A Semantic Region Growing Algorithm: Extraction of Urban Settings

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Abstract Recent years have witnessed a growing production of Volunteer Geographic Information (VGI). This led to the general availability of semantically rich datasets, allowing for novel ways to understand, analyze or generalize urban areas. This paper presents an approach that exploits this semantic richness to extract *urban settings*, i.e., conceptually-uniform geographic areas with respect to certain activities. We argue that *urban settings* are a more accurate way of generalizing cities, since it more closely models human sense-making of urban spaces. To this end, we formalized and implemented a *semantic region growing* algorithm—a modification of a standard image segmentation procedure. To evaluate our approach, shopping areas of two European capital cities (Vienna and London) were extracted from an OpenStreetMap dataset. Finally, we explored the use of our approach to search for urban settings (e.g., shopping areas) in one city, that are similar to a setting in another.

Keywords Semantic region growing · Image segmentation · Urban settings · Place affordances

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1 Introduction

Human conceptualization of space is one of the main research questions in Geographic Information Science, Spatial Information Theory, and Urban Planning and many other disciplines (Lynch 1960; Mark and Frank 1991; Tuan 1979). Many have studied the way humans navigate through or reason about space (Lynch 1960; Raubal 2001). Building upon the findings of such studies, computational models and applications have been developed that simulate human conceptualization in order to improve usability of software or to equip computer systems with basic intelligence.

A particularly interesting question concerns the conceptualization of places: The ambiguous meaning of the term poses a considerable challenge to knowledge engineers whose task is to design computational models of places. As of today, the most commonly adopted strategy is to represent places by means of points of interest (POIs). This approach, however, disregards many of the aspects that seem to characterize human conceptualization of places: (i) there is empirical evidence (Montello et al. 2003) that people typically conceive a place as a region; (ii) different persons tend to associate different spatial footprints to the same place (Montello et al. 2003); (iii) there are indications (Schatzki 1991, p. 655) that conceptualization of a place relies on the activities that are possible to carry out at that spatial location—i.e., what some refer to as place affordances (Jordan et al. 1998). Accordingly, the approach of representing places with POIs suffers from several drawbacks: places are indicated as specific points rather than vague or approximated regions; while a POI is associated with a precise feature type, the place affordances are not explicitly indicated and it is up to the user to map from an activity (e.g., to eat) to a feature type (e.g., a restaurant or a fast-food). Going even further and focusing our attention on activities, it is easy to see that activities are usually not restricted to a single place and have an extent in space and time that involves several places of different kinds. Shopping, for example, can involve sitting down at a cafe, or going to a bank to withdraw money. Humans are able to search for areas that *afford* an activity without having to specify the exact type of place they are looking for. For example, if the task is "to buy a pair of shoes and perhaps a coat", humans can, based on experience or knowledge, think of areas where they are most likely to find such things (e.g., a shopping street or shopping mall). In such a case, the individual shop is less of concern since the exact object to buy is not determined yet. Rather, it is the constellation or setting of shops and maybe restaurants, that is of importance when attempting to find an area suitable for an activity.

Inspired by techniques employed in image processing and land use detection, we present a semantic region growing algorithm that exploits tag information from OpenStreetMap[1] data to produce areas corresponding to a setting of interest. The

[1]http://www.openstreetmap.org.

question of how to find such settings is, to our knowledge, not well addressed and this paper presents preliminary results of an attempt to extract urban settings based on activities (or affordances). The underlying hypothesis is that people form regions by mentally grouping space into conceptually homogeneous areas in terms of the activities they potentially offer. Therefore, place types (represented by tags) are employed as a means of computing potential activities. This work aims at extending an ongoing effort to find generalization techniques of urban areas that transcend common administrative partitions. The contributions of this paper are twofold:

- An implementation of a semantic region growing algorithm, that can be used to find Urban Settings from point data with place-type information (POI's);
- A discussion and preliminary evaluation of using the approach to search for similar areas in other cities.

The paper is structured as follows: Sect. 2 discusses some of the literature on Place and Settings, introduces some work on Image Processing, and outlines OpenStreetMap's knowledge representation scheme and main data quality issues. Section 3 introduces the proposed method to find appropriate settings. Section 4 presents preliminary results of a case study and Sect. 5 will discuss the outcomes, limitations and future work. In Sect. 6, we conclude our work.

