a country.

Algorithm 1: Mechanical procedure to identify hierarchical structures in place descriptions.
Data: A complex place description.
Result: Hierarchical structure of the place description.
1 Identify the locative noun phrases in a place description.
2 To each noun phrase, apply a classification schema identifying the level of spatial granularity.
3 Construct a list of granularity levels in the place description, in order of noun phrase appearance.

We suggest a mechanistic procedure to identify hierarchical structures in place descriptions as laid out-in Algorithm 1. Applying this algorithm, a complex place description can expose one of the following hierarchy patterns:

- *Strictly hierarchical*: place descriptions showing a strictly monotonically increasing or decreasing behaviour towards the spatial hierarchy. The sequence of granularity levels is either zooming in or zooming out; no duplicates of the same levels occur.

- *Partially hierarchical*: place descriptions showing a monotonically increasing or decreasing behaviour. Duplicates of the same levels occur.
- *Flat*: place descriptions that show constant behaviour towards the spatial hierarchy; at the same time monotonically increasing and decreasing (no zooming in or out). They form a special type of partially hierarchical descriptions.
- *Unordered*: non-monotonic place descriptions.

Compound locative NPs may challenge the classification schema. For example, 'Flemington Racecourse' is a compound and a proper geographic name. Classifying this compound at one level of the spatial hierarchy (as granularity level street in this case) can be defended, but it can also be split up into two locative NPs, 'Flemington' (a suburb, district level) and 'Racecourse' (street level). If both NPs were classified according to their individual spatial granularity, the compound would be treated as a complex place description and accordingly as strictly hierarchical. For the purposes of this chapter compounds are treated as single names without limiting generality.

Only the strictly or partially hierarchical patterns from the above four patterns would satisfy the first part of the hypothesis. However, place descriptions with flat or unordered patterns may illuminate other hierarchy structures and need further investigation, in accordance with the second part of the hypothesis.

3.3 Adding Other Cognitive Patterns to the Study

Exceptions to the spatial hierarchical structure of place descriptions may reveal other hierarchy structures in the construction of human place descriptions. Design patterns to be discovered in flat or unordered descriptions may apply to spatially hierarchical place descriptions as well, but this is not considered further.

Place descriptions (either simple or complex), which anchor one's place to a known place, reflect a hierarchical order by cognitive salience that may be independent of spatial hierarchies. For example, 'the building opposite the library' is spatially flat (two buildings), but one NP is known, the other is not (or less) known. More drastically, the spatial hierarchy can be inversed, as in 'the place at Cleopatra's Needle', which links an unnamed place to a better known structure that is part of the place itself. Nevertheless, a correlation exists between spatial hierarchies and salience rankings. For example, 'Switzerland' is globally better known than 'Lake Zurich', or 'Küsnacht' on Lake Zurich.

Cognitive salience imposes an order, but in the absence of absolute comparison measures not a proper global hierarchy. While one might generally distinguish global, regional and local landmarks, or point-, line- and area-like landmarks (Hansen et al. 2006), this distinction describes a function of a reference to a geographic feature, which can change with context. Salience itself depends on the communication context, especially on the communication partners. Hence, when investigating flat and unordered place descriptions for hierarchical structures based on salience, applying Algorithm 1 is not revealing of such structures. Instead we apply a weaker Algorithm 2, which will reveal those flat and unordered place descriptions that are (strictly or partially) hierarchically ordered by salience rankings. Hierarchies by salience are based on the assumption that (personally or communally) more significant features anchor less important (less salient) ones, which again can be anchor points for features of lower significance, and so on. Properties to define such an order may be relational spatial (such as frequency of interaction), relational non-spatial (such as personal meaning) or by referring to intrinsic properties of objects, such as perceptual or symbolic salience (cf. Couclelis et al. 1987). Some examples to illustrate this are 'at the train station near my house' anchoring the train station (less salient) to a more salient feature 'my house' (more salient because of its significance to the person), or 'a café opposite to the big red building', where the 'big red building' (more salient by its visual properties) serves as an anchor point for 'the café'. Adding salience rankings to the interpretation tool set will provide further supporting evidence for our hypothesis.

Algorithm 2: Identification of salience ranking in place descriptions.
Data: The union set of all flat and unordered place descriptions.
Result: A set of all place descriptions that are hierarchic by salience.

```
forall flat and unordered place descriptions do
    Identify the salience rankings of component parts by a semantic, context-aware
    interpretation.
    Construct a ranking sequence in the place description.
```

Finally, a third algorithm is suggested for those unordered place descriptions that have not exposed hierarchal structures after applying Algorithms 1 and 2. The algorithm tests whether a place description classified by the mechanistic Algorithm 1 as unordered is semantically flat or hierarchic. Consider the example 'I'm in the café across the street from the library'. To Algorithm 1 it appears as unordered, switching from a building level to a street level and back to building level. But the string 'across the street' is not an independent PP. The sequence can only be read as 'across the street from the library' (an extension of 'from the library'). 'Street' is best viewed as part of a complex prepositional construction, not as an independent reference to a geographic feature. Algorithm 3 will remove spatial granularity levels in sequences produced by Algorithm 1 as a result of locative noun phrases that are part of a complex PP. Adding complex PPs to the interpretation tool set, we may find final supporting evidence for our hypothesis.

Algorithm 3: Semantic filtering of unordered place descriptions.
Data: A set of unordered place descriptions.
Result: A set of unordered place descriptions filtered for semantic hierarchy.

forall unordered place descriptions **do**
  Identify isolated violations of monotonic spatial granularity orders.
  if this occurrence is part of a dependent PP **then**
    remove it from sequence.
  if after all removals the place description is flat **then**
    re-apply Algorithm 2.

4 Data and Methods for Analysis

4.1 Corpus of Place Descriptions

In this chapter a subset of place descriptions collected through the mobile location-based game Tell-Us-Where (Winter et al. 2011) is analysed by means of a classification schema, and by manually applying the presented algorithms.

In Tell-Us-Where participants were encouraged to confirm their GPS self-localization on a smartphone-map and to submit a textual description of their location answering the question 'tell us where you are'. Apart from these tasks and knowing they may win a gift voucher, no further context was specified. No further information about the location and knowledge of the recipient was collected. Participants could freely choose where, and also what to submit. The game was implemented as a web-browser based application to run platform-independent on various current smartphone operating systems. All place descriptions were stored server-side. Records were directly attributed with a record number, the latitude and longitude of the self-localization, the map zoom level of the self-localization confirmation, the date, and an indication whether the submitted place description won a voucher. Tell-Us-Where was promoted in Melbourne and beyond via social networks, the press, and the local radio. Within six months of running the game, 2,221 geocoded place descriptions were collected with a large variety of styles or assumed communication contexts—primarily of locations in and around Melbourne. Since there were no data acquired about the participants, information about age, gender or educational background are not available.

For the following analysis of hierarchic structures, a classification schema for the spatial granularity of each spatial cue is needed. We are using the schema presented in Table 1. The granularity of cues classifies seven different levels of spatial granularity, and place descriptions have further been labelled for spatial relations, such as qualitative and quantitative distances, relative or absolute orientation, and topology.

Table 1 Classification of granularity

Class	Description
Furniture	Location within a room, referring to furniture ('at my desk', 'in bed', 'on a bench'), small vehicles (bike) or natural features ('under a tree')
Room	Location within a building, or within parts belonging to it ('in my lab', 'hallway on the second floor', 'back yard') or medium vehicles (car, boat)
Building	Location of a building, e.g., street no, street corner, building name ('engineering dept', 'spencer street station', 'at work'), large vehicles (train, ferry)
Street	Institution, public space or street level, i.e., larger than building and/or vaguer boundaries than building. Included are infrastructure (railway, tramline, Ave, Ln, Boulevard, circuit, way, Cres, Pl.), public spaces (golf course, sports ground, school, university, cemetery, hospital, mall), natural features (port, bay, lake, hill, park, reserve, paddock)
District	Suburb, rural district or locality, post code areas ('carlton', 'South Melbourne'), categorical information ('central business district', 'downtown', 'city center')
City	Town or city level, and metropolitan areas ('Canberra', 'South of Melbourne', 'near geelong')
Country	Everything beyond city level. This includes highways, freeways ('black spur Hwy'), islands ('Phillip island'), national parks, rivers, states ('In Australia', 'WA somewhere')

Since place descriptions were manually classified, a random sample of 10 % of the corpus was independently classified a second time. An inter-annotator agreement of 95 % supports the robustness of the specification of the classification schema.

4.2 Spatial Hierarchic Structures

From the total of 2,221 place descriptions, a subset of 722 descriptions that contain at least two spatial cues were extracted to investigate granularity of elements, as well as the order and direction of order (zooming in or out) within hierarchic elements.

The classification of spatial cues in place descriptions requires abstraction and definition of granularity levels, especially for features that may be ambiguous or show great variations in size (e.g., rivers, parks or islands) compared to features that are more assessable (e.g., 'at home', 'in my car'). The classification schema establishes seven levels of granularity, namely *country, city, district, street, building, room,* and *furniture* (see Table 1 for specifications and examples). These levels reflect human perception of spatial scales (Montello 1993). And given the elements referred to in the Tell-Us-Where corpus, these levels proved to be most appropriate, even though the restriction to seven levels may ignore some potentially hierarchic structures (e.g. 'Victoria, Australia' are both categorized on level country). Elements beyond these levels were not observed.

The classification of cues according to spatial granularity captures the difference in levels as well as the difference in the number of mentioned cues. Spatial cues are assessed regardless of the spatial relationships involved, i.e. ‘South of Melbourne’ and ‘near Geelong’ will be classified as granularity level city. Partial features were reduced in granularity level. For example ‘South Melbourne’ is classified as district level, referring to the southern part of Melbourne. Similarly, ‘end of Arnold Crt’ would be reduced from street level to building level. Multitudes of objects (e.g., apartments) are classified as a coarser granularity level, i.e., whereas one single ‘apartment’ is classified as room level the plural form ‘apartments’ is classified as building level. The distinction between city and town (level city) and suburb, localities, township, and village (level district) was made according to VicNames.[2]

Place descriptions are strictly hierarchic, partially hierarchic, flat or unordered (Sect. 3.2). Strict and partial hierarchic place descriptions were classified to be either *zooming in* or *zooming out*. An example of a place description with zooming in order is ‘little lonsdale street near the parliament house’, since the coarser element ‘little lonsdale street’ (street level) is followed by the finer element ‘parliament house’ (building level). A zooming out example is ‘behind kfc on swanston st’, which zooms out from the finer element ‘kfc’ (‘Kentucky Fried Chicken’; building level) to the coarser element ‘swanston st’ (street level). An unordered place description is ‘In Bok Choi, the Chinese restaurant at federation square—top floor’. It starts with a zooming out from building level (‘Chinese restaurant’) to street level (‘at federation square’), and then zooms into room level (‘top floor’) again.

After a first pass coding of descriptions according to spatial granularity, Algorithm 2 is applied to all descriptions that were identified as flat or unordered. This identifies a number of flat hierarchies to be semantically hierarchical. For example, the description ‘diagonally opposite St. Francis church, at a tram stop’ is according to spatial granularity flat (all spatial cues are at building level). However, the PP ‘diagonally opposite St. Francis church’ defines a wider area behind a landmark or anchor point (‘St. Francis church’), while the PP ‘at a tram stop’ refines the exact position in this area. As a result, there is a semantic hierarchy identified in the spatially flat description that zooms in from the general area defined by a salient feature to the more specific location (or less salient feature) within it. For all remaining unordered descriptions, Algorithm 3 reveals certain patterns that allow for the categorization of these descriptions as semantically flat or hierarchic.

While in this chapter the algorithms were applied manually, it seems possible to automate the process in principle. Natural language processing allows extraction of information from text by means of named entity recognition. Using an open-source framework such as GATE (Cunningham 2002)[3] in combination with gazetteers for place name detection would enable an implementation of Algorithm 1. For the identification of salience rankings and semantic filtering of unordered

2 http://services.land.vic.gov.au/vicnames/

3 http://gate.ac.uk, implemented in Java

place descriptions (Algorithm 2 and 3) further parsing rules have to be established, to interpret complex descriptions and to assess salience based on context knowledge.

5 Results

Regarding the types of descriptions, the vast majority of place descriptions (91 %) contained location positions, 2 % route descriptions, and 9 % locomotions (the classes could overlap). In terms of granularity, 40 % of all spatial references were classified as street level, 30 % as building level, and 13 % as district level, with smaller percentages for the other levels.

Table 2 shows the frequency distribution of the number of different granularity levels within place descriptions, grouped by the different types of hierarchic order.

5.1 Hierarchic Place Descriptions

623 descriptions (86.3 %) contain different levels of granularity. The majority of these (514 descriptions) are hierarchic with a sequential order of different levels. 109 of the descriptions are unordered, and the remaining 99 place descriptions are flat. The hierarchic place descriptions were further distinguished as 386 (53.5 %) strictly hierarchic and 128 (17.7 %) partially hierarchic. Table 3 shows the distribution of strictly and partially hierarchic place descriptions for the respective directions of order, and with further subdivision into different description types.

