StreetExplorer: Visual Exploration of Feature-based Patterns in Urban Street Networks

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Abstract: The analysis of street networks is an important problem in applications like city planning, comparison of urban street properties, or transportation network analysis. Graph-theoretic computation schemes today provide street network analysts with a range of topological features relating e.g., to connectivity properties of street networks. Typically, an abundance of different network features is available, and some or all of these features may be relevant for within- and between comparison tasks at different scales across the network. Therefore, it is desirable to interactively explore the large segment feature space, with the goal of finding interesting patterns based on extracted features, taking into account also the geospatial properties of a given network. We introduce StreetExplorer, an interactive visualization system for the exploration of global and local properties of urban street networks. The system is based on a set of appropriate similarity functions, which take into account both topological and geometric features of a street network. Together with a set of suitable interaction functions that allow the selection of portions of a given street network, we support the analysis and comparison of street network properties between and across features and areas. We enhance the visual comparison of street network patterns by a suitable color-mapping and boosting scheme to visualize both the similarity between street network portions as well as the distribution of network features on the segment level. Together with experts from the urban morphology analysis domain, we apply our approach to analyze and compare two urban street networks, identifying patterns of historic development and modern planning approaches, demonstrating the usefulness of StreetExplorer.

1 INTRODUCTION

The analysis of network-oriented data is a recurring problem in many data analysis tasks, and to date knowledge discovery and visualization has provided many successful approaches to study network data. Many relevant phenomena can be described by network-oriented data structures, e.g., modeling social networks in social science, communication networks in data infrastructure, or gene regulation networks in bioinformatics applications.

One particular application of network-oriented data analysis arises in the investigation of street networks in urban areas as part of geographic data analysis. Street networks are an integral part of any urban structure, as they allow flows of traffic and pedestrians to connect and commute between different parts of the city. In conjunction with respective features within a city e.g., land usage or traffic, street networks may determine important functional, social and perceptual properties of urban settlements, such as the efficiency of transportation and space utilization, social residential segregation and wayfinding. Recently, graph-theoretic methods have become popular to study topological properties of street networks (see Section 2.1). In practice, topological measures (also called features) like connectivity, integration or axiality can be computed for each street segment of a larger street network. Each of these features are typically given as real numbers, indicating e.g., how central a street segment is to the whole network. Experts are interested in investigating the properties of street networks, by inspecting the distribution of the different features across the street network, and correlating them with geometric and other

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properties of the street segments. However, the analysis and comparison of local patterns based on different street network's configurational attributes is a common problem to city planners and geographers. The similarity of these local patterns may depend on several criteria, e.g., extracted features, geometric properties or provenience, and the identification of outstanding pattern classes can help to enhance urban designs, city planning, transit-oriented development, or to study historic developments. For this purpose, it is useful to investigate meaningful patterns within and between cities, and apply the conclusions drawn from the analysis to future urban development.

We have worked with experts from urban morphology on the problem of analyzing topological and geometric features occurring in street networks. We identified the need for exploratory approaches to cope with the analysis problem, due to several factors, which make rule-based or purely automatic data analysis not fully effective. First, computational graph analysis provides a multitude of different topological features. Which of the feature is important for the current analysis is, however, not known a priori. Then, by consideration of geometric features, relevant patterns may occur at different scales with respect to the network, e.g., a smaller or larger local area may be of interest for comparison. Both calls for a highly interactive, exploratory approach to investigate street network features since it is not known a priori, which features are of interest, and at which scales.

We contribute an application for highly interactive visual exploration and comparison of local patterns across a network. We apply interactive search and appropriate visualization for local patterns of street features for a domain expert to investigate his data collection. At the heart of our approach is a flexible search function, by which the expert can quickly indicate for a specific network feature the regions of interest. We define a suitable similarity function to rank and compare street network properties, taking into account topological features, but also spatial properties of the network. We introduce a suitable color-mapping and boosting scheme, which allows visualizing local similarity to a user query in context of the overall feature distribution. It allows the user to quickly verify different hypothesis regarding to recurrent patterns, and arrive at meaningful findings on a given street network.

The remainder of this paper is structured as follows. In Section 2, we recall related work on analysis of urban street networks, pattern analysis in graph data, and on visualization of spatial data. In Section 3, we introduce the basic idea of our approach, based on two modes of query specification and result visualization. Then, in Section 4 we describe in detail our search methods and the similarity function behind the search. Further, in Section 5, we demonstrate the effectiveness of StreetExplorer by a use case application on a real street network analysis, conducted together with our co-author domain experts. We also provide a discussion of advantages and limitations of our approach. Finally, Section 6 concludes.

2 RELATED WORK

We discuss related work in street network analysis, pattern extraction and visualization, and spatial visualization.