2 Related Work

In this section, we investigate related work concerning places and settings, image segmentation, and OpenStreetMap.

2.1 Places and Settings

The concept of *place* plays an increasingly important role in GIScience (Winter et al. 2009; Winter and Truelove 2013) and the ontological discussion about how to model it is ongoing (Couclelis 1992; Humayun and Schwering 2012; Jones et al. 2001; Vasardani et al. 2013; Winter and Truelove 2013). Many suggest that the semantics of the term *Place* is tightly bound to the idea of affordance and activities (Jordan et al. 1998; Scheider and Janowicz 2014). As a matter of fact, drawing the connection of action to place, is essential for the ability to plan (Abdalla and Frank 2012). Schatzki asserted that: "[…] places are defined by reference to human activity" (Schatzki 1991, p. 655). He positions human activities as the central concept for understanding the construction of places. Furthermore, he explains that such representations of places organize into settings, local areas and regions. This general notion of hierarchical structuring of space is relatively undisputed and supported by findings of other researchers (Couclelis and Gale 1986; Freundschuh and Egenhofer 1997; Montello 1993; Richter et al. 2013). How these levels of abstractions are formed, though, is unclear. For example, common administrative units of abstraction do not always correspond to what people have in mind about regions (Meegan and Mitchell 2001).

The focus of this work lies on *settings* which, according to Schatzki, can either be demarcated by barriers (e.g., apartment building) or identified by bundles of activities that occur in them (e.g., a park, or shopping street). Ontologically speaking, they can either be categorized as entities of *bona fide* (i.e. physical, sharp, crisp) or *fiat* (i.e. non-physical, imaginary, human-driven) type (Smith 1995). Since this work is concerned with entities larger than apartment buildings, such as shopping areas, fiat objects will be the main type of inquiry. The entities are therefore of the vista-space scale (Montello 1993), since they can be learned by human activity.

2.2 Image Segmentation

Image segmentation builds on the idea of grouping pixels into areas. Professionals in Remote Sensing make use of image segmentation techniques to categorize satellite images in terms of land use or land cover, e.g., see (Shimabukuro et al. 1998). One implementation of such an image segmentation algorithm is known as *Region Growing*, where homogeneous pixels of the image are coalesced (Adams and Bischof 1994; Fan et al. 2005). Starting from a seed pixel, the algorithm recursively expands into the adjacent neighborhood and classifies each pixel in it as similar or not, according to certain constraints. All adjacent pixels similar to the initial pixel are then merged into a group, referred to as *segment*.

2.3 OpenStreetMap

OpenStreetMap is a web project, whose main goal is to create a digital map of the entire world, and is essentially the prototype of Volunteer Geographic Information (Goodchild 2007). The geometric footprint of spatial features is represented by means of a simple and exceptionally flexible scheme consisting of

- *nodes*: pairs of coordinates (longitude and latitude) used to represent point features;
- *ways*: lists of nodes used to represent line and surface features;
- *relations*: sets of nodes, ways, or other relations mainly used to represent features consisting of several parts.

The thematic or semantic aspect of spatial features is managed through a tagging system where each geometric feature is described by an arbitrary number of tags. As the OpenStreetMap project evolved and prospered over time, its community developed a set of *tagging guidelines* that describe which tags should be used for a specific feature. Before contributing new information to the database, mappers are asked to carefully read these guidelines. Yet, they are neither obligated to respect such guidelines nor are their contributions subject to rigorous control.

It has been shown that geometric-wise the OpenStreetMap dataset is rapidly approaching the coverage and the precision of commercial ones (Zielstra and Zipf 2010). The freedom granted by the tagging system yielded a semantically very heterogeneous dataset (Mooney and Corcoran 2012). Thus, different volunteers tag the same feature differently or, conversely, use the same tag to annotate conceptually different features. Moreover, some recent works (D'Antonio et al. 2014; Keßler and de Groot 2013) investigated the possibility of assessing the trustworthiness of VGI data by analyzing the historical evolution of features in a dataset. However, semantic quality of VGI data remains, at the time of writing, a major issue.

3 Conceptual Spatial Region Growing Algorithm

In this section, we explain the idea of conceptual settings, the formalization of setting segmentation, and the implementation of the algorithm.