5.2 Flat and Unordered Place Descriptions

Flat place descriptions that contain references on one level of granularity have been identified on building level (28 %), street level (68 %), district level (2 %), city level (1 %), and country level (3 %). Most flat place descriptions contain two spatial cues on building or street level (80 %) and 14 % contain three cues on these levels. The flat descriptions were examined for salience hierarchies by

Table 2 Frequency distribution of place descriptions

No. of levels	Strict. hierarchic	Part. hierarchic	Unordered	Total	(%)
1 = 'Flat'	–	–	–	99	(13.7)
2	336	82	49	467	(64.7)
3	39	23	36	98	(13.6)
4	9	19	19	47	(6.5)
5	2	4	3	9	(1.2)
6	–	–	2	2	(0.3)
Total	386	128	109	722	(100.0)

Table 3 Frequency distribution of hierarchic place descriptions according to the different directions of order

		Strict. hierarchic	Part. hierarchic	Total (%)
Zooming out		278	98	376 (52.1)
	Position	256	95	
	Locomotion	18	3	
	Route	2	–	
	Position + locom.	1	–	
	Position + route	1	–	
Zooming in		108	30	138 (19.1)
	Position	85	28	
	Locomotion	20	2	
	Route	1	–	
	Position + locom.	2	–	
Total		386 (53.5 %)	128 (17.7 %)	514 (71.2)

applying Algorithm 2. 17 cases were classified as locomotion descriptions and were not further analyzed (their construction principles are beyond the scope of this chapter). Nine cases are compound NPs treated as a proper geographic name (e.g., 'Melbourne central shopping centre'), and thus were excluded from further analysis. In some flat descriptions, a hierarchical structure was implied by the preposition 'in' (e.g., 'on the footpath in a little side street'). The preposition 'in' induces a hierarchical part of relation for the two spatial cues 'footpath' and 'little side street' that belong to the same granularity level street.

Algorithm 2's results show that nearly half of the descriptions (47) contain references to a more salient feature. This acts as an anchoring element that indicates an (assumed) better known location, implying a salience hierarchy. The preposition 'near' also suggests a hierarchy in flat descriptions. In 13 cases, the feature following 'near' acts as a refining element (e.g., 'frawley road near tennis courts', where the PP 'near tennis courts' refines the location on 'frawley road'), while in three cases the PP acts as a disambiguating feature (e.g., 'tram stop near mayer', where the PP 'near mayer' disambiguates the 'tram stop'). In seven place descriptions other refining elements to specify a location within a wider area are used. The flat description 'At the park where the eastern freeway bike path is' zooms in from the general area of the park to the more specific part defined by the compound NP 'eastern freeway bike path'.

The unordered place descriptions contain at least three different cues. 29 % of them contain exactly three cues, 28 % contain four cues, 15 % contain five cues, 10 % contain six cues, 12 % contain seven, eight, or nine cues, and 6 % contain ten or more cues. Although unordered place descriptions show a high number of spatial cues, 45 % use only two different levels of granularity (usually adjacent levels), 33 % use three levels, 17 % four, and 5 % use five or six levels (cf. Table 2). 39 % of the unordered descriptions start with zooming in and then zoom out again. Of these, 7 % continue with a zoom in, further 4 % with a zoom out, and 1 % with a zoom in. Thus, the latter 1 % have a zooming structure of in–out–

in–out–in. On the other hand, 61 % of the descriptions start with a zoom out followed by a zoom in. Therein are 26 % of the descriptions that continue to zoom out, further 14 % zoom in, 3 % that zoom out and 2 % zoom in (the latter have a structure of out-in–out–in–out–in).

Due to the small number of unordered place descriptions, correlations between different types of place descriptions are not significant. However, 75 % of locomotions start with zooming in, whereas 80 % of route directions start with zooming out. 37 % of location descriptions start with zooming in, 63 % with zooming out. Algorithm 3 identifies some of the zooming in–out patterns to be hierarchic.

6 Discussion

6.1 Hierarchies in Place Descriptions

The analysis of the Tell-Us-Where corpus clearly supports Hypothesis 1: a vast majority of place descriptions (86 %) refer to two or more geographic features on different levels of spatial granularity. More than two-thirds of them (71 %) exhibit either a strictly or partially hierarchical structure. At the same time, these numbers indicate that other mechanisms than simply differences in spatial granularity are at play as well, when people describe where they are.

These other mechanisms manifest themselves in the observed deviations from zooming in or zooming out structures, namely flat and unordered structures. Some of these deviations reveal hierarchical structures based on salience, which supports Hypothesis 2. Some deviations result from the chosen order of analysis (Algorithms 1–3). Hierarchies based on spatial granularity are identified first; salience is only considered for those descriptions not yet classified as hierarchic. This processing order is to some extent arbitrary, and ignores possible interplays between granularity and salience, which prohibits further analysis of preferences or links between the two. This is left for future work. Other deviations seem to be the consequence of not using static, locative place descriptions; some are artifacts resulting from how the classification schema defines granularity levels.

A significant number of the flat or unordered place descriptions are in fact hierarchic based on salience of features or on spatial relationships, as has been shown in Sect. 5.2. For example, consider the flat description 'In Gopal's restaurant, diagonally opposite of Melbourne City Hall'. Here, 'Melbourne City Hall' is the prominent landmark that defines an anchoring region; within it 'Gopal's restaurant' defines a more exact location. In many other flat descriptions, use of similar prepositions (e.g., 'in front of', 'behind', 'next to') define a semantic or salience hierarchy. These prepositions anchor a place relative to other features in an environment, which are often seen to be more salient than the place itself. Some of the prepositions (e.g., 'near') may also be used to refine the location with respect to a larger region, as in 'frawley road near tennis courts'.

The existence and number of unordered descriptions seems a surprising result, and contrary to what has previously been reported in the literature (Plumert et al. 2001). However, a closer examination of the grammatical, semantic and referential structure of these expressions, and of other potential ordering patterns such as salience of locations, motivates the apparent switching between granularity levels in many cases. A full description of the grammatical and semantic structure of the expressions is beyond the chapter's scope, but a few observations illustrate the kinds of patterns observed. For example, many of those descriptions involving three spatial cues turn out to have a two-part structure as locational descriptions. We observed three different kinds of such two-part structures:

1. General location (overall place, usually building or institution) + more specific location within it, OR
2. Location + salient reference point to help further identification, OR
3. Apposed location + alternative description of the same location (e.g., street address + name of the building).

As an example of the first pattern consider 'In the University of Melbourne in the building number 174 near to Grattan street from south'. This description goes from street level ('University of Melbourne' as institution) to building level ('in the building 174') to street level again ('near Grattan street from south'). If semantically interpreted, the description can be decomposed into two locational descriptions and classified as hierarchical, going from the first general location ('In the University of Melbourne') to the more specific location within it ('in the building number 174 near to Grattan street from south'). The description '483 swanston st. opposite public city bath' is an example of the second pattern, going from building level to street level to building level again. Semantically, the first spatial reference provides a location (the address '483 swanston st.', classified as building plus street level), followed by a PP that uses a more salient feature ('public city bath') to support identifying the location. In this case, the description can be considered as flat, comprising two locational descriptions of the same (building) level. An example of the third pattern is '570 Bourke Street, DSE building' that goes from building, to street, to building level. It can be considered as the composition of two alternative descriptions of the same place (address and building name) resulting in a conceptually flat description.

Locomotion descriptions and route directions are other observed deviations from static hierarchical place descriptions. Their detailed analysis is part of future work. Since the producers of locomotion descriptions are moving, an exact localization of their current place is not helpful. Rather, their final destination or the geographical feature they are travelling on is of interest, often expressed at coarser levels of granularity (city level, or highways classified as country level). If such a description also contains the mode of transportation ('in my car' classified as room level), descriptions become hierarchical with references to very different granularity levels because references to elements on the intermediate granularity levels are not relevant here—in fact, they would likely be confusing.

The way the experiment was designed the participants represented only a particular subset of the general population. Because the game was promoted through social networks in an academic environment, most likely the majority of participants were students. An investigation of place descriptions with respect to different groups of participants is certainly interesting. But such information on the participants was not captured by the game. This, however, could be considered in another implementation.

Also the participants were not told about a particular task or context of their task. It would be interesting to investigate if, for example, time-critical tasks in a mobile environment produce certain types of place descriptions. The corpus contains 120 place descriptions during locomotion (directed) and 136 involving activities (undirected) that could already be used for this purpose.

6.2 Implications for Location-Based Services

Place descriptions are an everyday means for people to describe their environment, to tell others where they are, to locate features in an environment, or to request information about an area. These place descriptions reflect human spatial memory (Hirtle and Jonides 1985; Siegel and White 1975). Their integration into location-based services that can interpret and produce such descriptions would greatly benefit the utility of these services and improve human–computer interaction in areas such as emergency response (locating callers), search (defining spatial search queries), and navigation services (understanding destination requests, providing concise instructions).

The analysis of the Tell-Us-Where corpus illustrates that Algorithms 1–3 would provide a useful first step in this direction. These algorithms have been applied manually for the analysis presented in this chapter. Many descriptions are indeed hierarchical based on spatial granularity, which can be captured in spatial data structures. However, a non-trivial subset of place descriptions requires a careful semantic interpretation, which is dependent on specific contexts. This is clearly much harder to perform automatically. Algorithms 2 and 3 provide means for this in principle, but need further, more detailed specification to be really applicable automatically. High quality computational syntactic and semantic parsing systems may take us some way further towards this goal. It also seems worthwhile to develop (qualitative) interpretation models for the spatial relations used in place descriptions. These relations often induce a hierarchical relationship that allows for interpreting the intended meaning. The models would need to be adaptable to different contexts, and need to provide both anchoring and refinement operations. Also, better models for capturing salience of geographical features (cf. Richter and Winter 2011; Tomko et al. 2008) are required to enable the identification of hierarchies beyond spatial granularity.

7 Conclusions

This chapter presents an analysis of a place description corpus collected through a mobile game. The context in the game was largely underspecified, allowing for the collection of a wide range of different descriptions. The aims of the chapter were to test the hypothesis that place descriptions are typically hierarchical in their structure, and to explain any observed deviations from such hierarchies. The hypothesis was found to be true with most of the place descriptions showing a spatially hierarchical structure of either zooming into or zooming out from the place of 'where people are.' Results also illustrate that people employ hierarchies of salience in addition to hierarchies of spatial granularity. The chapter suggests a sequence of three (high-level) algorithms for the interpretation of place descriptions. Implementing these algorithms would allow for automatically interpreting most of the collected place descriptions. However, several descriptions have been found to be context-dependent and requiring careful semantic analysis, which has implications for the inclusion of place descriptions in location-based services. Results are preliminary because the proposed algorithms are based on place descriptions given in English only. A general application of the algorithms will need further investigation of certain similarities in structures of place descriptions with respect to other languages and cultures.

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5.3 Paper "Granularity of Locations Referred to by Place Descriptions"

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Granularity of locations referred to by place descriptions

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Place descriptions are a predominant means of human spatial communication. Their automated interpretation still poses a challenge for geospatial services. This paper explores one issue of this interpretation process: determining the level of granularity to which a localization of a described place is possible. Knowing this finest possible level of granularity supports resolving place descriptions, for example, in geographic information retrieval. In particular, the focus is on integrating spatial relations into this process. To this end, a mechanistic procedure for determining the level of granularity is proposed and applied to a place descriptions corpus. Feasibility of the procedure is evaluated in a comparison of place descriptions with people's self-reported position on a map. Findings show that the procedure delivers generally good results in agreement with the corresponding map locations.

1. Introduction

Natural language expressions describing locations would provide a powerful interface to interact with geospatial services since queries such as 'a hotel in downtown New York' or 'the library opposite the main station' are a natural way for people to refer to geographic features they conceptualize as *places*. However, an automated interpretation of such expressions is still challenging, while at the same time the need for better automated interpretation becomes more urgent with the ever increasing availability of user-generated data containing place descriptions.

Current best practice in the interpretation of place descriptions is place name resolution, looking at the nouns in the description only (Winter & Truelove, 2013). In contrast (or to enhance such approaches), this paper postulates that more sophisticated algorithms are needed for understanding place descriptions, based on a smart combination of human concepts of place, geographic data, and especially the relationships between the named features in the place descriptions. This paper will specifically focus on granularity and the role of spatial relations, studying whether and when they make descriptions more or less precise, i.e., whether they impact the granularity level of the corresponding noun phrase.

Granularity in our approach builds on the idea of Hobbs (1985) that people conceptualize the world in different, hierarchically nested levels of abstraction (also called grain-sizes) and choose a level dependent on what is of current interest. Knowing this level of granularity may help to inform and structure the dialog between machine and user. If an application specifies a particular level of granularity as required to guarantee a quality of service, then a dialog has to be continued until this level has been reached (or passed).