2.1 Analysis of Urban Street Networks

Street network patterns are a dominant component of a city's spatial properties. They have been shown to be significant for human spatial behavior, such as transportation mobility and accessibility (Marshall, 2004) and vitality of urban life (Wheeler, 2008). Urban street networks have been investigated with respect to their geometric and configurational attributes (e.g., number of intersections, number and size of blocks, connectivity, integration, fragmentation, etc.), their dynamics as well as their relations with other morphological components such as buildings, lots and the like. *Space syntax* is currently the dominant theoretical and methodological approach, which is based on configurational attributes of urban street networks (Hillier, 2002; Hillier, 2007). This approach concentrates on the integration between urban streets (or places) and their relative accessibility and centrality in terms of intermediacy (Kropf, 2009). These configurational aspects have been found to be reliable indicators for purposes of comparison between street patterns (Hillier, 2002; Vaughan et al., 2010) and for distinguishing street pattern development, e.g., self-organized versus planned-cities ((Porta et al., 2006; Jiang, 2007)). This body of research has produced classifications of these patterns according to the spatial configuration attributes of street network.

The space syntax attributes, which are based on axial maps, i.e., the smallest set of direct axial lines map of each investigated city (Hillier, 2002; Hillier, 2007), represent several aspects of accessibility and centrality at different scales that can be used for a classification of street networks. However, due to the multidimensional character of street networks' spatial configuration, the identification and classification of street patterns in urban areas is not a simple task. Space syntax studies have shown that street patterns can be identified by measuring axial lines or segments through a presentation of geographic distribution of spatial configuration attributes at different geographic scales. Such presentation can support the definition of spatial pattern patches in the street network at different scale in terms of their internal structure, contextual structure and relations between the two (Yang and Hillier, 2007). Such task requires interactive and complex actions by experts in the field of urban morphology.

2.2 Pattern Analysis in Graph Data

In graph and network analysis, similar to street network analysis, experts are interested in recognizing local patterns or subgraphs containing meaningful and relevant information. Since both research areas are highly connected they also share similar approaches to address related challenges. (Yang et al., 2014; Tian et al., 2012) use graph based approaches to identify significant patterns in street networks. Street networks were represented as graphs, whereas streets are considered as edges and road junction as nodes. A large body of previous work addresses the visual analysis of graphs by search-based pattern exploration, of which we here can only give a small, illustrative sample. In (von Landesberger et al., 2009) a visual analysis system was introduced, which automatically identifies common graph patterns (motifs) that are used as basis for navigation and exploration in graph data. In (Yan et al., 2006), a graph-substructure similarity search based on graph features was discussed. One key aspect of graph analysis is the representation of patterns in a suitable manner. (Dunne and Shneiderman, 2013) introduced a motif simplification technique, in which common patterns are replaced by meaningful glyphs. More generally, a survey of methods for visual analysis of graphs is given by (von Landesberger et al., 2011).

2.3 Visualizations of Spatial and Movement Data

Many useful visualizations to date support interactive analysis of geospatial and movement data, of which we again can only give a small overview here. An encompassing overview of visual analytics approaches and tools for movement data is covered by (Andrienko et al., 2013). (Bak et al., 2010) introduced an approach for joint visual analysis of urban land usage and street network properties based on visual cluster analysis. In (Chu et al., 2014; Ferreira et al., 2013) mobility patterns of taxi movements were investigated by extracting geographical information and using visualization techniques. Recent work in street network analysis (Wang et al., 2013) uses taxi GPS data to compute traffic flow rates and estimate traffic jams in the city. A visual analysis tool for support of urban space and place decision-making processes was developed in (Pettit et al., 2012), relying on visualization techniques including time cubes, heat maps, and choropleth maps.

We build on these works for visualization of network and spatial data, contributing an approach for the explorative analysis of street network features based on adaptive selection-based search over geographic and topological properties of the street network, including appropriate data visualization.

3 OVERVIEW OF OUR APPROACH

The aim of StreetExplorer[1] is to support street network analysts during their investigation by supporting interactive search for similarities within the network, giving rise to potentially interesting local patterns. We rely on a wealth of currently existing computational methods for topological street network features, which we help to explore and understand by means of a search-based visual analysis system.

The exploration design of StreetExplorer is based on a two-step comparison approach that enables an investigation of street patterns on the global and local scale within and between urban networks. The design is depicted in Figure 2. We adhere to Shneiderman's *Information Visualization Mantra* - Overview First, Zoom and Filter, Details on Demand (Shneiderman, 1996) and propose to start the analysis session with a global overview comparison of features in a given network (shown in Figure 1). By means of our small multiple view, analysts may recognize feature similarities, dependencies or correlations that help to find an interesting feature for further investigation.

We start the exploration by applying a global comparison of all available network features, to find a starting point for the exploration, and to identify interesting local patterns from a large number of pre-computed features. All available features are given by a list view to select from in the left hand side of Figure 1. This view displays all features in a hierarchical structure based on the street-networks' configurational attributes and resolution levels. Thus, features containing a high number of resolutions will be aggregated in the list and provide a better overview than a plain list. From this list, several features may be chosen and visualized in a small multiple view that represents the feature values

[1]A demonstration of StreetExplorer can be found at: https://vimeo.com/149003539

Figure 1: Feature exploration in StreetExplorer to compare space syntax configurational attributes of two cities, namely Kfar Saba and Ashdod. The system creates a small multiple view of all selected features for comparison and further in-depth investigation for similarity in the street-network.

by their original proportion of the city's street network. This allows for global comparison of the features. To support the global comparison, the features (or maps) can also be sorted according to the similarity of a selected one, by means of the below discussed similarity function (Section 4).