3.1 Conceptual Spatial Settings

City maps are cartographic representations of spatial data partitioning space into discrete chunks that represent physical or social (administrative) objects. These objects are either defined by their physical extent or by authoritative institutions. Following the argument of Schatzki (1991), there are places that are falling into the same abstract category due to certain constellations of things present and activities possible. It is the focus of this work to use a data driven approach to find such conceptual spatial settings derived from the places an activity needs. For instance, the description of a shopping area—exemplarily illustrated in Fig. 1—should obviously contain shops, but can also include parking spots, playgrounds, restaurants, and so on.

Furthermore, once homogeneous areas have been defined, a formal description of the area offers abilities to search, compare or cluster such regions. Figure 1 depicts three conceptual shopping settings together with their respective frequency

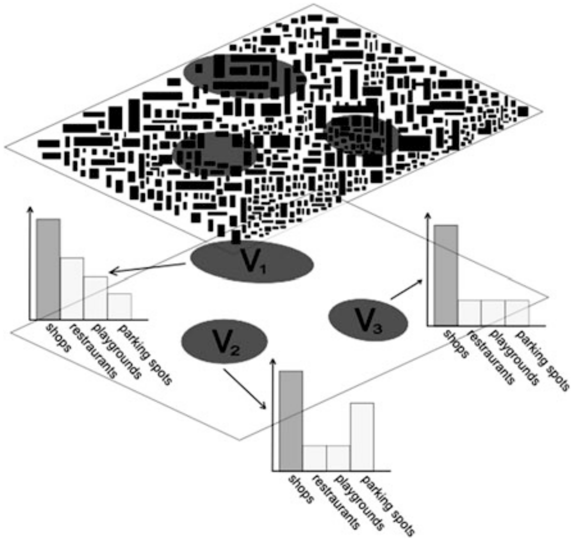

Fig. 1 Schematic visualization of conceptual shopping areas: V_1, V_2, V_3

distribution tags. While each one of them contains shops, places like parking spots and restaurants are also part of the constellation "shopping area" (see Fig. 1).

Fine-grained or significant differences in place constellations can reveal how much the composition of a setting is suitable for someone's preferences, or can be used to identify flaws in the naturally evolved or planned structure of a city. For instance, when people are required to drive with a car due to an inefficient public transport system, or out of personal necessity, shopping areas with parking spots are certainly more attractive destinations. Cities without dedicated parking spots in the vicinity of shopping areas will ideally have an efficient public transport. Therefore, using an aggregate description of the coalesced areas as a semantic signature enables comparison and assessment of conceptual settings. The composed area offers not only single place affordances, but rather encompasses a set of affordances which are seamlessly interconnected.

3.2 Formalization

The goal of the proposed approach is to identify areas according to the activities *afforded* by constellation of places contained in it. We draw inspiration from a technique used in image segmentation and adapted the region growing algorithm (Adams and Bischof 1994) to become a *semantic region growing* algorithm in the following manner:

1. The area of interest $\mathscr{M}$ (a city map in our case) is partitioned into n non-overlapping cells $C = \{c_i : i = 1, \ldots, n\}$ such that $\mathscr{M} = \bigcup_{i=1}^{n} c_i$.
2. The essential concept of our region growing approach is that of a description D: a formula consisting of one or more predicates specifying the membership of a single cell c_i to a specified setting S, e.g., a description can be: "contains at least one shop and restaurant".
3. What in image segmentation jargon is called a *segment*, is directly comparable to a setting: a set of contiguous cells satisfying the same description D. A setting $S \subseteq C$ is a subset of the cell partition C and is called *complete* if it cannot be extended further with adjacent cells.
4. The segmentation of a map $\mathscr{M}$ according to a description D produces a (possibly empty) set $\mathscr{S}$ of settings such that $\bigcup_{S \in \mathscr{S}} S \subseteq C$. A segmentation $\mathscr{S} = \{S\}$ is called *complete* if it consists of only one setting such that $S = C$.
5. As image segmentation relies on a similarity function that is used to decide if two neighbor pixels are similar, so does our approach rely on a Boolean function f_{sim} which, given a cell c and a description D, verifies whether c adheres to D.
6. Settings identified through the same description D are pairwise disjoint, i.e. it holds that for all $x, y \wedge x \neq y : S_x \cap S_y = \emptyset$. Settings that adhere to different descriptions can overlap, e.g., a park that crosses a shopping street.