Place descriptions—descriptions answering a *where* question—typically have a structure, which is hierarchical by granularity (Shanon, 1979) that reflects the spatial knowledge organization in the minds of people (Hirtle & Jonides, 1985). These hierarchical structures are employed to decrease the cognitive effort of storing and retrieving information, and decrease ambiguity in spatial knowledge sharing. While information on coarser granularity levels normally disambiguates or anchors information at finer levels, the finest level is of particular interest when resolving the described location. Consider, for example, a person's location in 'an office on the second floor of the Engineering Building on Grattan Street'. An intelligent system should identify from all given references 'office' as the most relevant—in this case, the finest level of granularity. Additionally, the system should be able to handle a description such as 'in a café, opposite the Engineering Building', identifying the location 'in a café' as the relevant one, rather than 'opposite the Engineering Building', which would be less specific. This means, spatial relationships have to be interpreted because the influence region of a referenced feature differs in combination with different relations, for example, 'in', 'opposite' or 'near'.

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The automatic estimation of locations of human place descriptions is of high interest in applications that need to process large volumes of data in real time, for example, in crisis-mapping, but also in geographic information retrieval or in location-based services, such as automatic taxi call services, or car navigation systems with voice input. Inferring locations based on granularity and spatial relations is an important contribution towards the goal of an automatic interpretation of place descriptions.

The paper will suggest formal algorithms to identify the finest level of granularity to which a place description can be resolved. Overall, the hypothesis is that looking at spatial relations is essential in determining this level, and that the noun phrase of the finest level of granularity used in the description is only the lower bound for the granularity of locating a place.

To evaluate the hypothesis a corpus of place descriptions collected through a mobile game is analyzed. In previous work (Richter, Richter, Winter, & Stirling, 2012; Richter, Vasardani, Stirling, Richter, & Winter, 2013) a classification scheme for granularity levels and hierarchical structures has been developed that is applied here again, facilitating a systematic analysis of granularity in place descriptions. While the previous work used granularity to study hierarchical structures with a focus on the order of levels, the present work applies it to determine the finest level of localizability and to study the influence of spatial relations.

The next section presents relevant previous work. Section 3 elaborates this research in more detail and introduces a mechanistic procedure for determining the location granularity level. Section 4 explains how the mechanistic procedure has been evaluated, with the results of this evaluation presented in Section 5. Section 6 then discusses the evaluation and highlights its implications for place-based geospatial services.

2. Literature review

2.1. Location and place

Location refers to a placement in geographic space, describing an object either by spatial relations to other spatial objects—a relative placement—or by information such as coordinates or addresses—an absolute placement. The concept of *place* is the way people perceive, conceptualize, memorize, reason and communicate about space. The central role of place for cognitive spatial representations, and their externalization in language or sketches, has been broadly recognized (e.g., Couclelis, Golledge, Gale, & Tobler, 1987; Cresswell, 2004; Lynch, 1960; Mark, Freksa, Hirtle, Lloyd, & Tversky, 1999; Tuan, 1977). People rarely use geometry or metric expressions, but refer to named and unnamed places and qualitative spatial relations between them (Landau & Jackendoff, 1993; Levinson, 2003; van der Zee & Slack, 2003). Human place descriptions are linguistic expressions, and hence externalizations of what is in the minds of people.

Today's gazetteers (place name directories) collect communally recognized place names together with their types and a georeference, typically in the form of a point (Hill, 2006). However, human concepts of place differ from being points and are hard to formalize due to their context-dependency and their indeterminacy (Burrough & Frank, 1996; Bennett & Agarwal, 2007; Winter & Freksa, 2012).

2.2. Place descriptions

Place descriptions are expressions referring to places by their proper names ('Southern Cross Station') or by the names of their category ('the train station'). They may also be complex, linking different references by spatial relationships, either explicitly as in 'the hotel opposite the train station', or implicitly as in 'Carlton, Victoria', implying Carlton in Victoria. The structure of place descriptions has been studied in linguistics for a long time (e.g., Jarvella & Klein, 1982; Levinson, 2003; Schegloff, 1972; Talmy, 1983).

Place descriptions reflect the pragmatic principle of relevance (Sperber & Wilson, 1986). A place description is selected to be as efficient as possible, and as elaborate as necessary to avoid ambiguities or uncertainties (Dale, Geldof, & Prost, 2005; Tomko & Winter, 2009). Place descriptions are dependent on contextual factors such as the roles and relationships of the speaker and recipient, the assumed knowledge of the recipient, the location of the interlocutors, the communication channel and the purpose of the communication (Garfinkel, 1967).

If the context changes the description can change as well. For example, previous work has demonstrated different conceptualizations of indoor environments depending on tasks (Richter, Winter, & Santosa, 2011). Even types and relations can swap between contexts (Freksa & Barkowsky, 1996). Hirtle, Timpf, and Tenbrink (2011) address the effect of activity on granularity and relevance of information in the context of route directions.

2.3. Granularity in place descriptions

Discussing human perception of scale of space, Montello (1993) classified granularity of spatial information into four levels: geographic space, environmental space, vista space and figural space. Geographic space pertains to space of geographic scale much larger than the human body that can only be experienced through symbolic representations. Environmental space describes space much larger than the human body such that it needs multiple view points to perceive, whereas vista space concerns space that can be fully perceived from a single view point. Finally, figural space refers to locations of objects smaller than the human body. A related classification of levels of spatial granularity has been recently used to study hierarchical structures in place descriptions(Richter, Vasardani, Stirling, Richter, & Winter, 2013). In a comparison with other approaches to classifying space (Richter, Richter, & Winter, 2013), this scheme was found to be particularly suitable for classifying complex place descriptions on human scale—in this case in English. This scheme will be used in this study (cf. Section 4.2).

Place descriptions have been shown to be hierarchically organized by *part-of* relationships, which are reflected in cognitive representations and reasoning (e.g., Hirtle & Jonides, 1985) as well as in language (e.g., Plumert, Carswell, DeVet, & Ihrig, 1995; Shanon, 1979). An example is a postal address: a street is part of a city, which is part of a state. Also route descriptions typically apply hierarchical organization principles by granularity (Tenbrink & Winter, 2009; Tomko & Winter, 2009).

As pointed out by Levinson (2003), there are differences between languages in how locations are typically referred to in descriptions. For example, navigation instructions given and understood in Chinese differ from those given in English (Jacob, Zheng, Winstanley, Ciepłuch, & Mooney, 2009). Thus, making any approach applicable to another language would require a consideration of both the variable semantics of terms, and also the syntax of that language.

2.4. Spatial relations in place descriptions

Spatial relations are used to describe the location of one object in relation to another, normally by spatial prepositions. The semantics of spatial relations has been broadly studied in linguistics, psychology and cognitive science (Landau & Jackendoff, 1993; Talmy, 1983; Tenbrink, 2005). Qualitative relationships are typically preferred over quantitative relationships (Levinson, 2003; Talmy, 1983; van der Zee & Slack, 2003). Qualitative spatial relationships can be distinguished into topological relations (e.g., 'in'), distance relations (e.g., 'near'), and orientation relations (both projective and directional, e.g., 'left of', 'behind').

2.5. Representation and processing of spatial information in language

Qualitative spatial relations have been formalized in computational models for distances and directions (Cohn & Hazarika, 2001; Frank, 1992; Freksa, 1992) as well as for topology (Cui, Cohn, & Randell, 1993; Egenhofer & Robert, 1991). These models laid the foundations for qualitative spatial and temporal reasoning (e.g., Bhatt, Guesgen, Wölfl, & Hazarika, 2011), for geographic information retrieval (Jones, Abdelmoty, Finch, Fu, & Vaid, 2004), and for approaches to support qualitative spatial queries in spatial information systems (e.g., Yao & Thill, 2006). Furthermore, research concerning the semantics of place (Bennett & Agarwal, 2007) and semantics of linguistic spatial expressions (Bateman, Hois, Ross, & Tenbrink, 2010) is of relevance here, as semantics determines the applicability of specific relations. Tezuka, Lee, Kambayashi, and Takakura (2001) proposed using inference rules to define the semantics of spatial relations by means of geographic information retrieval, for example, analyzing web pages that claim to be *near* a specific landmark. However, despite the research on qualitative relations and locations, geospatial services still lack capabilities to adequately deal with complex place descriptions or to capture and store qualitative information about place and spatial relations (Winter & Truelove, 2013).

Place descriptions (or place names) are usually represented using coordinates or bounding box methods (Hill, 2006) in current information systems. Several studies suggest more elaborate methods addressing the uncertainty and shapes of the described locations, for example, using the point-radius method (Wieczorek, Guo, & Hijmans, 2004), probabilistic methods (e.g., Liu, Guo, Wieczorek, & Goodchild, 2009), or fuzzy-set approaches (Zadeh, 1975).

In contrast to methods for the representation of places that have been proposed in the literature, this study evaluates the identification of spatial granularity of a location specified by a place description. As the interest is purely in the classification of granularity, geo-references or shapes remain irrelevant. The automatic classification of granularity proposed here is novel.

3. Determining the location granularity of place descriptions

A place description is a verbal description answering a *where* question. A typical form to describe the location of something is:

PD : [[subject verb] preposition] NP

Brackets indicate optional elements of the place description *PD*. We expect the noun phrase *NP* to be a locative noun phrase, as in answering 'Where are you?' with '[[I'm] in] Brunswick'. A place description can be formed as a full sentence containing a subject and verbal phrase ('I am'). The subject (also figure object, locatum, or referent) is the entity whose location is specified. A preposition (e.g., 'in', 'at', 'near') indicating a spatial relationship defines the subject's location with respect to a reference object (also ground or relatum)—here identified by the noun phrase. The noun phrase can consist of simply a noun ('Brunswick'), a compound ('Brunswick Baths'), or a complex phrase aggregated from simpler noun phrases and relationships ('Brunswick, near the train station'). We will call a place description using only a single noun or compound a *simple* place description ('in Brunswick'), and those using a complex phrase a *complex* place description. Complex forms can be nested noun phrases (as in postal addresses), nested prepositional phrases (as in 'in the pub on Grattan St'), or independent sequences (as in ternary relationships, or in appositions).

This paper investigates spatial granularity in place descriptions, i.e., differences in (perceived or actual) extent of referenced geographic features. If these features are related (e.g., by containment) a hierarchy emerges. For example, in an address scheme of *street*, *city*, *state*, the complex place description 'Grattan St, Parkville, Victoria' is hierarchical because the features at finer granularity levels are contained in those at coarser levels.

People use different strategies for describing their location in complex descriptions (Plumert, Spalding, & Nichols-Whitehead, 2001); they can zoom out (relate a key locational feature to a feature of coarser granularity, as in 'in the pub on Grattan Street'), or they can zoom in (refine locations by place names of finer granularity, as in 'on Lygon Street, in front of Readings'). The purpose of these strategies is to disambiguate (there are many pubs in Melbourne) or to anchor unknown features to better known ones (Grattan Street is supposed to be known by the recipient). Algorithm 1 devises a formal procedure to identify noun phrases of finest level of granularity. As input, this procedure takes a classification scheme for spatial granularity (cf. Richter, Vasardani, Stirling, Richter, & Winter, 2013) and a place description that has been parsed using some natural language processing (NLP) approach. This paper is not further concerned with NLP, but takes this as given (for some state-of-the-art approaches see, e.g., Cunningham, 2002; Jurafsky & Martin, 2008; Manning & Schütze, 1999). The classification scheme used in the evaluation is presented in Section 4.2, however, the algorithms defined in this section would work with other hierarchical schemes as well.

More formally, the algorithm assumes that a given classification scheme *CL* assigns all locative nouns or compounds in a place description to a granularity level L_i that is part of a hierarchy consisting of 1 to *m* levels. L_1 is the lowest level (the most fine-grained) in the hierarchy; L_m the highest (most coarse-grained) level, ($L_1 < \cdots < L_m$).

Algorithm 1 first assembles the set of all locative nouns and compounds. This is expected to be straightforward after a place description has been NLP-parsed. It then determines the granularity level of each of these nouns, and finally identifies those that are on the finest level of granularity according to *CL*. Please note that the algorithm is notated for readability; it is not necessarily the most efficient way of implementing this.

For example, for 'I am on Lygon Street, in front of Readings' Algorithm 1 would return a building as the feature of finest granularity (Readings is a bookstore) assuming a nested hierarchy of granularities in which a building is on a finer level than a street.

The features of finest granularity level determine the particular level of granularity to which a locatum can be localized. That means in place descriptions there is one (explicit or implied) preposition characterizing a designated spatial relationship, which is the relationship between the locatum and one (binary relation) or two features (ternary relation) on finest granularity level. We will call this designated relationship the *primary relationship* of the place description. Correspondingly, we will call the given feature(s) the *primary feature(s)* of the place description. For binary relationships there will be one primary feature; for ternary relationships there can be two primary features.

Primary features are not necessarily the only features of finest granularity in a place description. For example, in '[I am] in the café [that is] opposite the library' both nouns are of the same level of granularity—building—but only the café has a direct relationship with the locatum (myself) even though, by transitivity, I am also

D. Richter et al./Computers, Environment and Urban Systems 41 (2013) 88–99 91

Algorithm 1. A formal procedure for identifying the features at finest level of granularity in a place description.