As a next step, the analyst could apply zooming and panning interactions to explore the features for interesting local patterns. To find locally interesting patterns, we support the query formulation by two selection-based methods, which are depicted on the left of Figure 2. The definition of query patterns can also directly be performed on the map by selecting certain street segments. Thereby, the analyst may define patterns of interest, which are composed of geometrical, topological and connectivity information of the individually chosen segments. The similarity search

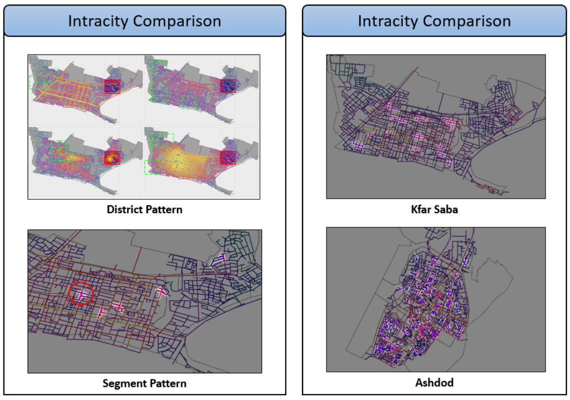


Figure 2: Our proposed procedure to analyze street network patterns. The exploration starts with an interactive comparison of local patterns for a selected feature. This can be done by a district search or a user-defined search based on the segment level. Matching results will be highlighted on the map, and thus provide an overview of the availability, frequency and distribution of feature-based patterns. After interesting patterns were found, the analysis can be expanded to compare among several cities.

occurs interactively and the best matching results will be directly highlighted on the map.

Finally, after some interesting local patterns have been identified for a given street network, the analysis may continue by comparing the found pattern across different features and possibly, also across networks of different cities (depicted on the right of Figure 2).

4 EXPLORATION OF STREET NETWORK PATTERNS

We describe the similarity functions of StreetExplorer as an important part of our supported exploration approach outlined in Figure 2. Further, we discuss novel colormapping techniques to enhance the readability of topological features in street networks and to support interactive highlighting.

4.1 Comparison of District Patterns

StreetExplorer enables the search and comparison of feature similarities on the global and local scale within and between street networks. In case these properties cannot be seen at first sight, the interactive search methods of StreetExplorer can be utilized to explore the street network for locally interesting properties. We support the small multiple view by a concurrent search, meaning that a given query is run against all maps currently shown in the small multiple view, and matches are highlighted on all features maps at the same time. To this end, we provide two *local* search functions for street network patterns. The first search function is a *district comparison*, which identifies similar regions based on user-defined districts. Analysts may define a rectangular region by using a rubber band selection and detect similar districts based on geometric properties and feature values of the particular street segments. This is particularly suited if analysts want to approximately compare an area of interest e.g., east or west peripheral area of a city. The technique we use to compute similarity between districts in a street network is adapted from image retrieval (Liu et al., 2007) and relies on the distribution of feature values as a basis for the similarity function.

In our approach, we use an equal-width histogram of all street segment features within the given selection. The histogram is normalized according to our color-mapping scheme (see Figure 3 and Section 4.3). The bin size configuration is an ill-defined problem, which depends on the data set. This configuration can be adjusted by the analyst himself, but to achieve similar areas in accordance with the visual perception of the color-mapping, we suggest a minimum bin size that contains a stable color interval and covers all feature values that are visually in the same range. We figured out that the good results were achieved by using a histogram with 10 bins (one bin for each color) that contain further 10 interpolated hues, as demonstrated in Figure 3. Consequently, the histogram comprises in total a range of 100 units in the normalized feature interval between $[0,1]$. We then store the length of all segments lying in the query district to the corresponding histogram bins and iterate the search over the entire map using a sliding window approach to find the most similar regions. The sliding window approach is a method that sequentially compares local regions for similarity search. In this approach, a street network is divided into a two-dimensional grid and the similarity search is performed in each window. Consequently, the histogram will take all intersecting segments into account and is weighted by the length of street segments. To assess the district similarity, we divide the street network into a uniform-sized grid and translate the rectangular district box over the grid including overlapping areas. For each iteration, a new histogram is computed and compared with the query district by the Euclidean distance. Due to the complex problem of scaling, the grid size can be interactively adjusted by the user, but at this point we would like to point out that a too small grid could cause many matching results at the same region (slightly shifted) and a too coarse grid could lead to missing associations. By default, the grid size will automatically be determined according to the query size, e.g., a smaller