3.3 Implementation

Semantic region growing as used here, is aimed at segmenting or extracting settings according to a description D and a set of m cells, referred to as *seeding cells* $C_{seed} = \{\tilde{c}_1, \tilde{c}_2, \ldots, \tilde{c}_m\}$. In the case that a seeding cell $\tilde{c} \in C_{seed}$ matches a given description D—i.e., $f_{sim}(\tilde{c}, D) = TRUE$—and it is not yet classified as a member of another setting adhering to the same description D, $\tilde{c}$ will be the starting point of a new setting: A recursive process extends the starting cell until the adjacent neighborhood does not adhere any longer to the description D. We can either process all cells as seeding cells $(C_{seed} = C)$, or find all cells in C that adhere to the description D and use them as C_{seed}—both cases yield a robust result in contrast to random seed generation. For instance, if C_{seed} contains only five seeding cells, then the result will be at most five segments/settings. Note that a settings S will not be identified by the algorithm if $S \cap C_{seed} = \emptyset$—i.e., if no seeding cell lies within S. Additionally, it is possible that during the growing process starting from a seeding cell $\tilde{c}_i$ and building a setting S_i, another seeding cell $\tilde{c}_j$ is integrated in S_i. When the algorithm will process the seeding cell $\tilde{c}_j$, this will not give raise to a new setting since it has already been assigned to the setting S_i. The *semantic region growing* technique is implemented as shown in Algorithm 1.

Algorithm 1 Semantic Region Growing Algorithm

procedure FindSettings(*description* D, *seeding cells* C_{seed}, *cells* C)
    new $\mathscr{S} \leftarrow \emptyset$
    for all $\tilde{c} \in C_{seed}$ **do**
        if $(\forall S_i \in \mathscr{S} : \tilde{c} \notin S_i) \wedge f_{sim}(\tilde{c},\, D)$ **then**
            new $S \leftarrow \{\tilde{c}\}$
            $\mathscr{S} \leftarrow \mathscr{S} \cup \{S\}$
            RegionGrowing(D, $\tilde{c}$, C, S, $\mathscr{S}$)
        end if
    end for
end procedure

procedure RegionGrowing(*description* D, *cell* c, *setting* S, *list of settings* $\mathscr{S}$, *cells* C)
    new $N \leftarrow neighbours(c, C)$
    for all $n \in N$ **do**
        if $(\forall S_i \in \mathscr{S} : n \notin S_i) \wedge f_{sim}(n,\, D)$ **then**
            $S \leftarrow S \cup \{n\}$
            RegionGrowing(D, n, S, $\mathscr{S}$, C)
        end if
    end for
end procedure

As can be seen in the implementation of Algorithm 1, the size of the adjacent neighborhood of a cell can be adapted by using a customized implementation of $neighbours(c, C)$ to specify requirements such as larger or restricted neighborhoods. In any case, a larger neighborhood can be used to ensure a better coverage or restrictions can be used to separate settings.

4 Case Study

In this section, we present a first evaluation of our approach, explain in an illustrative use case how to differentiate between settings of the same conceptualization, and analyze the results.

4.1 Setup

For a first evaluation of our approach, we attempted to identify shopping areas in two cities. Therefore, we collected data from Metro Extracts,[2] a website that provides parts of the OSM datasets for cities and their surroundings. We

[2]http://metro.teczno.com/.

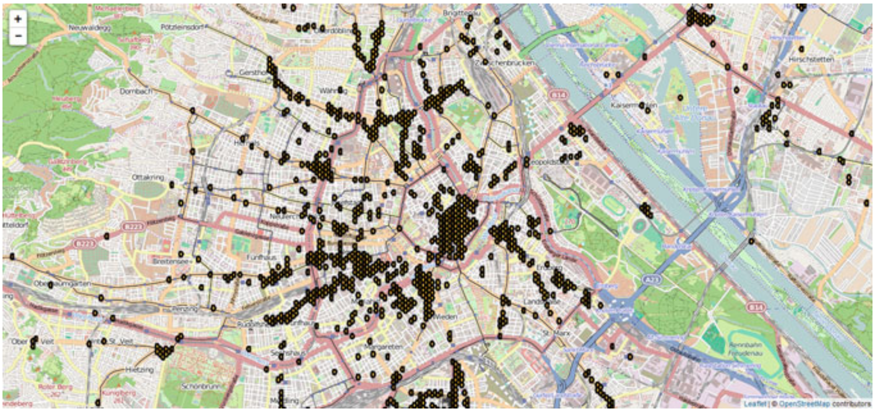

Fig. 2 Visualization of the results identified by the semantic region growing algorithm in Vienna

downloaded and parsed the datasets for Vienna and London. By using GeoTools,[3] an open source library for geospatial data, we set up a fine grained hexagonal grid, whereby the side length of the cells was set to 0.0005 degrees, and preprocessed the OSM data by assigning the nodes and their tags to the cells. The rules for our description are based on the following assumptions.