Algorithm 1: A formal procedure for identifying the features at finest level of granularity in a place description.

Data: PD: a simple or complex NLP place description; CL: a hierarchical classification scheme.
Result: F_{L_f}: a set of features of finest granularity level in PD

$N \leftarrow \{n_1 \dots n_k\}$; */* Determine the set N of all locative nouns and compounds n_i in PD. */*
forall the $n_i \in N$ **do**
  $L(n_i) \leftarrow CL(n_i)$; */* Identify level of spatial granularity of n_i. */*
  $F_L = F_L \cup \{(n_i, L(n_i))\}$; */* Add tuple of n_i and its granularity level to set of specified features F_L. */*
end
fgl $\leftarrow m$; */* Set finest granularity level to m, the coarsest level of CL. */*
forall the $f_L \in F_L$ **do**
  if `second(`f_L`)`<fgl **then**
    // If granularity of f_L is finer than fgl
    $fgl \leftarrow$ `second(`f_L`)` ; */* Set* fgl *to granularity of f_L */*
    F_{L_f}={`first(`f_L`)`} ; */* f_L becomes the new set F_{L_f} */*
  end
  else if `second(`f_L`)`=fgl **then**
    // Else if f_L is on granularity level fgl
    $F_{L_f} = F_{L_f} \cup$ {`first(`f_L`)`} ; */* Add f_L to F_{L_f} */*
  end
end
return F_{L_f}

opposite the library. As a consequence, if Algorithm 1 returns more than one result, i.e., if a place description has more than one element of finest granularity, the set of results has to be further processed to isolate the primary feature(s).

The primary relation may impact on the level of granularity to which the locatum can be localized. In the example 'I am on Lygon Street, in front of Readings', the location is not properly described by a building since the person is 'in front of', i.e., somehow related to the building, but not confined to the building. Thus, once the features on finest granularity level have been determined, these spatial relationships become the focus of analysis. Based on them, we need to reconsider the level of finest granularity to which a place description is localizable. While the finest granularity of a noun or compound is defined by the applied classification scheme, the location granularity needs to be defined with respect to the involved locative preposition that may modify the granularity of the classified noun or compound.

To resolve the granularity using the primary relations in a place description, a categorization of spatial relationships is needed. Different types of relationships will show different behavior in this respect. Research in formal models for qualitative spatial relations has distinguished topological relations, absolute and relative direction relations, and distance relations. However, prepositional phrases in language may vary in their degree of specification, i.e., they may be ambiguous in their classification with respect to these formal relations. For example, *at* can be used as one of two topological relations, either meaning inside ('[I am] at school') or outside but connected ('[arriving] at the school'—in front of the door), but it can also stand for the qualitative distance relation *near* ('[arriving] at the school'—having the building already in sight). Nouns without any preposition are similarly underspecified. For example, it is not entirely clear what is meant when someone only answers 'school' to the question 'Where are you?'.

Due to their highly underspecified meaning, cases including 'at' as primary relationship as well as noun phrases with no preposition will be excluded for this particular study. We have partly reported on them in separate work (Vasardani, Winter, Richter, Stirling, & Richter, 2012). However, our filtering method may result in the inclusion of some occurrences of noun phrases with no preposition, if a place description contains multiple features on finest granularity. We will treat these cases as topological relationships of containment in this paper, and will discuss the implications later.

We use the following categorization of spatial relationships in order to determine the actual level of granularity to which a place description is localizable. This categorization is based on commonsense reasoning and makes some default assumptions, which may be refined in future work.

1. Topological relations, including all nouns or compounds with no preposition (for which a default containment relationship is assumed), do not change the level of granularity found in the primary reference. As an example consider 'I am in the house'. While my own location is clearly smaller than the location of the house, my location is still not specified with more detail than down to the level of the house. I can be anywhere in the house. Similar arguments can be made for other topological relationships.
2. Relative orientation relations such as *in front of*, *behind*, or *left of*, do not change the level of granularity found in the primary reference. As an example consider 'in front of the house'. While this location is outside of the house, i.e., in principle in open space, such as on the street, it is still vaguely bound by a region of acceptance for being *in front of*. We argue that this region is of the same level of granularity as the primary feature; it is not a dimension coarser or finer. Similar arguments would be made for the other relative orientation relationships.

3. Absolute orientation relations such as *north of* do not possess this tight local flavor. Being 'north of my house' applies to a much larger region than the house itself occupies. Formal models work with sectoral regions, which are unbounded. While unboundedness in principle might be true, from the perspective of pragmatics one would expect some relevance of the chosen primary feature. Thus, we claim that absolute direction relations demarcate vaguely an acceptance region of one level coarser than the primary feature. One would refer to 'north of my house' when they are up the road, but not when they are in another city, north of their hometown. In this category of absolute directions we also count place descriptions that contain references to directed movements, such as '[I am walking] to the train station'. While relations, such as *to*, are not actually absolute direction relations, we expect similar behavior of these relations. The attached region of acceptance is larger than the primary feature since the approach can be from any direction towards this feature. The region contains the surroundings of the primary feature and is, thus, one level coarser than this feature.
4. Qualitative distance relations, especially *near* (other ones are rarely used), do coarsen the granularity found in the primary reference. Consider, for example, 'near the house'. The acceptance region for such a statement would clearly be larger than left of or in front of the house, hence categorically one level of granularity coarser than for relative directions.
5. Quantitative distance relations will be examined individually. These can include various measures, such as '75 m from Meville Road', '2 min past the train station', and can further occur in combination with orientation relations ('two buildings east of'). Given a certain distance measure from a reference object one could expect that the granularity stays the same if orientation relations are involved, and will be coarsened if not. This will depend on the ratio between the extent of the reference object and the distance from that object, i.e., whether the influence region of that object has been left or not.

Based on the considerations above, spatial relations r indicated by a locative preposition are assigned to an ordered set of spatial relation classes (RO), namely 1–*none*, 2–*topology*, 3–*relative orientation*, 4–*qualitative distance*, 5–*absolute orientation* (with $none <_{RO} \cdots <_{RO}$ *absolute orientation*). The class *none* is used if a primary feature occurs without a locative preposition. This order corresponds to a preference ranking of relations in determining the primary feature(s).

Algorithm 2 allows to identify the granularity of the location that is described by the primary feature(s) taking into account the primary relation(s). The algorithm takes as an input a NLP-parsed place description, a set of all features on finest granularity level (the output of Algorithm 1), and an ordered set of spatial relation classes (RO). It identifies all spatial relations that refer to features on the finest granularity level (lines 2–7). Next, it iterates these relations to find the primary relation(s), i.e., determines the relation(s) that are first in the order RO (lines 9–16). Finally, following the arguments made above, the algorithm increases the finest level of granularity to which a place description can be localized by one, if the primary relation is an absolute orientation or qualitative distance relation (lines 17–19). Again, this algorithm is notated for readability, not for efficiency.

As an example of how Algorithm 2 works, consider the place description 'near the train station, opposite McDonald's'. Both noun phrases are of finest granularity (building), and it would be reasonable to assign both relations as primary relation since both relations have the locatum as first argument. However, using the categorization RO of spatial relations, the relative orientation relation ('near the train station') is higher (later) in the order than the qualitative distance relation 'opposite McDonald's'. Accordingly, 'opposite' will be selected as a primary relation, and the finest level of granularity remains unchanged on building level.

The algorithm may return more than one instance of a primary relation if the locatum is used several times with the same relation (class) (e.g., in place descriptions such as 'near the pub, near the bank, and near the post office'), which currently is ignored. Section 6.1 discusses the implications of having more than one primary relation.

4. Experimental evaluation

This section presents an experimental evaluation of the algorithms of Section 3. The evaluation uses a corpus of place descriptions collected through a mobile game (Section 4.1), and a classification scheme for locative nouns and compounds (Section 4.2) that was originally developed to systematically study hierarchical structures in place descriptions. The outcomes of Algorithm 2 were manually checked for plausibility, which is made possible because the place descriptions in the corpus were all geo-referenced at time of collection (Section 4.3).

4.1. Corpus collection

The corpus of place descriptions was collected through the mobile location-based game *Tell-Us-Where* (Winter et al., 2011). The game was promoted in Melbourne and beyond via social networks, press and the local radio, and implemented to run on various current smartphone operating systems. In the game, players first had to confirm their GPS self-localization shown on a map (Fig. 1, left). To this end, they were able to adjust the phone's localization and change the zoom level of the presented map. In a second step, players submitted a textual description of their location (Fig. 1, right).

Players were motivated by the chance to win a gift voucher. The game did not capture any further information such as distribution of gender, age or educational backgrounds of the participants. Likewise, no information is available as to whether a participant generated a description based on observation or based on the map, and, therefore, no information as to how this might have influenced spatial judgements. However, while giving their descriptions players had no access to the map anymore, and preliminary tests did not show any clear correlation between map and place description.

All place descriptions were stored server-side. Records were directly attributed with a record number, the latitude and longitude of the self-localization, the map zoom level of the self-localization confirmation, the date, and an indication whether the submitted place description won a voucher.

4.2. Classification scheme

A multi-faceted classification scheme had been developed to label characteristics within the collected place descriptions (Richter, Richter, Winter, & Stirling, 2012; Richter, Vasardani, Stirling, Richter, & Winter, 2013). One of the characteristics classified is the granularity of the noun phrases. This classification was used in this paper's experimental evaluation. The corpus was manually annotated using the classification scheme. To test the robustness of the classification, a random sample of 10% of the corpus was independently annotated a second time, with sufficient support (interannotator agreement of 95%).

The classification scheme distinguishes between seven levels of granularity, namely L_1–*furniture*, L_2–*room*, L_3–*building*, L_4–*street*, L_5–*district*, L_6–*city*, and L_7–*country* (Table 1). These levels reflect the scales of space discussed by Montello (1993) in that they dis-

Algorithm 2. Identifying the finest level of location granularity of a place description considering spatial relations.

Algorithm 2: Identifying the finest level of location granularity of a place description considering spatial relations.

Data: PD: a NLP place description; F_{L_f}: the set of all features of PD on finest granularity level (output of Algorithm 1); RO: an order of spatial relation classes.

Result: llg: the locatable finest level of granularity for the place description PD.

```
llg ← second(head(F_Lf)) ;  /* Set current locatable granularity
to granularity level of the features in F_Lf.  */
R = {r_1 ... r_k} ;  /* Determine all spatial relations in PD.  */
forall the r ∈ R do
  | if f(r) ∉ F_Lf then
  |   | R = R\{r} ;          /* Only keep relations that refer to
  |   | features on finest granularity level.  */
  | end
end
pr = ∅ ;                     /* The set of primary relations.  */
forall the r ∈ R do
  | if pr = ∅ or r <_RO head(pr) then
  |   |   // If there are no primary relations yet or r's class
  |   | of relation is lower in the order of spatial relations
  |   | than those in pr
  |   | pr = {r} ; /* r becomes the new set of primary relations.
  |   | */
  | end
  | else if r =_RO head(pr) then
  |   |   // If the class of relation r is on the same level as
  |   | those in pr according to RO
  |   | pr = pr ∪ {r} ;                        /* add r to pr.  */
  | end
end
if r >_RO relative orientation then
  |   // If the relation class is higher in RO than relative
  | orientation relations
  | llg =llg +1;        /* increase the locatable finest level of
  | granularity by one.  */
end
return llg
```

tinguish differences in extent and accessibility as experienced by humans in their everyday lives.

4.3. Application and evaluation of algorithms

The algorithms presented in Section 3 were manually applied to the subset of the Tell-Us-Where corpus, which contains simple and complex place descriptions with explicit spatial relations between locatum and the feature(s) of finest granularity. Manually applying the algorithms ensured consistent quality in interpretation of place descriptions without the need to actually implement a NLP processing chain.

To produce this subset, the Tell-Us-Where corpus was filtered for topological relations, qualitative distance relations, relative orientation relations, and the relation *towards*. Descriptions referring to indoor places were excluded as here the GPS coordinates are assumed to be erroneous (usually, there is no GPS reception indoors, and a self-localization is too unreliable to position participants exactly). As noted above, further excluded were descriptions that contain the relation *at*. Quantitative distance relations as well as absolute orientation relations were not considered due to their small sample sizes in the corpus (see Section 5); place descriptions containing directed movement were included.

Given the recorded GPS coordinates each place description was visualized in Google Maps by constructing a KML-file with the Google APIs[1], which was used to check whether the finest granularity level obtained by the algorithms was appropriate. The comparison between position and verbal place description yielded one of three judgements:

1. Match: the granularity level to which a place description is locatable as returned by Algorithm 2 matches the position on the map. For example, 'near curtain street'[2] has a primary feature at street level and a primary relation that lifts the described location to district level. The mapped coordinate of the player is within the suburb of Carlton (a district containing Curtain Street), which means the classified granularity of the described location matches with the situation.

[1] http://maps.google.com.au/, https://developers.google.com/maps/.

[2] All examples from the Tell-Us-Where corpus are given in their original typing.

