Identification of structural landmarks in a park using movement data collected in a location-based game

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ABSTRACT

The goal of this paper is to investigate the possibility to identify structural landmarks using movement data collected during an event of a location-based game. Landmarks are visually, structurally or cognitively salient, spatial features used for example for navigation purposes to situate and to orientate oneself within the own world and to locate proximate or distant objects or locations within this space. Structural salience is a characteristic of a landmark defined by the prominence of its spatial position. We use relations between movement and landmarks in order to reason about the structural significance of locations in a city park, based on the movement behavior exhibited by the players of the location-based game called Ostereiersuche. The results of this study suggest that structurally salient landmarks can be identified based on an analysis of movement events recorded in a location-based game. The introduced „player movement - landmark detection loop" represents a first instance of a landmark management system as one layer of a mobile game play ecosystem, the mobile game lab.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Retrieval models

H.2.8 [**Database Applications**]: Spatial databases and GIS

General Terms

Algorithms, Measurement, Experimentation, Human Factors.

Keywords

Landmark identification, movement analysis, games with purpose, location-based games.

1. INTRODUCTION

A Location-Based Game (LBG) is a special type of game that, being played, involves physical movement of players in geographical space. LBGs require some form of localization to track positions of their players and their game objects. The availability of the global positioning system (GPS) and the increasing distribution of smartphones deliver LBG a powerful platform for precise positioning, computation, and communication. As a result, most of the LBGs nowadays are built upon this platform. Recent remarkable examples include "Shadow Cities" (Grey Area) and "Ingress" (Google).

Enabling data collection on user movement in space like other mobile services, a LBG seem to be additionally a candidate to apply concepts of "games with purpose" to solve some computational problems in geographic information science (GIScience). "Games with purpose" is a concept of turning the process of solving complex computational problems into entertaining activities. "People play not because they are personally interested in solving an instance of a computational problem but because they wish to be entertained" (von Ahn, 2008). An application of simple game mechanics allows *foursquare*[1] to collect and maintain an expanding dataset of places. A similar approach can help, for example, openstreetmap to involve non-mappers into mapping activities.

Much of the research in GIScience is done to improve navigation devices for pedestrians by including landmarks (e.g. Elias et al., 2003, Raubal et al., 2002, Hile et al., 2008). Many of existing systems for pedestrian navigation work however as those used for cars – only communicating street networks and metrics. The main reason for this is the difficulty to retrieve data that allow extracting landmarks. Automatic determination of landmarks is limited, because of complex nature of landmarks. Meaning and relevance of a landmark may depend on the specific person and this person's activity within a particular situation. Landmarks may change over time. Eventually a landmark unfolds its particular meaning as a node within a system of landmarks. What follows is that the automatic determination of landmarks has to be supplemented by human's activities and implicit validation of landmarks or by analyzing human behavior (see Section 2).

Within the BMBF[2]-Research Project „Landmarken Mobiler Unterhaltung – Landmarks of Mobile Entertainment" (2010 – 2015) we are building[3] a mobile game play ecosystem, the Mobile Game Lab. Local communities of players continuously playing mobile games participate indirectly in the creation of local landmark systems and dynamic maps by means of an in-built landmark management system (LMS). The LMS is designed to analyze semi-automatically movement data of players and to extract landmarks for local maps to be used for navigation purposes. From where we stand today we will have two local instances of the Mobile Game Lab in January 2014 beside the online-platform already working since spring 2011: (1) A Mobile

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[1]Foursquare is a free app that helps you and your friends make the most of where you are. https://foursquare.com/

[2]BMBF: Bundesministerium für Bildung und Forschung, Federal Ministry of Education and Research

[3]To build an eco-system seems to be an appropriate concept regarding the technical elements of an eco-system. Regarding the social and cultural dimensions of an eco-system however, to initiate, grow or cultivate seem to be more appropriate.

Game Lab am Postamt 5 in Bremen, which allows players to play and to develop mobile games themselves and which supports the collaboration of players, developers and researchers of Mobile Games; (2) The Mobile Game Lab Ahaus, which allows players of different ages to experience the small city of Ahaus by means of mobile games, to develop local games themselves by means of game editors and to participate indirectly in the creation of local maps.