> A cell has to encompass at least two places where you can *shop* (i.e., shops of every type) or a cell has to encompass at least two tags that relate to places where someone can get something to eat or drink a coffee (e.g., restaurants, fast-foods, cafes).

These simple constraints were sufficient to find the commonly-known *shopping areas* in Vienna, plus many smaller clusters that can be interpreted as local shopping and leisure areas. The segmentation result for Vienna is shown in Fig. 2. Using the same description, we employed the algorithm on the dataset of London and obtained a comparable result (see Fig. 3).

Arguably, there is no *hard* method to evaluate the result, since the topics of interest are conceptual settings, that do not really allow for a ground truth. Nevertheless, an estimation of feasibility is still possible, either by looking at descriptions found on the internet (e.g., Wikipedia, Tourism Guides) or by comparing the results to expert knowledge (i.e., people familiar with the city). Indeed, Mariahilferstraße and Oxford Street are well-known shopping streets that have been correctly identified as part of shopping settings by our algorithm. Also, detailed explorations of some other clusters identified in the Vienna dataset, consistently revealed that all larger found regions can be considered shopping areas.

[3] http://docs.geotools.org/.

Fig. 3 Visualization of the results identified by the semantic region growing algorithm in London

4.2 Use Case Example and Analysis

Now that the areas are identified, the next step is to compare the identified shopping areas in Vienna and London. Consider the following scenario.

> Alice grew up in London and she knows from experience that in the *urban setting* of Oxford Street there are plenty of places to withdraw money (i.e., ATMs and banks), that there is a big choice of cafes and restaurants to go for lunch or get something to drink. Also, there is a large diversity of shops and several tourism attractions that she sees when moving from a shop to another. Alice plans a trip to Vienna and she would like to find, in advance, areas of the city that are similar to her idea of Oxford Street.

To model these preferences and action possibilities, we defined the following four features, which will later be used to define a similarity-distance to other identified shopping areas/settings:

1. The number of tags in a setting of type bank or ATM n_1
2. The number of tags in a setting of type restaurant or cafe or fast food n_2
3. The number of tags in a setting of type tourism n_3
4. The number of different shopping types (i.e., subcategories of shops) n_4

We denote by $\tau_{(S)}$ the total number of cells in a given segment/setting S. We set the absolute values n_1, n_2, n_3 and n_4, which we defined in the list above, in relation to the area of the setting, which yields normalized density values (where m is the number of defined features):

$$r_i = \frac{n_i}{\tau_{(S)}} \quad \forall i = 1, \ldots, m \tag{1}$$

To explore the similarity in respect to our defined feature vector, we are now considering the following distance measure:

$$\sum_{i=1}^{m} |r_i^{(S_1)} - r_i^{(S_2)}| \tag{2}$$

Equation (2) formalizes the sum of the absolute values of the differences between corresponding features for two settings with normalized values $r_{(\cdot)}^{(S_1)}$ and $r_{(\cdot)}^{(S_2)}$.

Based on the use case scenario explained above, Alice wants to know what are similar shopping areas in comparison to London's Oxford Street in Vienna. Therefore, we denote by $r_i^{(S_1)}$ the values of Oxford Street and make a comparison with the larger sized extracted conceptual shopping settings of Vienna, since we normalized the data based on the size of the settings. According to the total deviation [see Eq. (2)] the best matching setting is the area found around the *Inner City* and the second one is the cluster around the lower part of *Mariahilferstraße*, which is illustrated in Fig. 4.