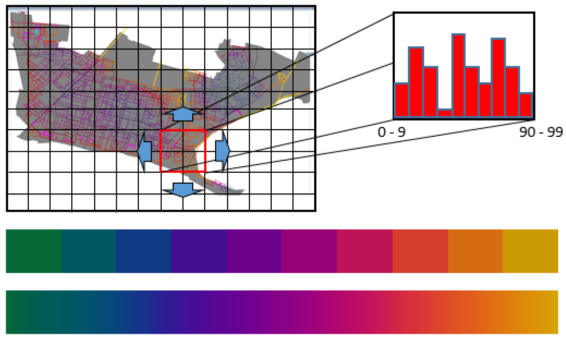


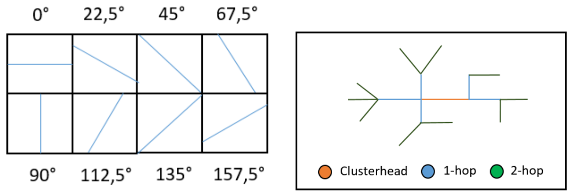
Figure 3: Illustration of our histogram approach to compute district similarity. The histogram contains 10 bins that cover further 10 interpolated hues according to a spiral colormap. Street networks are partitioned into a regular grid and a sliding window approach iterates the search through the grid.

query district will also produce a smaller grid size. The grid size corresponds to a quarter of the original query size, and thus enables an overlapping degree of a half width and length. In the end, the regions with the most similar histograms will be emphasized on the map, as shown in Figure 2 (District Pattern).

4.2 Comparison of Segment Patterns

To find more fine grained street patterns the second local search function of StreetExplorer can be used, which is shown in the lower left corner of Figure 2 (segment pattern). It takes the connectivity as well as the length, direction and feature value of individual street segments into account. To distinguish the main segment orientations our domain experts defined 8 types of directions as shown in Figure 4 (a). Segments are considered as similar if they possess approximately equal direction, and are within a tolerance margin of length and feature value. This ensures that similar street patterns also consist of approximately the same segments irrespective of connection. Furthermore, we propose two different selection-based approaches to specify the neighborhood of a given segment and form a pattern.

The first selection is defined by a connected k-hop clustering, which uses a selected segment as clusterhead and groups several neighbors as members based on the hop distance. For instance, a 1-hop street pattern consists of one segment (clusterhead) and connected segments, in which the distance between the clusterhead and its members is 1 hop (junction). For better performance, we pre-calculated all segment connections in advance. An illustration of our k-hop selection is shown in Figure 4 (b). The orange marked segment denotes the selected segment, whereas the blue and



(a) Direction types. (b) Illustration of k-hop.

Figure 4: Illustration of our similarity properties for searching k-hop based patterns. (a) shows the eight different direction types; (b) illustrates the members of a street pattern based on 2-hops (blue and green segments).

green ones are the members that are reachable by a path of one and two hops respectively. By means of this selection approach a street pattern can easily be enlarged by increasing the number of k (shown in Figure 7 (a) - (c)). In this approach, the selection of the first segment is crucial since it builds the basis of the street patterns and initializes the similarity search based on its neighborhood. After a street segment has been defined as core segment (clusterhead), a single segment search over all target segments takes place, and computes an overall similarity score for its connected neighbors. Consequently, the analyst can quickly investigate similar local areas of a street network by changing the clusterhead segment. Since street patterns may have different neighborhood sizes, we compute a similarity score by comparing the average of feature value and the segment length of all segments that belong to one street pattern. Equation 1 shows the computation of the weighted average feature value where n is the number of neighboring segments of one street pattern. Accordingly, we determine the distance of the query to the target street patterns ($Feature_{avg}$) and eliminate those patterns, which exceed a certain threshold. Analysts may determine k for the neighborhood size as well as the tolerance margin for segment length and feature value to steer the analysis process.

$$Feature_{avg} = \frac{\sum_{i=1}^{n} SegmentLength_i \times FeatureValue_i}{\sum_{i=1}^{n} SegmentLength_i} \tag{1}$$

Alternatively, the analyst can also switch to a *free-form selection* in order to define an interesting pattern. By means of this selection approach, the analysts are able to specify even more accurate street patterns by selecting individual segments. In this way, it is possible to form complex street patterns that contain, e.g., stringy, circular or chain-like structures. The basic similarity search step is applied for each added segment and a *connectivity comparison* verifies whether the matched segments are connected correctly or not. Beginning from the first segment, the connectivity comparison stores the connection of each new added segment and observes the connectivity of query and target patterns in real time. Figure 5 demonstrates an example with four correct and one incorrect connected patterns referring to the query instance. After each new added segment, query and target patterns are compared for structural similarity of their neighboring segments. This means that every potentially similar segment is required to have an identical connected ancestors, otherwise it will be eliminated from the result set. For instance, all four correct target patterns in 5 have an equal connection to their ancestor segments (segment 1 is connected to segment 2 and segment 2 is again connected to segment 3), and thus are considered as similar. The problem with the negative example is that the last added segment (segment 3) is connected to both ancestor segments (segment 1 and segment 2), and are thus considered as dissimilar. To this end, our approach is invariant to rotation and allows slight variations of target patterns.