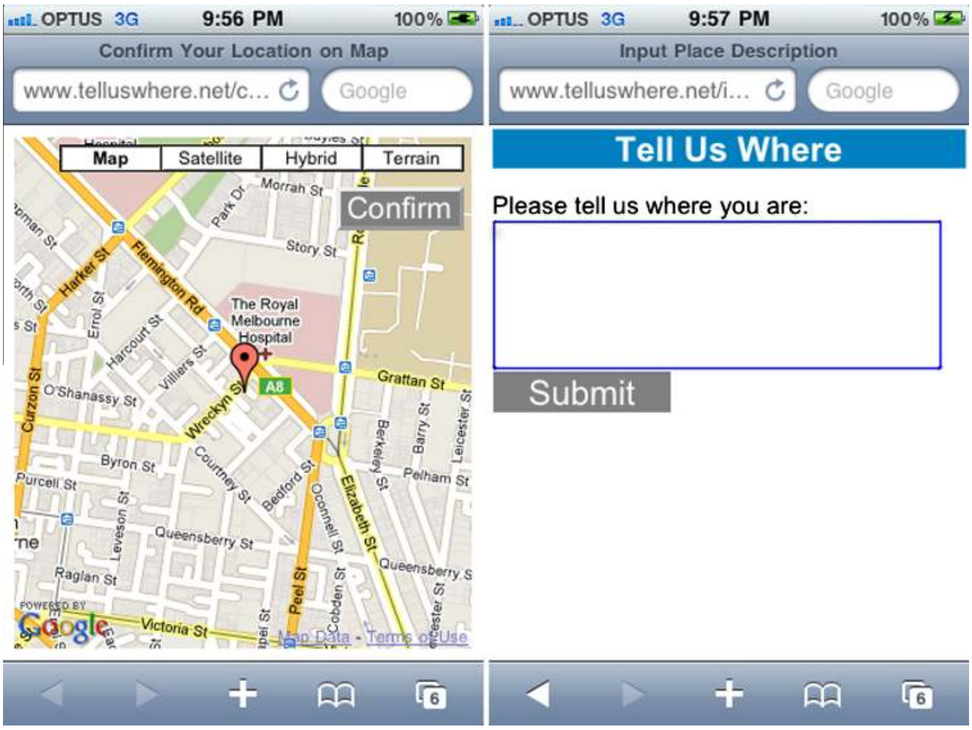

Fig. 1. Tell-Us-Where starts with a self-localization of the players (left), and then asks for a verbal description of where the players are (right).

Table 1
Granularity levels applied in classification.

Level	Description
Furniture	Location within a room referring to furniture (desk and bed), including small vehicles (bike) or natural features (tree)
Room	Location within a building (floor and office), or medium vehicles (car and boat)
Building	Location of a building, e.g., house number, street corner, building name, or large vehicles (train and ferry)
Street	Institution, public space or street level, i.e. larger than building and/or vague boundaries (park, hospital, mall, and university)
District	Suburb, rural district or locality, post code areas ('South Melbourne', 'downtown')
City	Town or city level, metropolitan areas ('Sydney')
Country	Everything beyond city level, including highways, rivers, states

2.
Mismatch: the coordinates do not match with the calculated granularity level. Consider again the example above. If a person reported 'near curtain street', but their mapped coordinates were outside Carlton, then we would observe a mismatch. However, cases where a coarsening actually was not necessary will not be classified as a mismatch as further discussed below (e.g., if in the example above the person was still 'on' the street according to the mapped coordinates). Reasons for mismatch can be due to user inaccuracy, or due to our proposed classification and interpretation of spatial relationships.
3. Not verifiable: the description cannot be verified as it contains unidentifiable references that require specific background knowledge about the participant (e.g., 'near my new job').

The evaluation assumes sufficient accuracy of the mapped coordinates. However, GPS accuracy from smartphone positioning is highly variable. Thus, initial localization by the phone may be off, requiring manual adjustments by the participants—which is assumed to have happened since the game explicitly asks for it.

To verify the identified granularity of a place description, its coordinates and geographic objects displayed in Google Maps were used for a visual assessment of the location. The following rules were applied to determine a match between calculated granularity level and participant's location according to their self-positioning. These rules distinguish between the primary relations that do not change the level of granularity (topology relations and relative orientation relations) and primary relations that change the granularity level (absolute directions and qualitative distances).

1. For place descriptions on district, city, and country level
   (a) Unchanged granularity: The coordinate position has to be in the given boundaries of the object referred to in the place descriptions.

Table 2
Frequency distribution of finest level of granularity (results of Algorithm 1).

Level	Number	Example
Furniture	4	'I'm next to the big *tree* near maccas', 'I'm sitting on a *bench*. near a building.'
Room	6	'I'm in the *court* in the estate opposite the new primary school.'
Building	84	'Selborne road near my *house*', 'I am near *Coles* in Noble Park.' 'at 604 St kilda rd near union St'
Street	129	'Just off *hoystead ave*', 'princes highway to *soldiers road*'
District	28	'Near *coburg*'
City	21	'About to get on hume to *sydney*' 'Near *gelong*'
Country	15	'Next to the *m*1'
Total	287	

   (b) Coarsened granularity: The coordinate position has to be within the next higher level ('near Brunswick' (district level) has to be still within Melbourne (city level) of which Brunswick is a suburb).
2. Street level
   (a) Unchanged granularity: The coordinate position has to be on street level including the bordering objects of a lower level of granularity (e.g., houses along a street).
   (b) Coarsened granularity: The coordinate position has to be within district level ('near Lygon Street' (street level) has to be within a suburb (district level) Lygon Street runs through).
3. Building level
   (a) Unchanged granularity: The coordinate position has to be in or in the vicinity of referenced objects including bordering objects of lower or higher levels ('opposite' of a building can be on the other side of a road—but not across two roads).
   (b) Coarsened granularity: The coordinate position has to be on street level of the reference object, including the street(s) that border the reference object.
4. Room and furniture level (in this study only outdoor references are considered, e.g. bench or tree; see Table 1)
   (a) Unchanged granularity: The coordinate position has to be within or outside the reference object, using its footprint extended by an edge length on each side, but not beyond.
   (b) Coarsened granularity: The coordinate position has to be within the building (for room level) or the room (for furniture level). For outdoor descriptions we assume a line of sight, and a border by features of the next higher level, (e.g. buildings) to define the matching area.

5. Results

A corpus of 2221 place descriptions was collected during six - months. Tell-Us-Where intentionally avoided automatic filtering mechanisms so as not to reject shortened or colloquial descriptions. Erroneous data, such as duplicates, nonsense or empty strings, had to be manually removed resulting in 1911 place descriptions. The data shows an unequal distribution within Australia related to population distribution, mobile internet coverage, and, most importantly, the social networks through which the game was promoted. Its highest concentration is in and around Melbourne.

In this paper, focus is on a subset of 287 place descriptions that contain explicit spatial relations in their finest level of granularity. As noted, indoor descriptions were excluded, as well as quantitative distance relations and absolute orientation relations.

In the following presentation of results it is important to keep in mind that the evaluation is not judging whether the submitted place descriptions are correct (e.g., match with what is seen on a corresponding map view), but rather evaluates whether the application of Algorithms 1 and 2 delivers meaningful results that correctly identify the finest level of granularity to which a given place description can be located. In other words, this evaluation is about the algorithms, not about the participants. Still, some mismatches may be attributed to participant errors or carelessness.

5.1. Primary features and the modification of finest granularity

Algorithm 1 returns the following distribution of finest granularity levels for the 287 place descriptions: 45% of the descriptions (129 out of 287) contain a primary feature on street level, 29% (84 out of 287) on building level, all other levels individually account for less than 10% of the subset. Table 2 displays the distribution of levels with examples illustrating the results (italics indicate primary features).

Algorithm 2 then identifies the finest level of granularity to which a place description is locatable when taking into account the involved primary relations. For 23% (67 out of 287) place descriptions there are multiple relations on finest level of granularity, and thus the spatial relation categorization is used to determine the actual primary relation. In most cases these are topological relations.

Algorithm 2 also determines whether the granularity to which the described place can be identified needs to be modified or remains unchanged. For 68% of place descriptions (196 out of 287) the granularity level was not modified as a topological relation (166 cases) or a relative orientation relation (30 cases) is used. The 166 cases of topological relations also include 39 cases that contain no primary relation (class 1–*none*); as discussed in Section 3 containment is assumed in these cases. For 32% or 91 out of the 287 place descriptions the finest level of granularity gets coarsened by Algorithm 2—in 60 cases due to the use of qualitative distance relations, in 31 cases directed movement is expressed using the relation *to[wards]*.

5.2. Comparison of location granularity and GPS coordinates

The computed granularity levels were compared against the coordinates submitted with the place descriptions to determine (mis-)matches of calculating the granularity levels to which place descriptions are locatable. The results of this test are shown in Table 3. 85% (244 out of 287) of the calculated granularity levels match, i.e., the respective coordinates are within the admissible geographic bounds according to the test procedure detailed in Section 4.3. Ignoring 18 cases of non-verifiable descriptions, the matching rate is 91% for the unmodified (167 of 184) as well as for the modified (77 of 85) granularity levels. Three place descriptions with their primary feature on country level contain primary relationships that would coarsen the granularity level beyond country level, which is the highest level in the classification (e.g. 'near the m3 freeway'). These specific cases are indicated in brackets in Table 3.

Table 3
Evaluation of results.

Level	Not modified		Modified		Not verifiable	Total
	Match	Mismatch	Match	Mismatch		
Furniture		1			1	2
Room	4				2	6
Building	40	7	2		5	54
Street	92	8	23	5	10	138
District	14	1	20	3		38
City	5		13			18
Country	12		16 (+3)			28 (+3)
Total	167	17	77	8	18	287

Table 4
Evaluation classified by primary spatial relations (preposition).

Preposition	Match	Mismatch	Not verifiable	Total
Topology				
Along	2		1	3
In	40	5	1	46
None	35	3	1	39
On	58	6	5	69
Outside	4	2		6
Through	2			2
Up	1			1
Relative orientation				
Across	1	1		2
In front of	16			16
Opposite	7		2	9
Over the road			1	1
Under	1		1	2
Qualitative distance				
By	2			2
Close to	2			2
Just off	4			4
Near	37	6	3	46
Next to	3	1	2	6
Towards				
To[wards]	29	1	1	31
Total	244	25	18	287

Looking at the results in detail, Table 4 lists (mis-)matches and verifiability for specific prepositions. The most common prepositions used are *on* (69 cases), *in* (46 cases), and *near* (46 cases). The algorithms achieve a match of 91% for *on*, 89% for *in*, and 86% for *near*. The 39 cases of *no preposition* that are taken to express containment match for 92% of the cases.

The mismatches (9%; 25 out of 287 cases) occur because the coordinates associated with the place descriptions are outside the admissible geographic bounds. All of the non-matching results differ in one or two levels of granularity to what would be acceptable. 13 of these mismatches occur on street level, seven on building level, four on district level, one is on furniture level. 16 of them contain topological relations, seven qualitative distances, one relative orientation, and one relation *to[wards]*. Ten of the 25 mismatches contain multiple features on the finest level of granularity, i.e., here one relation has been selected over another as primary relation according to the relation order.

The relative orientation mismatch is ‘across the road from crown casino, [...]’. Here, the coordinate is located one kilometer away from Crown Casino which is not admissible for the relation *across the road*. The mismatch for the relation *to* is on district level: ‘on way to phillip island’. According to the classification scheme islands are categorized on street level. The relation *to* coarsens this level to district level. However, the participant is still 40 km away from Philipp Island, which corresponds to country level. Among the 25 mismatches are also two locomotion descriptions: ‘about to get off at spencer street to go down to collins street’ (the person’s location is already on Collins Street); ‘just on scottsdale turning on to linsell’ (this person is already on Linsell Boulevard; see discussion in Section 6.1).

Six percentage of the place descriptions cannot be verified. Two unverifiable place descriptions are related to personal information requiring background knowledge (‘right near my new job’, ‘near our hotel across the road from the cemetery’), 16 of the descriptions use geographic features or addresses that are not locatable.

For 13 of the 77 descriptions (17%) that are modified in their granularity and identified as correct matches, this modification is not actually required. For example, with the description ‘near coburg’ (a suburb of Melbourne) Algorithm 2 coarsens the granularity to city level. A coordinate position within Coburg itself is still a correct match on city level (as it is within Melbourne), but the coarsening from district level would not be necessary in this case.

6. Discussion

At the outset of this paper, we assumed that the level of granularity to which the location of a person can be identified initially may be defined by the finest granularity level of all noun phrases used in a place description, but will then differ from this finest level depending on certain types of spatial relations used in the description. To this end, we defined two algorithms implementing a mechanistic procedure for the determination of the appropriate granularity level.

Overall, the results of the evaluation confirm both our hypothesis and the developed procedure. For 85% of the 287 place descriptions the user-submitted coordinate position is within the bounds of the admissible geographic region that is determined based on the given place description.