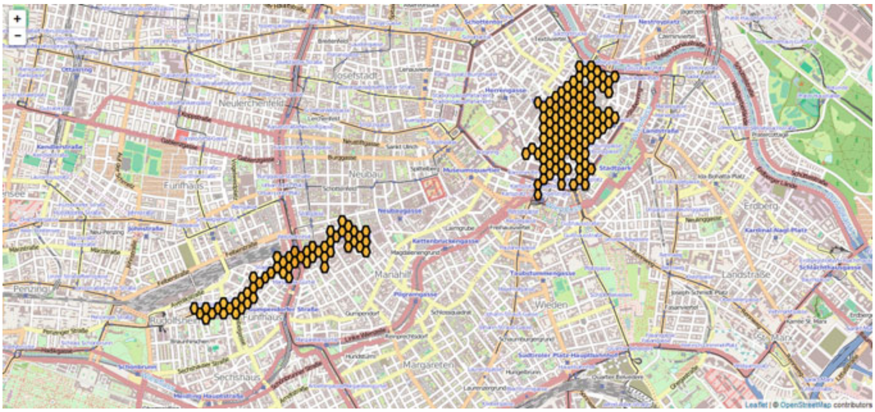

Fig. 4 Visualization of the identified shopping areas in Vienna, which are most *similar* to the Oxford Street (London)

Figure 5 illustrates the deviations of the defined preferences between the areas of *Inner City* and *Oxford Street* (black), as well as the *Mariahilferstraße* and *Oxford Street* (grey). The total deviation, which is defined through the similarity-distance given in Eq. (2), can be read off the *absolute deviation* axis. Thereby, a lower deviation is indicated when the instance in comparison, i.e. the line for *Inner City* or *Mariahilferstraße*, is nearer to the center. In this case, it can be clearly seen that the total deviation of the Inner City is lower than the deviation of the *Mariahilferstraße* in comparison to the *Oxford Street* area. To enable a more fine grained comparison, we plotted for each $i = 1,\ldots, 4$ the value of $|r_i^{(S_1)} - r_i^{(S_j)}|$, which is the single deviation on an independent axis. In the previous formula, the variable j stands for either 2 or 3, which corresponds to *Inner City* or *Mariahilferstraße*, respectively. We briefly elaborate on the individual feature differences according to Fig. 5:

1. Regarding the density of banks and ATMs, the area found in the *Inner City* as well as the one around *Mariahilferstraße* are both relatively close to the area that contains *Oxford Street*.
2. In terms of the density of tourism attractions *Mariahilferstraße* is a bit closer to *Oxford Street* than the *Inner City*.
3. The higher deviations in terms of density of Restaurants, Cafe, and Fast Food places, and shop diversity of the *Mariahilferstraße* indicate that the *Inner City* is more similar to the *Oxford Street*.

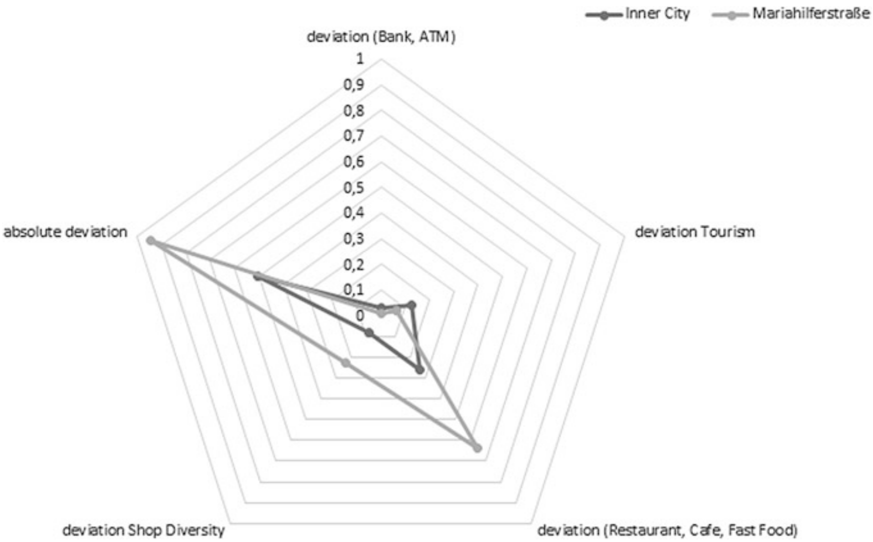

Fig. 5 The deviations of the conceptual shopping area Oxford Street (London) to the conceptual Mariahilferstraße and Inner City (Vienna) in respect to the defined feature vector

This section showed that our approach allows to search for urban settings. By discriminating areas suitable for certain activities, it is possible to compare those on the basis of a formal description of preferences. The type descriptions of places, as available in OpenStreetMap, do provide the basis for a mapping of activity possibilities to conceptual Settings.