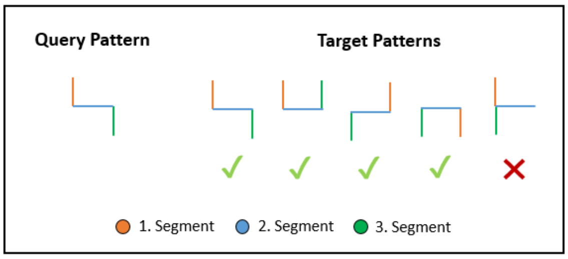
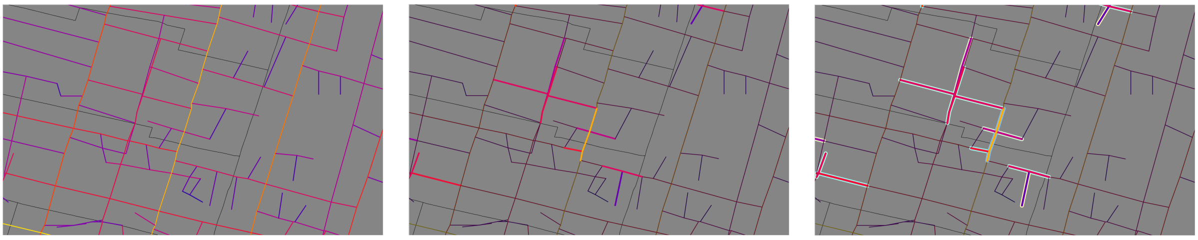


Figure 5: Demonstration of our segment connectivity comparison for searching individual segment patterns. The color coding indicates the order of selected / matched segments. Based on the ancestor connection property, the search is invariant against pattern transformations.

These local search functions can also be applied for intercity comparison. Basically, the search techniques and interaction possibilities for this application are the same as for intracity comparison. The only difference is that additional street networks are displayed in separate small multiple views and can include individual features (see Figure 1). In this case, it might be beneficial to compare local patterns in different street networks (cities / features), which the analysts have considered as interesting. Hence, we designed a portable pattern search that can easily transfer street patterns (queries) of one city to another city. Accordingly, it enables additional comparison tasks and can reveal interesting findings, e.g., searching for certain patterns in all street networks; or comparison for spatially similar located patterns (northern part of the city or downtown); or searching for similar kinds of roads (main streets).

4.3 Visual Boosting

The visualization and selection of segments can be



(a) Without any boosting schemes. (b) With visual attention boosting. (c) With color contrast boosting.

Figure 6: Demonstration of our visual boosting approach on the street network of Kfar Saba. To enhance visual perception of local patterns, we used a spiral colormap to show the feature values of street segments (a); reduced the saliency of unselected segments (b) and adapted the border color of located street patterns (c).

perceptually supported by novel colormapping and visual boosting approaches that we discuss in the following.

Colormapping. (Mittelstädt et al., 2015) provide state-of-the-art guidelines and the tool ColorCAT to design colormaps for combined analysis tasks. In our application, the color encoded features are continuous and their interpretation requires the *identification* and *comparison* of metric quantities. We use ColorCAT to design our color encoding (see Figure 3) for our application. The number of distinct colors is maximized for accurate *identification* of color values (Ware, 1988; Kindlmann et al., 2002; **?**) and the perceptual linearity is preserved by linear increasing intensity, which is required for *comparing* color encoded data.

Boosting with Color Contrasts. If many streets are sharing dense areas of the display, it is hard for the user to perceive single streets. Studies showed that the visibility of low contrasts is reduced in high spatial frequency areas of the display (Barten, 1999). The method of Mittelstädt et al. (Mittelstädt et al., 2014) compensates for harmful contrast effects in order to accurately visualize color encoded data. The method applies a perception model (Fairchild and Johnson, 2004) in order to estimate the bias of contrast effects, which are amplified in the cones of our eye. With this approach it is possible to approximate a color c' that is in maximum color contrast to a target color c with $c'_x = D65_x - c_x$ (with x being the LMS channel in the CAT02 color space and $D65$ is the standardized reference light). Note, that this is only valid for saturated colors with one of the channels being close to zero. In order to visually boost the readability of streets in our visualization, we draw borders around the segments of streets. These borders are encolored with maximum color contrast to the segment color, which accords to *boosting with color* (Oelke et al., 2011). Further, we enable the user to control the segment and border sizes which enhances readability. On the one hand, these contrast effects can bias the user in reading color encoded features if the task is focused on a detailed analysis of specific (zoomed-in) data objects. On the other hand, this approach enhances the perception and recognition of streets in overviews, which enables us to read features even for dense areas on the screen. Therefore, we recommend the approach for tasks that require overviews of high frequency data. Further, this approach can be applied to highlight segments and street patterns (see Figure 7).