In this paper we present a first step in building the LMS and discuss a method for identifying structural landmarks based on the analysis of movement data of people playing the mobile game Ostereiersuche. The movement data collected provide geospatial, non-continuous trajectories of players. Analyzing the data our current goal is to identify areas, which stand out from their environment in terms of attractiveness and accessibility. We applied a variation of the PageRank algorithm (Page et al., 1999) to find such areas that we call structural landmarks (see below). Our qualitative validation of the results of this method reveals that many of the identified areas are meaningful with regard to navigation purposes. Some identified areas, however, seem to be artifacts.

The paper is structured as follows. First, we offer a definition of a landmark and discuss approaches for landmark identification. Second, we describe the location based-game called Ostereiersuche, which we use to collect movement data of players and thereby to identify structural landmarks. Third, we offer a simple model of space and its representation in form of a directed graph. Then, we describe the analytical methods implemented as algorithms for the identification of structurally salient nodes in this graph. Finally, we present the results of the application of these methods to a data sample. We, then, discuss the results and limitations of the method.

2. LANDMARK IDENTIFICATION BASED ON MOVEMENT DATA

Landmarks are visually, structurally or cognitively salient, spatial features that people use to understand the world, to situate and orientate themselves, to locate objects or locations within this world and to navigate. The key characteristic of a landmark is "singularity, some aspect that is unique or memorable in the context" (Lynch, 1960). The singularity of a landmark is defined through a *particular combination* of visual, or more general discernible, cognitive, and/or structural characteristics (cf. Sorrows and Hirtle, 1999), by means of which, this geographical feature becomes distinguishable in its environment. Visual salience describes objects that stand out due to the visually perceivable contrast with their surroundings. Cognitive salience is measured through the special unique meaning of an object. Structural salience is a characteristic of a landmark defined by the prominence of its spatial position.

Landmark knowledge is one of the basic conditions of spatial cognition (Mark et al., 1999). It allows humans to identify objects and their position in space in relation to their own position. The quality of landmark knowledge impacts success and efficiency of navigation. There have been numerous attempts to use landmarks in GIS. Winter et al., in 1999, Hile et al. in 2008, Fang et al. in 2011, demonstrated the benefits of employing landmarks in pedestrian navigation. Sorrows, Hirtle (Sorrows et al., 1999), and Vinson (Vinson, 1999) discussed the use of landmarks in virtual spaces. Elias offered methods for automated landmark identification using cadastral datasets through application of data mining techniques (Elias, 2003). She also offered guidelines for using landmarks in cartography (Elias, 2008). Similarly to Elias, Nothegger, Winter, Raubal (Nothegger et al., 2004) addressed the challenges of automated landmark identification. They offered a computational model for assessing the salience of spatial objects as a combination of visual, cognitive and structural components. This model was used to automatically select salient features, from a cadastral dataset, for route directions.

Despite these advances, landmark identification remains unsatisfactory. Sadeghian and Kantardzic outlined several reasons for this in their work on "the new generation of automatic landmark detection systems" (Sadeghian et al., 2008). Among others, they "advocate the importance of analyzing *dynamic object attributes*" (Highlighted by Jordan et al.) for landmark identification[4]. Those attributes represent "previous people's associations, interactions and dealings with the objects". In contrast, the static attributes are measurable physical properties like "height, width, color", etc. All methods of automatic landmark identification discussed earlier were applied only to cadastral databases. Often, these datasets contain a registry of spatial objects and their attributes but little information on how people actually use these objects. Such information may contain hints for increasing the quality of landmark identification systems. Trajectories of human's movement alone could reveal what spatial objects are more or less significant for humans but automatic extraction of such information from the trajectories is often non-trivial.

Tracks of human movement (GPS trajectories) have been a subject of analysis in several studies searching for identification of significant locations. Ashbrook and Starner (Ashbrook et al., 2003) used GPS tracks of people driving cars in order "to learn significant locations and predict movement across multiple users". They identified significant locations by clustering locations where people spent enough time to consider it a meaningful stop. For prediction the authors deployed a second order Markov model. Karagiorgou and Pfoser used GPS tracks of cars to construct the transportation network graph (Karagiorgou et al., 2012). They offered a computational model for identifying intersections. Zheng et al. (Zheng et al., 2009) used recorded trajectories to build a hyperlinked network of visited locations. Ranking this network with a HITS-based algorithm helped authors to extract a collection of interesting locations (Kleinberg et al., 1999). This approach demonstrates applicability of the algorithms found in the network theory for evaluating the ranking of locations. All these studies focus more on significant locations rather than on landmarks. However, the definitions of significant locations and landmarks share many overlapping aspects. Therefore, methods used in these studies should be at least partly applicable to the identification of landmarks.