The high match rate for the modified cases might be explained by the fact that Algorithm 2 always coarsens the granularity level if a change is made, which consequently enlarges the admissible region for the coordinate position. The evaluation has shown that a coarsening is not always necessary. In specific situations (5% of the 287 place descriptions) the participant location could be located on a finer granularity level than the procedure suggests. This is the case if a participant submitting a place description is actually in a geographic feature while stating they would be in the area around it (e.g., by using ‘near’). It may be argued that this constitutes a mismatch, but the use of the preposition *near* implies a larger uncertainty by the participant regarding their own location, which is reflected by the coarsening.

In place descriptions with multiple features of finest granularity a relatively small percentage of mismatches (15%) strengthens the suggested preference order of spatial relationships to select primary feature and relation. For those cases where no primary relationship is used with the primary feature, we assumed a topological relation of containment. A match rate of 92% for these descriptions seems to justify this interpretation, still further research is needed here.

6.1. Limitations of the proposed mechanistic procedure and the evaluation

The proposed mechanistic procedure only accounts for information contained in a given place description, i.e., NPs and spatial relations. It ignores any contextual information (such as available from discourse history) or potentially available geographic data which might help resolve ambiguities. Accordingly, there are some cases where the algorithms cannot resolve the finest level of granularity. For example, 'just near the cemetery on lee street' contains two spatial references on the same level of granularity, 'near the cemetery' and 'on lee street', which are both on street level. According to the selection order detailed in Section 3, the algorithm would pick the reference containing topology relations ('on lee street') over that containing qualitative distance relations ('near the cemetery'). However, in this particular example the relationship between 'lee street' and 'the cemetery' is ambiguous and not resolvable without further information. The intended meaning may be 'I am just near the cemetery that is on lee street' or 'I am on lee street just near the cemetery' (in the latter case the cemetery might not be on Lee Street itself; in the former, I might not be on Lee Street even if some part of the cemetery is). In the former case, applying Algorithm 2 would result in a coarsening, as the relevant relation would be a qualitative distance relation. In the latter case, no coarsening would occur as the 'near the cemetery' part would serve to disambiguate and would be disregarded in determining the finest granularity level. Incorporating more knowledge into the procedure would help to resolve this example: in fact there is no cemetery on Lee Street, so the former interpretation could be discarded by incorporating a spatial query in the determination process. The person was indeed located on Lee Street.

Similar issues arise for place descriptions that use a primary relation several times, for example, 'I am near the pub, near the bank, and near the post office'. Because currently only the information contained in the place description is used, using three NPs instead of only one has no effect on determining the finest level of granularity. In this case, it will be street level (one up from building level). However, likely the person is located somewhere in the intersection of the 'nearness' regions of all referenced buildings. This can only be determined by first geo-referencing the NPs and then calculating this intersection region. Incorporating geo-referencing is an important part of future work (see below). A geometric interpretation of spatial relations is one of the long-term goals of this research; however, this involves being able to handle several context factors that require more and different data than available for this study. The Tell-Us-Where corpus only contains two examples where more than one primary relation is identified.

In some cases, the applied classification scheme results in granularity levels that are coarser than they would need to be. For example, 'off the princess' will result in a country level granularity classification, as highways ('the Princess Highway') are classified on country level. In this particular case, the person is actually in Melbourne (city level) as the Princess Highway runs through the city for a good part. Again, this can only be detected by geo-referencing features.

There are also some limitations to the evaluation methodology used in this study. First, it assumes that participants submitted a correct self-localization, as they were explicitly asked to verify their location on a map. However, there is no guarantee that all participants took the same level of care here. Further, assessing whether there is a match between coordinates and determined finest level of granularity relies on the accuracy and completeness of Google Maps. While the quality of Google's data is generally high, with many businesses, points of interests and other places of significance labeled on the map on higher zoom levels, some of the non-verifiable cases may be attributed to gaps in Google's data. Cross-checking with other data sources may (or may not) resolve these cases. Still, there is no data set available that would allow for verifying place descriptions, such as 'near my home,' that require background knowledge about the person giving the description.

Locomotion descriptions (e.g., 'heading to perth', 'just on scottsdale turning on to linsell') may need special considerations. Because the reporting person is in motion, by the time they submit their place description this may already be outdated. This is especially true for those describing short distances, as the second example. Here, the submitted coordinates indicate that the person is in fact already on Linsell Boulevard. Our procedure results in a mismatch for this example; however, at the time the person started typing their description might well have been accurate. But as noted above, such issues may also arise for locomotion descriptions covering longer distances. Dynamics in place descriptions provide a challenge to both the proposed mechanistic procedure and the evaluation method.

6.2. Future work

Currently, the proposed algorithms treat all relations of a given type equally. For example, the relations *next to*, *close to* and *just off* are all treated as qualitative distance relations and, thus, the same as the relation *near*; they are seen to be synonymous. However, there might be differences in their semantics that may alter the admissible geographic area for these relations and, consequently, potentially change their effect on determining the finest level of granularity. An analysis of these effects is one step in future work. Applicability and meaning of different relations may also change depending on the granularity of the reference objects. For example, we did not observe any relative orientation relations on district, city, or country level. The analysis in this paper excluded quantitative distances and absolute orientation relations (e.g., 'north of'). This is not a principled decision, but was based on the lack of sufficient samples. Further data collection, possibly encouraging such descriptions, may allow for their analysis as well, but it seems such relations are not a preferred option in producing place descriptions.

Also, to validate the categorization of spatial relationships proposed in Section 3 well-designed cognitive experiments are needed. These experiments would likely either have a large number of participants describe various spatial scenes, or have them (dis-)agree to such descriptions, in order to collect a statistically relevant sample of how spatial relationships are used.

Further, prominence of features may result in increased size of the area defined by the *near* relation, or conversely the area may be narrowed if there exists a more prominent landmark close to the referred location (cf. Tezuka, Lee, Kambayashi, & Takakura, 2001). Accounting for such effects—if they exist—requires a measure of a feature's prominence, which is ongoing research in geographic information science.

Extending the algorithms to also account for geographic data in determining the level of finest granularity seems like a logical next step. Among others, this would allow us to also consider those parts of a place description that serve to disambiguate a place. As mentioned above, currently the proposed procedure only takes into account information explicitly contained in the place descriptions. Therefore, it is safe to ignore disambiguating expressions. However, if the procedure is extended to exploit geographic data, these expressions would support a localization of the described place. Such references may further partition the region identified by the algorithms, restricting possible locations. Consider the example 'in front of melbourne central station at swanston street'. Here, 'at swanston street' is a disambiguating expression that would restrict the location of the participant (to being on the side of Melbourne Central Station where Swanston Street is), thus, partitioning the area defined by the 'in front of' relation. The 'front' of Melbourne Central Station is not unambiguous as the station is within a large shopping center that has at least four entrances on four different streets, and the main entrance (most likely defining the front) may be assumed to be on either Swanston Street or Elisabeth Street on the opposite side of the station.

Although the application of the proposed algorithms has been carried out manually, their implementation can be realized by natural language processing frameworks and gazetteers to extract references to locations. A natural language processing component would have to identify locative nouns and compounds as well as respective locative prepositions indicating a spatial relation. Then an automated evaluation of the algorithms using the applied rules is basically possible given geo-referenced (vector) data, their appropriate allocation to different levels of granularity, and basic functionalities such as point-in-polygon tests or buffers.

Finally, the classification scheme may be revisited to include further levels of granularity, which may result in a better approximation of the respective location. For example, Google's Geocoding API distinguishes accuracy of geocoded addresses in levels of *country*, *region* (state, province, prefecture, etc.), *sub-region* (county, municipality, etc.), *town* (city, village), *post code* (zip code), *street*, *intersection*, *address*, and *premises* (building name, property name, shopping center, etc.). This is similar to the classification used in this paper, but introduces some intermediate levels not used so far. The effects of these additional levels may be tested in a follow-up study using the same evaluation method (cf. also Richter, Richter, & Winter, 2013).

7. Conclusions

This paper explores one aspect of the automated interpretation of natural language place descriptions, namely the level of granularity to which these are locatable. To this end, a mechanistic procedure was proposed and used to analyze a subset of the Tell-Us-Where mobile game corpus. Results show that the procedure is feasible. It produces results that match in most cases with the corresponding map positions. Some mismatches are caused by ambiguity in the structure of complex place descriptions. Integrating geographical data or contextual knowledge is required to identify and eliminate such cases. Other issues are underspecified concepts (for instance 'at'), and the potential refinement of granularity levels in combined place descriptions with multiple references. They should be considered in future to enhance the approach.

Overall, the presented findings contribute to the understanding of place descriptions in general and localization of the described places in particular. They present one step further towards an automated resolution of natural language descriptions of place, and thus support smart location based services and intelligent search techniques.

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5.4 Paper "Impact of Classification Approaches on the Detection of Hierarchies"

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The Impact of Classification Approaches on the Detection of Hierarchies in Place Descriptions

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Abstract The chapter investigates the identification of hierarchical structures in place descriptions. Different approaches to classify spatial granularity will be compared and applied to a corpus of human place descriptions. Results show how hierarchical structures as well as deviations depend on the respective classifications. They further indicate certain difficulties in developing a suitable classification of spatial references. Findings contribute to the understanding of human spatial language, and thus the development of flexible mechanisms for their interpretation and integration in location-based systems.

1 Introduction

Place descriptions are a common way to describe *where* things are. Their hierarchic organization is broadly recognized and evident from various studies (e.g., Plumert et al. 2001; Shanon 1979; Richter et al. 2013). People employ different concepts and perspectives when dealing with space dependent on the tasks that they perform. They conceptualize the world at different granularities (or grain-sizes) by abstracting from it those things that serve their present interests (Hobbs 1985). Accordingly, hierarchical structures emerge in place descriptions that reflect a

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hierarchical organization of spatial knowledge in the mind (Hirtle and Jonides 1985; Stevens and Coupe 1978), and serve the purpose of anchoring the location of a thing or event to known places and of disambiguating places of specific granularity levels.

Over the years, a number of classification schemes for spatial granularity have been proposed for various purposes. It often depends on which classification scheme is applied whether a particular place description has a recognizable hierarchical structure, and whether this structure is sequential or contains gaps. For example, using a typical address scheme of *street name*, *city*, *country* the place description 'Grattan St, Australia' is hierarchical, but contains a gap. Using instead a scheme inspired by embodied experience, say *personal space* (everything at arm's length) and *environmental space* the same place description becomes flat, i.e., non-hierarchical.

Since human place descriptions, for reasons of efficiency, usually follow Grice's maxims of conversation (Grice 1975) they usually refer to relevant places. Then levels of granularity matter: to characterize the resolution of a place description, and to identify the places of coarser resolution that disambiguate the ones of finer resolution (e.g., disambiguating Melbourne, Victoria, from Melbourne, Florida). While hierarchical structures in place descriptions are important in human conceptualization of and communication about space, we claim that their identification in automated processes will depend on the applied classification of spatial granularity. This may also cause the detection of gaps or flat structures. Alternatively, there may be other reasons for these deviations, for example, cognitive principles of salience and prominence, that may explain these deviations. We will investigate two research questions:

1. How are hierarchies of place descriptions related to the applied classification scheme; and,
2. Can deviations (in form of flat structures or gaps) be avoided by improving the classification?

To address these questions we will study a corpus of human place descriptions collected in a mobile game, in which participants had to answer the question 'Tell us where you are' (Winter et al. 2011). While place descriptions are context-specific and can refer to all kinds of things in space, our focus here is on people's locations, which suggests a finest resolution limit related to the size of the human body. The corpus was previously analyzed to learn about general hierarchical structures in place descriptions using a particular classification scheme (Richter et al. 2013). In this chapter the previous approach will be compared with other classification schemes to see whether we find support for the research questions above, and whether issues emerge from the comparison that were not known before.

The research findings will contribute to our knowledge on hierarchical organization principles in place descriptions. Granularity plays a crucial role for developing systems for automated interpretation of and reasoning on spatial information (e.g., answering *where* questions); understanding hierarchical structures is essential in this regard.

The chapter is structured as follows. Section 2 reviews related work; Sect. 3 presents our approach, Sect. 4 introduces the corpus and analysis methods, Sects. 5 and 6 then present and discuss the results.

2 Related Work

This section reviews related research regarding place descriptions and their hierarchical organization. It further summarizes approaches to classifying spatial granularity.

2.1 Hierarchical Place Descriptions

Spatial mental representations are acquired through direct and indirect interaction with the environment (Ishikawa and Montello 2006; Siegel and White 1975). The mental organization of spatial knowledge is based on an individual's acquisition of this knowledge, and distorted by preferential reasoning through anchor points (Sadalla et al. 1980), i.e., asymmetric relationships caused by different salience, and hierarchical structures defined by partonomies (Hirtle and Jonides 1985; Stevens and Coupe 1978). If salience causes asymmetric relationships it imposes an order independent from partonomies. Measures for salience have been suggested (e.g., Raubal and Winter 2002; Sorrows and Hirtle 1999), but they are local measures, providing an order only in a given context. They do not lend themselves to building a global hierarchy.