Boosting with Visual Attention. The most common reason to highlight visual elements with color is to attract visual attention. Studies of (Camgöz et al., 2004) show that humans are predominantly attracted by bright and saturated colors. Since we use both to visualize metric quantities and want to accurately encode the elements in the selection, we reduce the visual saliency for unselected elements. We argue that these segments are still important for the context information of the selection but they need not to be visualized as prominently as the selected elements. Therefore, we reduce the intensity and saturation of these segments (we set both to 50% of the original color in the HSI color space (Keim, 2000)). To further decrease the visual saliency, we use the borders of unselected elements and decrease the contrast to the segment as well to the background by selecting the same color for the border but adjust the lightness and saturation of the border color to 50% of the original color. The low brightness and color contrasts reduce the visual saliency of unselected elements and steer our attention towards the selection.

Visual Boosting Effect. Figure 6 demonstrates the effect of our visual boosting approach. First, a spiral colormap is applied to visualize the continuous feature values of each street segment in the entire city (a). The colormap ranges from green/blue (low values), through purple/red to orange/yellow (high values). Consequently, analysts can easily detect streets with high feature values or areas including low feature values. Second, we reduced the visual saliency of inconsiderable street segments and thus, highlight local patterns resulting from similarity search (b). However, one remaining challenge is to perceive the patterns and their feature values, in particular in the case of rapid changes during the exploration. To tackle this issue, we finally support the highlighting by increasing the segment size and adapting the border color of detected local patterns (c). By default, the segment sizes are adjusted to the global street network view (without zoom level). We suggest to increase the segment size when focusing the analysis on a local area (with higher zoom level) to maintain the colors and feature values of the particular street patterns.

We designed two search functions to investigate local similarities in street network features. Analysts are able to define local patterns based on geometrical features (length, direction and composition) and analyze the characteristics on topological features (angularity, axiality or connectivity), which is applied in Section 5. Feature values will be presented by our color-mapping and help together with our boosting scheme to reveal the similarity of discovered patterns. The search can be used within one chosen feature to detect similar street patterns, or over several features to identify the distributions of patterns based on different topological features. An analysis without network connectivity constraints is also possible and can be achieved by using the district search. Another possibility would be to analyze the pattern without the influence of topological features, which corresponds to a basic subgraph search in network data.

5 CASE STUDY

In the previous section, we introduced the StreetExplorer system for search-based exploration of feature properties of urban street networks. We have worked closely with urban modeling experts from a university to use our system, and will describe the findings next. The expertise of the users reaches back two decades in research and consulting for urban planing and modeling, progressing the state-of-the-art in the domain significantly. Relevant application and research fields of the experts include defining effect of land-use types on ethnic residential integration, commercialization developments of urban neighborhoods, and predicting street segments' pedestrian friendliness and walkability. Understanding and analyzing the topology and configurational attributes of street networks are indispensable to these research and application domains.

5.1 Features Exploration

The network data, together with topological features from street-networks' configurational attributes has been provided to us in standardized shape files. The investigation was carried out by the experts and assisted by the developers. Measurement of space syntax configurational attributes is based on topological analysis of axial maps that treats individual axial lines (see Section 2.1) as nodes and axial line intersections as edges of a connectivity graph. The resulting graph provides the basis for several space syntax measures that describe the centrality of individual axial lines. In the current study, we have used the following measures: *Connectivity*, *Local Integration*, *Global Integration*, *Local Choice* and *Global Choice*. For any particular axial line, *Connectivity* denotes the number of directly linked axial lines. *Global Integration* indicates the closeness of an axial line to all other axial lines in the system by computing the shortest distance (or step depth) of the respective line from every axial line in the entire urban area. The *Local Integration* limits this computation to a certain neighborhood size, which is limited by a defined number of directional changes. Against to the above *to-movement* measures that represent the accessibility of a given axial line, the measures of *Global Choice* (which is equivalent to the graph-based centrality measures of betweenness) and *Local Choice* are through-movement measures. These measures indicate the number of times a location is encountered on a path from origin to destination for all pairs of axial lines in the entire urban area (global choice) or up to a defined topological distance (local choice).

In this study we chose to investigate two cities - Kfar Saba and Ashdod - which are representative of the street patterns of Israeli urban space (Omer and Zafrir-Reuven, 2010). We started our investigation by selecting the five space syntax measures, as described before, in order to reveal the global and local similarity between these cities. Results for the two cities are shown in a small multiple view (Figure 1) for comparison. This representation clearly reflects the configurational differences between the cities, which has historical, developmental and topological reasons. Kfar Saba is a city with a nearly orthogonal street pattern that was established in the beginning of the 20th century and has developed mostly according to the pre-modern planning approach. In contrast, Ashdod is a relatively new city that was established in 1957 according to a comprehensive city plan based on modern planning approach. The city is characterized by a tree-like street layout associated with the idea of neighborhood units. These differences between these planning approaches and the associated street patterns are similar to other western cities (e.g. (Marshall, 2004)).

Data on the cities' street networks were obtained as GIS layers for the year 2012 from MAPA company (http://www.gisrael.co.il). The Depthmap software ((Turner, 2001)) was used for constructing and analyzing the axial and segment maps and for computation of space syntax measures.