Some studies show that PageRank produces good results in predicting and evaluating movement. Page et al. (Page et al., 1999) originally offered PageRank as "a method for rating Web pages objectively and mechanically". "The page has high rank if the sum of the ranks of its backlink is high". The rank represents a likelihood of a web user eventually lending on a web page following random links. El-Geneidy et al. used PageRank to calculate the attractiveness and accessibility of city parts based on the roaming of people between home and work (El-Geneidy et al., 2011). Jiang et al. (Jiang et al., 2008) applied PageRank to predict the amount of traffic using the underlying street network as the hyperlink-system. Ji et al. used PageRank in identifying landmarks from analyzing blog posts (Ji et al., 2010).

[4] Taking up the idea of dynamic object attributes, we prefer to further differentiate these non-static properties as stated in our introduction; semantic, dynamic (temporal), systemic attributes.

All these works demonstrate that recorded tracks of human movement contain information about the structure of space. Moreover, such tracks allow reasoning about significance of geographical features. The application of the analytical methods should, therefore, allow to identify structurally salient landmarks. In order to test this, we analyze tracks of player movement extracted from records of play actions. Multiple studies demonstrate that the PageRank algorithm is helpful in determining a significance of a place. We apply this algorithm to records of player movement and report the obtained results. In the following sections we describe the location-based game that can provide needed data, the chosen methods for trajectory analysis and the result of their application to the sample data.

3. LOCATION-BASED MOBILE GAMES

Matyas (2008) studied the applicability of location-based games to the acquisition of geographic information. He found that LBGs could be used to collect information about "geographic environment". This information refers to "geographic data about real world objects, like roads or points of interest". He suggests that this data can be retrieved from GPS coordinates found in game's log-files. The studies discussed in the previous section support the feasibility of such assumption (see Section 2).

Matyas et al. (2008) demonstrated possibility to acquire geographical information with CityExplorer. The game encourages players to take geographically referenced photographs of objects that fit into a predefined category. Players choose the categories themselves in the beginning of the game and may also add new categories. Picking a "landmark" related category would explicitly set CityExplorer for landmark identification. Using CityExplorer in this fashion would most likely result in harvesting a collection of salient landmarks. Using more precise categories like "structural landmark" could pose problems for players not familiar with landmark theory. Identification of structural landmarks could be achieved through the analysis of movement tracks of players (see Section 2). The CityExplorer, however, does not record movement paths of its players. Nevertheless, the game demonstrates that a location-based game can be used for solving problems in the domain of geographical information with "human computation" methods.

A problem of data acquisition through LBGs is in ensuring the validity of the data (Winter et al., 2011). CityExplorer addresses the problem of data quality and offers a complex after-game validation procedure carried out by the players themselves. This might rather discourage the potential players. Wetzel et al. offer a more elegant solution to the validation problem through the design of TidyCity (Wetzel et al., 2012). TidyCity is a LBG that encourages people to create riddles about the geographical whereabouts of phenomena, which they describe by means of texts or images. The riddles are then scattered around in the city. Found by other players, the riddles are solved as soon as the original phenomenon described is located and re-united with its description. Such mechanics make validation to be actual game play. Studies of Matyas et at., and Wetzel et al. demonstrate that not only LBGs can be a source of valuable geographic information, but also insure the information validity.

The goal of the BMBF-Project "Landmarks of Mobile Entertainment" is a system of landmarks, which comes into being as a side effect of persistent play activities. The project aims to achieve this goal by (1) developing mobile games that are (aesthetically) pleasurable to play in order to engage gamers into persistent play (2) initiating mobile games and (3) anchoring them within a Mobile Game Lab. Persistent play generates a stream of geographically referenced play actions. An analytical, automatable procedure takes these actions as input and produces novel geographical information. Finally, the produced information is fed back into the game improving the play experience. In such a manner a „player movement - landmark detection loop" emerges. In 2010 - 2012 the project members developed and play-tested several location-based games and started the Mobile Game Lab. Within 2013 we started to build the landmark management system. In the following chapters we introduce "Ostereiersuche", which is one of these games, we have play-tested at Easter 2011, 2012 and 2013. We use the movement data collected 2011 and 2012 to identify landmarks and to study this first instance of the „player movement - landmark detection loop".