Verbal place descriptions reflect these cognitive organization principles of spatial knowledge. They inherit the hierarchical organization of spatial knowledge (Plumert et al. 2001; Richter et al. 2013; Shanon 1979). Hierarchical structures are employed to decrease the cognitive effort of storing and retrieving information, and to decrease ambiguity in spatial knowledge sharing. From a linguistic perspective, place descriptions are referring expressions (Dale 1992) to locations of objects. Gestalt theory suggests that their focus on the object identifies the figure, and other location references are taken from the ground (the environment) (Talmy 1983). Normally people select the most relevant referents from a possible set of referents. The principles of relevance are two-fold: a cognitive principle that human cognition is geared to the maximisation of relevance, and a communicative principle that utterances create expectations of optimal relevance (Sperber and Wilson 1986). These conversation principles are reflected, for example, in *generating* hierarchically organized place descriptions (Kelleher and Kruijff 2006; Tomko and Winter 2009).

2.2 Classification Approaches for Spatial Granularity

Granularity describes varying levels of abstraction of a phenomenon, which form a hierarchy. Either the finer levels of a hierarchy contain representations that are more detailed than the coarser levels, as in cartographic generalizations, or the finer levels will contain smaller objects that are aggregated at coarser levels, as in partonomies (Timpf 1998). Different understandings and (formal) definitions of granularity exist (e.g., Bittner and Smith 2003; Hobbs 1985; Keet 2006). A hierarchy will necessarily contain at least two different levels of granularity.

Rosch et al. (1976) introduced the concept of *basic objects*, which relate to the preference of basic level categories in cognitive categorization from sub- or super-categories (e.g., the preference for using the word 'table' instead of 'kitchen table' or 'furniture', when asked 'where is the cup?'). Similarly, basic-level geographic categories exist (Smith and Mark 2001) (e.g., 'country', or 'city', with their superordinate category 'place', or subordinate categories such as 'home country').

To select references for destination descriptions Tomko and Winter (2009) developed a model based on three types of hierarchically structured data: a containment hierarchy of districts, the likelihood of using specific streets, and the visual and semantic salience of landmark buildings. Also *SpatialML* (Mani et al. 2010), a markup language for the annotation of natural language references to places, uses spatial granularity in form of tags for different feature types, such as *country*, *state* or *populated place*. Granularity was also applied for the study of place descriptions (Plumert et al. 2001; Richter et al. 2013; Tenbrink and Winter 2009).

3 Place Descriptions and Their Hierarchical Classification

This chapter studies spatial granularity as in differences in perceived or actual size of geographic entities. If these entities are related (e.g., by containment) a partonomy hierarchy emerges. In an address scheme of *street name*, *city*, *state*, 'Grattan St, Parkville, Victoria' is a hierarchical place description by virtue of the entities on finer granularity levels being contained in those on coarser level. Skipping 'Parkville' in that description, a *gap* emerges because there is an element of the schema missing in the sequence. Removing 'Grattan St' or 'Victoria' on the other hand would not create a gap as the remaining elements adhere to the sequence of granularity levels.

In their seminal work on basic categories, Rosch et al. (1976) pointed out that cognitive economy requires a balancing between fine-grained distinctions and fewer categories. With too few categories, relevant distinctions cannot be made, and with too many categories, cognitive representation and reasoning become slow and hard to maintain. Applied to place descriptions and their contained hierarchical structures, there needs to be a balance between enough granularity levels to pick up these structures, and few enough levels not to introduce gaps that are not really there.

This section will define place descriptions and the types of possible hierarchical structures (Sect. 3.1), and then introduce a selection of existing classification approaches (Sect. 3.2) that will be analyzed in the remainder of the chapter.

3.1 Hierarchies in Place Description

A place description is a verbal description answering a *where* question. A typical form to describe the location of something is:

$$PD : [[subject\,verb]\,preposition]\,NP$$

with brackets indicating optional elements of the place description *PD*.

The noun phrase *NP* is a locative noun phrase, as in '[[I'm] in] Brunswick'. It can consist of just a noun ('Brunswick'), a compound ('Brunswick Baths'), or a complex phrase aggregated from simpler noun phrases and relationships ('Brunswick, near the train station'). The noun phrases refer to geographic entities of a particular level of granularity. For example, 'intersection' is of finer granularity than 'downtown'. A hierarchical structure in a place description is defined as a structure consisting of 1 to n granularity levels. L_1 is the lowest level (the most fine-grained) in the hierarchy H; L_n the highest (most coarse-grained) level: H: $(L_1)(L_2)(L_3)\ldots(L_n)$. A place description can expose one or multiple levels of granularity that form one of the following hierarchy patterns (cf. Richter et al. 2013 for further details):

- *Strictly hierarchical*: a place description showing a strictly monotonically increasing or decreasing behavior towards the spatial hierarchy. The sequence of granularity levels is either zooming in or zooming out; no duplicates of the same levels occur.
- *Partially hierarchical*: a place description showing a monotonically increasing or decreasing behavior. Duplicates of the same levels occur.
- *Flat*: a place description that shows constant behavior towards the spatial hierarchy. At the same time monotonically increasing and decreasing (no zooming in or out), they form a special type of partially hierarchical descriptions.
- *Unordered*: a non-monotonic place description.

The order of granularity levels in hierarchical place descriptions determines zooming behavior, but also whether gaps within the pattern occur or a gap-less sequence is formed.

3.2 Classifying Spatial Granularity

Freundschuh and Egenhofer (1997) reviewed a number of classifications of spatial granularity with a focus on scales of *human conceptions of space*. The reviewed classification models cover varying numbers of distinguishing levels. Some only distinguish between large and small space (Kuipers 1978), or between elements of different dimensions to model the structure of a city (Lynch 1960). Others have four (Montello 1993; Zubin 1989), five (Couclelis and Gale 1986), or six levels of granularity (Kolars et al. 1975).

We will investigate a subset of these reviewed models here, selected by their potential to adequately capture spatial granularity in place descriptions. Coming back to the argument of distinctions versus number of categories (Rosch et al. 1976), having at least four different levels of granularity was identified as one prerequisite. The number of different levels alone is not sufficient, however. For example, while Zubin's taxonomy of spatial objects and spaces (Zubin 1989) has four levels, the classification is highly dependent on the view point. An object may be classified as type *A* in one situation, and as type *B* in another, which leads to ambiguous and unstable classifications.

Freundschuh and Egenhofer also developed their own categorization of space. In general, this classification is similar to that of Montello (1993) (see below), however, it also includes *panoramic* and *map* space, which are not useful for classifying human place descriptions. Their scheme is excluded from the investigation in favor of Montello's. The other classification scheme selected from their review is the one by Kolars et al. (1975). These two will be compared with a classification scheme by Richter et al. (2013), and the geocoding scheme of the Google Geocoding API Version 2.0, which provides also a geocoding accuracy value. In the remainder of the chapter these classifications will be referred to as *Montello*, *Kolars*, *Richter*, and *Google*, respectively.

Montello

Montello (1993) proposed four major classes of *psychological spaces*:

- *Figural space* is small in scale relative to the human body and is apprehended without any locomotion. It includes both the flat pictorial space and the space of small manipulable objects.
- *Vista space* is larger than the human body but can be visually scanned from a place without moving around.
- *Environmental space* is large in scale relative to the body. It includes the spaces of buildings, cities and neighborhoods and typically requires locomotion for its apprehension. It is learned over time.
- *Geographical space* is much larger than the human body and cannot be experienced directly, instead it is perceived only over time and typically through symbolic representations, such as maps.

Theoretically, vista space can range from small objects up to the world ('the surface of the earth as seen from an airplane, however, would constitute a vista space because of its small projective size and our consequent ability to apprehend it directly from our seat in the plane' (Montello 1993, pp. 315–316). However, place descriptions focus on the question *where* people are in their surrounding space ('in the plane'). The notion of vista space has thus been adapted to better reflect the context of place descriptions and to get a clearer separation between vista and environmental space.

Kolars

Kolars et al. (1975) defined a hierarchy of six geographic spaces based on the level of interaction among and between people and their surrounding environment:

- *Personal space* is the small space within a person's arm's length that involves only a few people and primary interaction modes of voice, touch, taste, and smell.
- *Living and working space* is the space of the personal daily life (the home, the office), the space of effective personal communication. It involves one-to-one interactions among 40–500 people and audio or visual modes of communication.
- *House and neighborhood space* constitutes, for example, a group of houses or structures along a street, such as gardens or small parks. It is the space of impersonal interactions beyond face-to-face communication that use amplified audio-visual communication modes. Distances may range from 30 to 300 m (may be limited by the line of sight). It may involve larger groups of people (100–1,000) who do not know each other but share some common purpose (e.g., places for meetings, private domiciles, parks, playgrounds).
- *City-hinterland space* consists of neighborhoods and specialized areas which have different functions than a cluster of households (e.g., towns and cities). It is the space of the daily information field within about 60 min travel distance, within the range of the local news media, and urban institutions such as local and metropolitan governments, involving 50,000–10 million people.
- *Regional-national space* constitutes of clusters of cities, is the space of legal-economic-political systems, and involves interaction via national network of news media among 200+ million people.
- *Global space* is the space of the trade and cultural exchange with interaction via international communication networks; that involves five billion and more people.

Richter

Richter et al. (2013) distinguished seven levels of spatial granularity. The *furniture level* refers to locations of furniture (in- or outdoor), including small vehicles (a bike) or natural features (a tree), whereas the *room level* describes a specified location within a building. It can also include medium vehicles, such as cars or

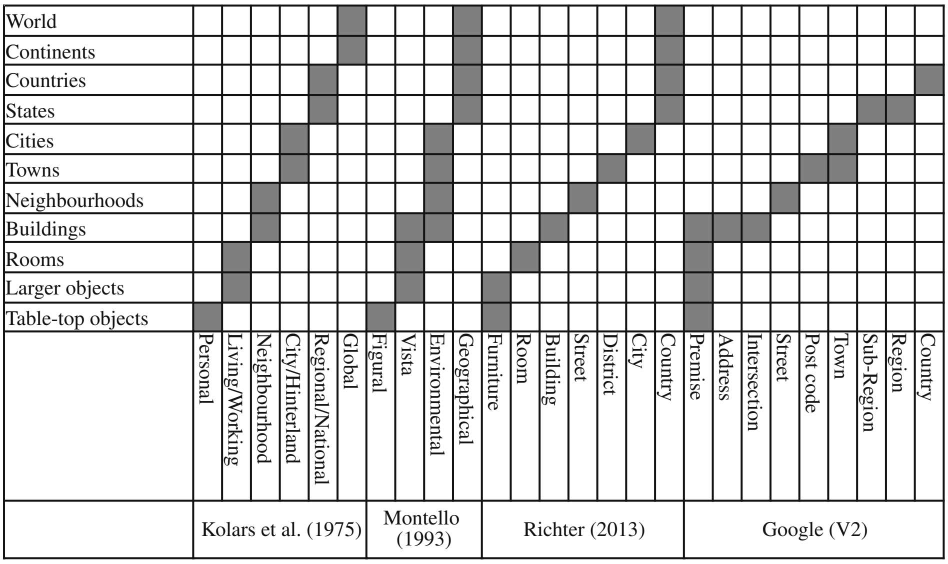

Fig. 1 Models of spatial granularity [extending on Freundschuh and Egenhofer (1997, p.369)]

boats. The *building level* refers to locations of a building, for example a house number, a street corner, a building name, or large vehicles (train, ferry). *Street level* refers to institutions, public spaces or streets. *District level* includes suburbs, rural districts, localities and post code areas. Finally, *city level* refers to a town or a city, including metropolitan areas, and *country level* to everything beyond city level, including highways, rivers, national parks, and states.

Google

The Google Geocoding API Version 2.0[1] returns an accuracy value with each returned placemark, which indicates the resolution of the given result. For example, the geocode ‘28/207 Queens Ave, Hawthorn 3122 Melbourne’ may return 8 (address level accuracy), i.e., the geocode is on the order of resolution of a street address. A geocode for ‘Australia’ would return 1 (country level accuracy). Overall, Google distinguishes the following accuracy levels: *0-unknown location*, *1-country*, *2-region* (state, province, prefecture), *3-sub-region* (county, municipality), *4-town* (city, village), *5-post code* (zip code), *6-street*, *7-intersection*, *8-address*, and *9-premise* (building name, property name, shopping center) level accuracy.