5.2 Interactive Search and Findings

We started our investigation with comparing similar local areas by using our district comparison tool. We realized very quickly that the distribution of similar local areas vary at most during the exploration of the feature *Local Integration* (second row of Figure 1) and decided to use this feature for further investigation. Moreover, previous research indicates that this measure best distinguished cities from each other (Omer and Zafrir-Reuven, 2010) and represent most effectively the differences in street patterns. Local integration measure describes integration only up to a defined number of changes of direction (topological distance), which is usually equal to three. The use of segments (the lines between junctions of axial lines) enables network analysis on a finer scale than using axial lines, it also extends with a consideration of angular distance (least angle distance) and metric distance that might be relevant to the purpose of investigation.

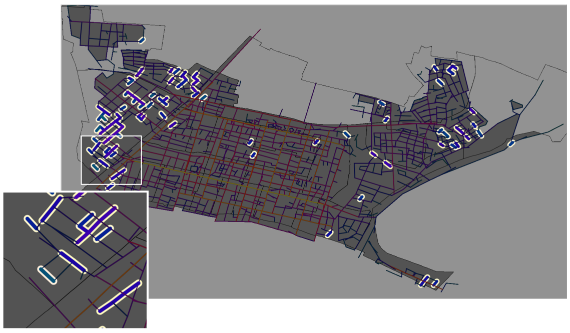
Our StreetExplorer implementation provided rapid response to a series of interactive queries we conducted, iteratively switching between selections of different segments in the overall street network, to find interesting repetitive structures in the map. We have been mainly focusing on areas that were established according to the modern planning approach. After a few trials, we selected one segment in the peripheral area of Kfar Saba (Figure 7) and in Ashdod (Figure 8). As a result, StreetExplorer highlighted all similar segments in the entire street-network for further investigation. Similar segments were found only on new areas that were developed in the second half of the 20th century: in the west and east peripheral areas of Kfar Saba, and almost in the entire area of Ashdod. We then increased the neighborhood level in a step-wise manner from no neighborhood (single segments are compared) to second and forth degrees of neighborhood (k-hop) included in the similarity function.

As shown in Figures 7 and 8, the geographic distributions of similar patterns in both cities remained stable and increased consistently across the neighborhood level. Even though, when neighborhood size increases, some of the smaller patters that were close by, merge to larger ones, but some of them drop out, as their similarity falls below the defined threshold. This means, that by selecting the neighborhood size, the user in StreetExplorer can interactively determine the size of the pattern of interest and get immediate visual feedback on the search results.

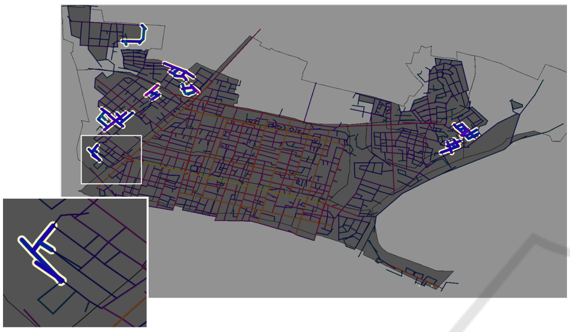
In the latter query modality, the users selects only a single query segment, and the system increases the neighborhood size resolution along connected segments, thereby providing several query alternatives with different size. We note that the geometric similarity of the matches to the queries (perceived mainly by segment length and direction) is more prominent when the neighborhood size used in the similarity computation is comparably low. From a domain analysis perspective this makes sense, as geometry and form are mainly considered more local configurations of attributes, and rather not applicable to district and city levels.

Overall, this quite accurate pattern retrieval can be related to the consideration of topological spatial integration level at different network scales as well as to the geometric properties of segment length and direction. The revealed similar patterns are characterized by the tree-like structure of the street network. In addition, distances between intersections on arterials are relatively larger than the distances in traditional patterns, and only streets at the same hierarchy or one above or below it, can intersect with the arterials. All these attributes do not exist in the traditional street patterns located in the older areas in the center of Kfar Saba.

Despite the similarity between street networks that are established at the same period in both cities regarding the location typical street patterns, they differ in the level of homogeneity within the street patterns. In Kfar Saba the neighborhoods are relatively homogeneous regarding their *Local Integration* value over all resolutions while in Ashdod the neighborhoods get quickly very heterogeneous when increasing the spatial resolution. This is visually salient in the number of distinct colors the segments have within a highlighted configuration. Moreover, while in Kfar Saba the similar neighborhoods remain in the periphery, independently of the resolution level, in Ashdod the neighborhoods spread to all districts of the city and quickly cover almost all the residential districts. The heterogeneity of the street patterns in Ashdod is a result of the hierarchical structure of the neighborhoods' street networks, which is reflected well in the spatial patterns of *Local Integration*, where arterial roads with the higher integration levels separate neighborhoods from each other. Against that, the hierarchy of importance in Kfar Saba is much weaker with no clear distinction



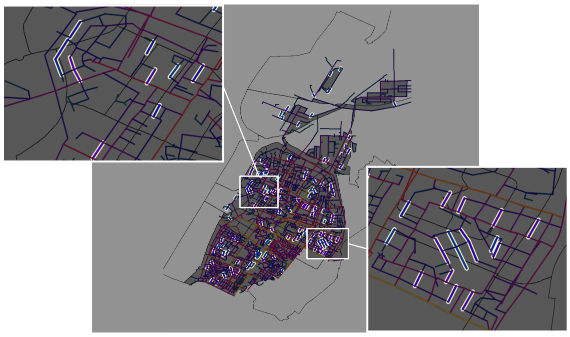
(a) No neighborhood selected.