5 Discussion, Limitations and Future Research Directions

The work presented in this paper is an excerpt of ongoing work that investigates a data driven approach of urban area generalization. Aside from many other challenges, this research has to face, two are most striking: (1) The choice of the description criteria *D* and evaluation of the results; and (2) the semantic ambiguity as well as incompleteness of VGI data.

The first point is a problem that cannot be solved, since there is no hard truth about what people consider a shopping area or not. Most likely, user studies will have to be conducted in order to compare the areas found to the areas users think are part of a category. The second problem is a well known problem and relates to the data-source itself.

The question of how people communicate and discuss about space is an important aspect in spatial information theory (Weiser and Frank 2013). Especially when intending to compare settings in different cities and countries, cultural and language specific differences might pose challenges for processing the data. For example, in some countries people would relate the place description cafe to a small restaurant, whereas in other countries people could relate the term to coffee company brands. Comparing these different concepts is not directly possible. Therefore, there is a need for more research in the mapping of place affordances to semantics used in VGI.

An issue to be addressed in future work concerns the consideration of spatial relations among objects or categories of objects. While the presence of a certain type of object allows for affording a certain activity, the relative configuration of such objects in space also plays a role. Consider, for example, one is interested in identifying panoramic areas: the simple existence and the vicinity of a visually-appealing entity (e.g., a lake) and of a walkable and recreational area (e.g., a green spot with some benches) is not enough to categorize the area as panoramic spot. There might be a wall or building in between, hindering the line of sight going from the benches to the lake. Accordingly, for future work, we plan to integrate spatial configuration analysis (Fogliaroni 2013), so that finer differentiation between the settings is possible.

Concerning the method itself, in the future we will explore the possibility of extracting the characteristics of a defined setting, to create a description *D* that finds settings in other areas. For instance, in the presented use case (Sect. 4), Alice would be able mark an area on the map, from which the descriptions for the region growing algorithm is extracted and used to search for interesting areas in Vienna.

6 Summary and Conclusion

In this paper, we propose a novel approach to find and extract urban settings from *typed* point data. We were able to implement a framework that can be used for spatial search or analysis. We presented a formalization of our approach that is based on the idea of region growing—an Image Segmentation technique—described the implementation of it, and illustrated its feasibility by applying it to a use case scenario. In the case study, we show that our implementation enabled us to find well-known shopping areas in Vienna and London by using raw data of OpenStreetMap as a source. We analyzed the results by applying similarity-metrics that potentially enable a user to compare well-known shopping areas between cities. Built upon the preliminary findings, we identified various improvements and open questions, that once solved can lead to novel ways of searching, analyzing or comparing cities.

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References

Abdalla, A., & Frank, A. U. (2012). Combining trip and task planning: How to get from a to passport. In *Geographic information science* (pp. 1–14). Berlin: Springer.

Adams, R., & Bischof, L. (1994). Seeded region growing. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 16*(6), 641–647.

Couclelis, H. (1992). Location, place, region, and space. *Geography's Inner Worlds, 2*, 15–233.

Couclelis, H., & Gale, N. (1986). Space and spaces. *Geografiska Annaler. Series B. Human Geography* (pp. 1–12).

D'Antonio, F., Fogliaroni, P., & Kauppinen, T. (2014). VGI edit history reveals data trustworthiness and user reputation. In *17th AGILE International Conference on Geographic Information Science (Short Paper)*.

Fan, J., Zeng, G., Body, M., & Hacid, M.-S. (2005). Seeded region growing: An extensive and comparative study. *Pattern Recognition Letters, 26*(8), 1139–1156.

Fogliaroni, P. (2013). *Qualitative spatial configuration queries: Towards next generation access methods for GIS*. AKA, Akad: Verlag-Ges.

Freundschuh, S. M., & Egenhofer, M. J. (1997). Human conceptions of spaces: Implications for GIS. *Transactions in GIS, 2*(4), 361–375.

Goodchild, M. F. (2007). Citizens as sensors: The world of volunteered geography. *GeoJournal, 69*(4), 211–221.