Summary

Figure 1 summarizes the four classification models investigated in this research, by matching their respective space categories to the categories introduced in

[1] https://developers.google.com/maps/documentation/geocoding/v2/index

Table 1 Categories of space and the corresponding geographic entities [category names according to Freundschuh and Egenhofer (1997)]

Class	Geographic entities
Table-top objects	Small manipulable objects (pen, book)
Larger objects	Furniture (desk, bed, bench), small vehicles (bike), or small natural features (tree)
Rooms	Location within a building, or within parts belonging to it (office, floor), or medium vehicles (car, boat, bus)
Buildings[a]	Location of a house or building (residential, commercial), e.g., house number or building name (engineering dept, Spencer street station, at work), home, street intersections, large vehicles (train, ferry)
Neighbourhoods	Institution, public space or street level, this includes infrastructure (railway, tramline), public spaces (golf course, university, cemetery, hospital, mall), natural features (port, bay, lake, hill, park, reserve, paddock)
Towns	Rural locality, suburb, post code areas (Brunswick, South Melbourne), or categorical information (central business district, downtown, city center)
Cities	Town or city level, and metropolitan areas (Canberra, Melbourne)
States	References beyond city level up to state level (Victoria)
Countries	References on country level, including highways, national parks, rivers
Continents	Continent level (Europe, Australia)
World	World level (Planet Earth)

[a] The distinction between *houses* and *buildings* made by Freundschuh and Egenhofer (1997) is not made here

(Freundschuh and Egenhofer 1997). Different geographic entities are assigned to these different categories according to Table 1.

4 Comparing Different Classification Models

The presented classification models were compared using a corpus of place descriptions collected through a mobile game (Winter et al. 2011). Participants in the game were asked to first confirm their GPS self-localization, and then to submit a textual description of their location to answer the question ‘tell us where you are’. Apart from these tasks and knowing they could win a gift voucher, no further context was given to the participants. 2,221 geocoded place descriptions of Australian locations were collected.

From these place descriptions, a subset of 722 place descriptions contains at least two spatial cues. These were analyzed regarding their hierarchical structure according to the different patterns identified in Sect. 3.1. Each of the four classification models was applied to each place description.

In the classification, all spatial relationships were ignored. A single exception to this has been made in classifying references at building level for Montello’s vista and environmental space. References at building level are classified as *environmental* *space* if the person is inside, taken either from prepositions such as *in*, *inside*, *at* (cf. Vasardani et al. 2012), or from the lack of prepositions (e.g., addresses). It is also classified *environmental space* if the person is outside, but uses a preposition synonymous to *near*. In all other cases, for example, in presence of prepositions such as *in front of* or *opposite*, a reference at building level will be classified as *vista space*.

Generally, references to multitudes of objects (e.g., apartments) are classified at their next coarser granularity level. For example, in some classification scheme 'apartment' may be classified as room level, but 'apartments' as building level. The finest and the coarsest granularity level in each classification schema are collectives of everything at and below, or everything at and beyond this level of granularity. For example, Google's classification scheme does not provide a granularity level below *premises*, so in this scheme everything smaller than a premise (e.g., an apartment) will be classified on this level.

As stated in Sect. 3.1, place descriptions may exhibit a strictly hierarchical, partially hierarchical, flat, or unordered structure. Applying the different classification schemes to the place descriptions will reveal how these schemes may result in different structures, i.e., how well they pick up variations in spatial granularity, or produce gaps in these structures. For example, 'I am at Union House, located in the University of Melbourne in Parkville, Melbourne' would result in a flat structure when applying Montello's classification, because all four references would be classified on an *environmental space* granularity level. Using Kolar's classification, the same description would be partially hierarchical (without gaps), classifying the Union House and the University of Melbourne as *houses and neighborhood space*, and Parkville and Melbourne as *city-hinterland space* granularity. The classification of Richter would identify a strictly hierarchical structure with a sequential order of the four levels *building* (Union House), *street* (the University of Melbourne), *district* (Parkville), and *city* (Melbourne). Likewise, Goolge's scheme results in three levels of granularity: *premise* (Union House), *street* (the University of Melbourne), and *town* (Parkville and Melbourne). With more than one cue on the same level of granularity, the latter structure is partially hierarchical.

5 Results

The text length of a place description in the subset varies between nine and 586 characters, and is 55 characters on average. The average number of cues (NPs) varies between two and 20 and is 2.9 on average. In total 2,071 NPs have been classified using all four classification schemes.

None of the place descriptions contains a reference to a table-top object. Likewise, none of the participants referred to an object on *world* level. Accordingly, only three of Montello's levels get used in the classification (namely *vista*, *environmental*, *geographic*); with Kolar's scheme only *living/working*, *neighborhood*, *city/hinterland*, and *regional/national* get used.

Using Montello's classification, most entities are on *environmental space* granularity (1,722, or 83 %), while *vista space* and *geographic space* levels only make up for 12 and 5 % of the NP respectively. Kolar's classification has the *neighborhood* level as predominant level, with 1,465 (71 %) of the NPs on this level; 395 (19 %) are on *city/hinterland* level, and 5 % each on *living/working* and *regional/national* level. The classification by Richter yields 16 NPs (1 %) in *furniture* level, 95 (5 %) in *room* level, 620 (30 %) in *building* level, 845 (41 %) in *street*, 275 (13 %) in *distric*t, 120 (6 %) in *city*, and 100 (5 %) in *country* level. Google's classification results in the following distribution: 568 (27 %) in *premise* level, 121 (6 %) in *address* level, 42 (2 %) in *intersection* level, 845 (41 %) in *street* level, 19 (1 %) *post code* level, 376 (18 %) *town* level, 29 (1 %) in *region* level, 71 (3 %) in *country* level. The granularity level *sub-region* for counties or municipalities was not used in the subset of place descriptions.

Table 2 presents the 722 place descriptions for which hierarchic (strict or partial), flat or unordered patterns have been identified for the different classification schemes. The numbers in brackets indicate the number of place descriptions that contain gaps.

Kolars' and Montello's classifications both result in a large number of flat patterns, 341 (47 %) patterns in Kolars' classification and 459 (64 %) in Montello's, respectively. On the other hand, both Montello's and Kollar's classifications only result in a few gaps, while both Richter's and Google's schemes have a significant number of gaps. However, in case of Google's scheme, the classes *premise*, *intersection*, and *address* do not truly form a (sequential) hierarchical structure; stating an address as place description, for example, essentially excludes also stating a street intersection. And a postcode actually provides the same information as the name of a town and, thus, can be considered optional (i.e., it is on the same granularity level as *town*). Taking this into account, the column Google* in Table 2 shows more realistic results for Google's classification scheme. Most notable, 80 % of the previous gaps disappear; on the other hand there are slightly fewer strictly, and more partially hierarchical and flat structures. In the following Google* will be used.

Most gaps only skip one or two levels in each of the classification schemata. Since Montello's scheme only covers three levels, only one-level gaps appear here. These gaps will also appear when applying the other schemata, because all other

Table 2 Comparison of hierarchical structures in different models

Hierarchy	Kolars	(gaps)	Montello	(gaps)	Richter	(gaps)	Google	(gaps)	Google*	(gaps)
Strict	181	(26)	91	(7)	386	(125)	381	(368)	354	(76)
Partial	130	(9)	134		128	(43)	123	(112)	135	(33)
Flat	341		459		99		111		127	
Unordered	70	(5)	38		109	(23)	107	(101)	106	(10)
Total	722	(40)	722	(7)	722	(191)	722	(581)	722	(119)

*This merges premise, intersection, address to one class, and *post code* and *town* to another, and excludes the class *sub-region* for counties and municipalities schemata distinguish between finer levels of granularity. There are seven place descriptions that contain one gap in Montello's *environmental space*. For Kolar's scheme, 33 of the place descriptions with gaps only skip one level (*neighborhood* or *city/hinterland space*); two of them skip two levels. The other two schemata have some place descriptions that skip over more than two levels, i.e., up to three (Google*) or four (Richter).

In some cases these gaps may also not be sequentially linked. For example, using the classification by Richter, 'on the skybus to the airport, entering tullamarine fwy' contains a reference on *room* level (the Skybus), on *street* level (airport), and on *country* level (Tullamarine Freeway), skipping *building*, *suburb*, and *city* level. In Montello's classification this description would be strictly hierarchical and sequentially linked with references located in *vista space* (the Skybus), *environmental space* (airport), and *geographical space* (Tullamarine Freeway).

In Kolar's classification 31 of 37 (or 84 %) of gaps are located on *city/hinterland* level ('just off the burwood highway at mcdonalds', 'billabong in the national park', or 'at the royal park opposite the princess highway'), 6 (16 %) on *neighborhood space* ('up at eildon this weekend on the drag boat'). As mentioned before, in Montello's classification seven place descriptions skip the *environmental space* (e.g. 'traveling down the nepean highway in the car'). In Richter's classification, from 244 gaps in hierarchical structures nine (or 4 %) are on *room* level ('in bed at home'), 25 (10 %) on *building* level, 71 (29 %) on *street* level ('in wallan outside coles'), 86 (35 %) on *district* level ('melbourne ligon street'), and 53 (22 %) on *city* level ('241 royal parade parkville vic 3,052'). Finally, the Google* classification yields 69 (or 45 %) on *street* level, 31 (21 %) on *postcode/town* level, and 51 (34 %) on *sub-region/region* level.

6 Discussion

Overall, the presented results support our hypothesis: Different classification schemes yield different results in their identification of hierarchical structures. They also differ in the identification of deviations from regular, sequential hierarchical structures. Montello's or Kolars' classifications, which distinguish fewer classes, tend to produce more *flat* structures than those by Richter or Google. However, the latter two result in many more gaps that appear in the hierarchical structures.

In some more detail, the results show an interplay between the number of categories used in a classification scheme, the distinctions they can pick up, and the deviations that appear. Some of the gaps in one scheme disappear by applying another. For example, applying Richter's classification scheme to 'Under the tree at marinda park' would skip *room* and *building* levels (trees are classified on *furniture* level, while parks are on *street* level), whereas applying Montello's classification scheme would result in only two granularity levels without a gap (classifying a tree on *vista space* and a park on *environmental space*). Some descriptions that are considered flat in other classification schemes, are classified as hierarchical in Montello's classification due to the special consideration of buildings regarding their categorization into *vista* or *environmental space* granularity. For example 'tram stop near myer', 'i'm in front of ella bache near the foodcourt, or 'In Gopal's restaurant, diagonally opposite of Melbourne City Hall would contain both references on *vista* ('tram stop', 'in front of ella bache', 'opposite or Melbourne City Hall') and also *environmental space* ('myer', 'near the footcourt', 'in Gopal's restaurant), whereas Richter's scheme would consider all these references to be on *building* level.

In general, the application of classification schemes to place descriptions (or any spatial description) requires to assign geographic entities to specific granularity levels. This may introduce some biases and may lead to results that are not always correct. For example, 'Melbourne' may be categorized to be on *city* level, however, the term 'Melbourne' is ambiguous, as it may refer to the suburb Melbourne, the 'City of Melbourne', which is the local government area incorporating the city center and a number of inner-city suburbs, or the region 'Greater Melbourne', which comprises of all suburbs that form the metropolitan area 'Melbourne'.

Other terms, such as 'home', are underspecified regarding the geographic area they refer to. It was classified on *building* level in Richter's classification scheme, but it could also refer to a city or country, depending on the context. And there are types of geographic entities which instances may be of significantly different scales, such as islands, rivers or highways. These would require a more flexible, case-based categorization. The same holds for businesses, such as cafes or restaurants, which sometimes may be part of a larger building (being on granularity level *room*), and sometimes occupying a whole building. Implementing such flexible categorization would avoid some of the gaps that emerged in the presented experiment.

Still, in the end there are deviations that cannot be explained just by the particularities of the respective classification schemes. There are 87 place descriptions that exhibit a flat structure regardless of the chosen classification scheme. These include locomotion descriptions (e.g., 'walking down greeves street to spring street'), and descriptions that just mention multiple references on the same granularity level (referring to several geographic entities of the same type), such as 'between melville rd and reynolds pde'. Furthermore seven place descriptions contain gaps regardless of the classification approach. Descriptions such as 'a loud street intersection, just before crossing the yarra', 'travelling down the napean highway in the car', 'yarra river sitting on the docks', 'whale rock, tidal river' contain all a gap in Montello's *environmental space*, and thus, as well when applying the other schemes.

7 Conclusion

We have investigated several classification schemes to characterize the levels of spatial granularity in place descriptions. These schemes were applied to human place descriptions to characterize their hierarchical structures. Place descriptions were collected through a mobile game a largely underspecified context, resulting in a wide range of different descriptions being collected. The aim of the paper was to test the hypothesis that the identification of hierarchical structures in place descriptions depends on the chosen classification schema. The results show support for the hypothesis. Most of the deviations from hierarchical structures can be related to the respective classification. However, a remaining 10 % can not be explained by the applied schemes, such as flat structures where people seem to employ hierarchies of salience, or locomotion descriptions.

We argued that too few categories in a scheme prevent from making relevant distinctions, and too many categories could exacerbate cognitive representation and reasoning. Applied to place descriptions, a balance between enough granularity levels to pick up these structures, and few enough levels to avoid artificial gaps is desirable. In this respect the classification schemata of Richter and Google behave better.

Studies of this kind will be context-dependent—place descriptions of the location of people will show different expectations to a classification scheme than place descriptions of geological faults line or of a fork on a table. However, in this chapter we have compared schemata all designed for the particular purpose. We have found strong evidence to use Richter’s (or alternatively Google’s) scheme for complex place descriptions at human scale.

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