(b) 2-hop neighborhood.

(c) 4-hop neighborhood.

Figure 7: Kfar Saba use case shows the distribution of similar patterns in the city's peripheral area at different scales. A typical configuration is highlighted at the bottom left.



(a) No neighborhood selected.

(b) 2-hop neighborhood.

(c) 4-hop neighborhood.

Figure 8: Ashdod use case shows the distribution of similar segments in the city's peripheral area. Geometric form, length and direction, are only marginally included in the similarity computation and only in the lowest neighborhood resolution.

between neighborhoods.

Thus, unlike previous space syntax works that were based on the spatial patterns of space syntax attribute values of individuals segment or axial lines (i.e. neighborhood at level 0), the investigation on pattern similarity in street networks here is conducted at different neighborhoods size and with simultaneous consideration of topological spatial integration and geometric aspects of street network (i.e. length and direction of segments). Due to these capabilities of this flexible search mechanism in StreetExplorer, we have identified street patterns that characterize urban planning approaches as well as sub-types street patterns, in this application, among modern street-based planning.

5.3 Expert Opinion

The unique contribution of StreetExplorer to the presentation and analysis of urban street network is twofold as stated by our co-author domain experts. At first, the simultaneous consideration of topological-visual (space syntax attributes) and geometric (i.e. length and direction of segments in Euclidean terms) aspects of spatial integration pattern in urban street network are innovative. Both aspects are essential for describing and identifying patterns in urban street networks (Marshall, 2004) and should be considered together in street network analysis. For instance, in (Marshall, 2008) topological features, such as continuity, connectivity and depth, of local street patterns were extracted and compared with a set of pre-defined patterns on a triangular projection space. StreetExplorer enables this simultaneous assessment and allows to represent user-defined patterns in their original spatial position. Secondly, for the analysis it is indispensable to represent similar patterns at different neighborhood sizes beyond the usual presentation at the level of individual segments. Consequently, the ability to identify street pattern pieces in urban street network as previously described enables the building of a typology of street patterns according to spatial cultures or urban planning approaches. This leads to exploration of street patterns for the emergence and design of urban phenomena such as walkable environment, retail activity and urban center, legible environments (wayfinding), residential segregation and crime. In addition to the current use of spatial integration values at the level of individual segments or axial lines in urban models (e.g. pedestrian or vehicle volume models) one could incorporate spatial integration values at the level of street pattern pieces that are defined by different neighborhood sizes. Finally, the experts stated, that they are not aware of any alternative tool or method that provides such interactive analytic functionality.

6 SUMMARY AND FUTURE WORK

We introduced StreetExplorer that helps analysts to explore a given space of network features in their context with a set of available topological street features provided by domain-specific software. The goal is to specifically support the exploration and visual comparison of street features on the global and local scale across and between features and regions in an effective way. We supported an interesting new application domain for visual analysis, and we provided three contributions in our work as follows. First, we defined a suitable similarity function to rank and compare street network properties, taking into account topological features, but also spatial properties of the network. Second, we defined suitable interaction functions, which allow the user to interactively select local areas of interest based on free-form selection and an adaptive neighborhood definition. Third, we defined a suitable color-mapping and boosting scheme, which allow the visualization of local similarity to a user query in context of the overall feature distribution. Additionally, we applied StreetExplorer together with domain experts, demonstrating the effectiveness and usefulness of the chosen designs by showing unexpected findings. While in the past the analysis has focused on predefined patterns like grid, star, or ring road patterns, now analysts are able to generate accurate patterns according to their interests. By means of StreetExplorer the domain experts were able to find the most informative feature and discovered interesting distributions of local patterns that can be traced back to historic development and modern planning of urban networks.

In the future, we plan to extend this work in different directions. We will enrich StreetExplorer on the metadata level by including additional features, such as landuse, barrier and general user comments, which can be extracted from openstreetmaps and provide an extensive search for local patterns in street networks. Moreover, StreetExplorer can be extended by different clustering methods for supporting comparison of interesting patterns. For instance, details-on-demand functions could be used to show the most significant or frequent patterns and propose further information for analysis. We want to investigate analytical methods to detect suitable parameter settings that reveal interesting patterns. This could be realized by using image-based techniques and comparison algorithms that consider several outcomes of parameter variations. We also would like to introduce functionalities for comparison of topological features and provide a semi-automatic feature selection approach based on statistical measurements. Furthermore, the visual representation and global arrangement of maps can be enhanced by specialized layouts that take the spatial properties of features into account.

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