Humayun, M. I., & Schwering, A. (2012). Representing vague places: Determining a suitable method. In *Proceedings of the International Workshop on Place-Related Knowledge Acquisition Research (P-KAR 2012), Monastery Seeon, Germany* (Vol. 881, pp. 19–25). Citeseer.

[4] http://www.openstreetmap.org/copyright.

[5] http://leafletjs.com.

Jones, C. B., Alani, H., & Tudhope, D. (2001). Geographical information retrieval with ontologies of place. In *Spatial information theory* (pp. 322–335). Berlin: Springer.

Jordan, T., Raubal, M., Gartrell, B., & Egenhofer, M. (1998). An affordance-based model of place in GIS. In *8th International Symposium on Spatial Data Handling, SDH* (Vol. 98, pp. 98–109).

Keßler, C., & de Groot, R. T. A. (2013). Trust as a proxy measure for the quality of volunteered geographic information in the case of OpenStreetMap. In *Geographic information science at the heart of Europe* (pp. 21–37). Berlin: Springer.

Lynch, K. (1960). *The image of the city* (Vol. 11). Cambridge: MIT Press.

Mark, D. M., & Frank, A. U. (1991). *Cognitive and linguistic aspects of geographic space* (Vol. 63). Berlin: Springer.

Meegan, R., & Mitchell, A. (2001). It's not community round here, it's neighbourhood: Neighbourhood change and cohesion in urban regeneration policies. *Urban Studies, 38*(12), 2167–2194.

Montello, D. R. (1993). Scale and multiple psychologies of space. In *Spatial information theory a theoretical basis for GIS* (pp. 312–321). Berlin: Springer.

Montello, D. R., Goodchild, M. F., Gottsegen, J., & Fohl, P. (2003). Where's downtown? Behavioral methods for determining referents of vague spatial queries. *Spatial Cognition and Computation, 3*(2–3), 185–204.

Mooney, P., & Corcoran, P. (2012). The annotation process in OpenStreetMap. *Transactions in GIS, 16*(4), 561–579.

Raubal, M. (2001). Human way finding in unfamiliar buildings: A simulation with a cognizing agent. *Cognitive Processing, 2*(3), 363–388.

Richter, D., Vasardani, M., Stirlng, L., Richter, K.-F., & Winter, S. (2013). Zooming in–zooming out hierarchies in place descriptions. In *Progress in location-based services* (pp. 339–355). Berlin: Springer.

Schatzki, T. R. (1991). Spatial ontology and explanation. *Annals of the Association of American Geographers, 81*(4), 650–670.

Scheider, S., & Janowicz, K. (2014). Place reference systems: A constructive activity model of reference to places. *Applied Ontology, 9*(2), 97–127.

Shimabukuro, Y. E., Batista, G. T., Mello, E. M. K., Moreira, J. C., & Duarte, V. (1998). Using shade fraction image segmentation to evaluate deforestation in landsat thematic mapper images of the amazon region. *International Journal of Remote Sensing, 19*(3), 535–541.

Smith, B. (1995). On drawing lines on a map. In: *Spatial information theory: A theoretical basis for GIS* (pp. 475–484).

Tuan, Y.-F. (1979). *Space and place: Humanistic perspective* (p. 1979). Berlin: Springer.

Vasardani, M., Winter, S., & Richter, K.-F. (2013). Locating place names from place descriptions. *International Journal of Geographical Information Science, 27*(12), 2509–2532.

Weiser, P., & Frank, A. U. (2013). Cognitive transactions: A communication model. In: T. Tenbrink, J. G. Stell, A. Galton, & Z. Wood (Eds.), *COSIT* (Vol. 8116, pp. 129–148). Lecture Notes in Computer Science. Berlin: Springer.

Winter, S., Kuhn, W., & Krüger, A. (2009). Guest editorial: Does place have a place in geographic information science? *Spatial Cognition & Computation: An Interdisciplinary Journal: Special Issue: Computational Models of Place*, *9*(3), 171−173.

Winter, S., & Truelove, M. (2013). Talking about place where it matters. In *Cognitive and linguistic aspects of geographic space* (pp. 121–139). Berlin: Springer.

Zielstra, D., & Zipf, A. (2010). A comparative study of proprietary geodata and volunteered geographic information for Germany. In *13th AGILE International Conference on Geographic Information Science*.

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