3.1 Ostereiersuche

Ostereiersuche, Easter egg hunt, is a mobile, location-based game resembling a popular German tradition according to which families go for a walk and the kids look for colorfully painted eggs hidden by the Easter bunny. Similarly following minimal navigational hints the players of the mobile game Ostereiersuche have to find hidden Easter eggs, each containing a coupon. A combination of three different coupons gives a player a chance to win a real prize in a lottery. As Ostereiersuche is a digital game, the eggs as well as the coupons are virtual but the locations they are hidden at are real. The organizers of the game semi-automatically hide the eggs in advance at places. Considering that the major target group of the game is families with young children, the locations are intentionally limited to public parks. Such limitation narrows the variety of spatial objects available for analysis to those present in parks. With regard to the first step of building the landmark management system both constraints, the simplicity of the game and the limitations of the geographical space helped to focus on the core of our study.

Ostereiersuche explicitly defines locations that a player must visit in order to progress in the game. These are the locations of hidden virtual eggs. The egg distribution is done as follows. For a play area outlined by a polygon, a computer program places eggs along parallel scan-lines. The distance between two neighbor eggs on the same scan-line as well as between scan-lines themselves is chosen to be 25 meters. After filling the complete area in this manner all eggs are shifted for a random offset of 0 to 10 meters. The algorithm would finally, eliminate the eggs placed at locations manually marked for exclusion (lakes, building roofs, streets with traffic). This procedure ensures an even distribution of eggs inside each play area. Such distribution of eggs creates a kind of a "sensor grid" over the play area. An example of the egg distribution can be found in Section 5 on the figure 5.3. Combining consequent actions of collecting an egg allows reconstructing the movement trajectory of a player. This trajectory can be used to infer the structure of space and reason about salience of spatial elements (see Section 2). Ostereiersuche records discrete positions of players and not continuously positions of its players. The game records geo-referenced play-actions.

The game rules, are very relaxed regarding the navigation and the order of collecting. The players are only provided with hints on the distance to the nearest hidden egg. When a player approaches an egg to a distance less than 20 meters the egg appears on a map. Only then the player may collect that egg. Players are free to choose the most efficient navigation strategy.

4. LANDMARK IDENTIFICATION IN PRACTICE

Existing studies of landmark identification (see Section 2) and location-based games (see Section 3) suggest that identification of structurally salient landmarks using play actions recorded with Ostereiersuche is possible. In order to test this in practice we developed the following method. The method consists of four steps divided into two general phases: 1) building the movement model and 2) computing structural salience. The steps in phase 1 turn the movement trajectories of players into a directed movement graph. The weights of the graph edges are derived from the probabilities of player movement. The probabilities are in turn derived from the actual play actions. The steps in the part 2 use the PageRank algorithm to compute the structural weight of the nodes in the graph. Finally, we select the nodes with the maximal local value assigned by the algorithm. The following sections describe the method in detail.

4.1 Building the movement graph

In the first step we partition a chosen play area into a grid of quadratic cells. The geometry of an area in Ostereiersuche is defined by a polygon. In order make the tessellation easier we first calculate an axis-aligned bounding box of the area that envelops the area completely. This bounding box is then filled with rows of equally sized cells starting in a northwest corner and proceeding towards southeast. Each row is populated with cells from west to east until a new cell is completely out of the bounding box. The main reason for partitioning the area is to enable a possibility to compare its different sub-regions with each other and locate those that stand out in their value.

The size of the grid cells is chosen respecting the following considerations. On one hand it must be big enough to generate meaningful results with a relatively small dataset compared to the size of the play-area. On the other hand it must allow unambiguous conclusions about underlying landmarks - at least in public parks where Ostereiersuche was played. For urban environments smaller cell-sizes might have to be selected, since there are more potential landmarks (Snowdon et al. 2009). This, however, also requires a high density of player actions.

The second step starts with a calculation of the movement probabilities based on the following movement model. Being at any cell of the generated grid only movement in four cardinal directions is allowed: north, east, south or west. Taking one of these directions would result in landing in one of the directly neighboring cells laying in corresponding direction. Additionally it is allowed to stay in the current cell. The light blue arrows on Figure 4.1 show the possibility of movement. The reason for selecting such constrained model is its simplicity.

Based on the movement model we calculate values of movement probability by applying a first order Markov chain to the data in the installed grid. The calculation of probability values is based on the actual movement trajectories of players. For a grid with no play actions each cell has equal probability of taking any movement decision. It is 0.2. The probability of moving in a certain direction would increase with each pair of a consequent play actions originating in the current cell and leaving the cell in that direction. The probability of staying in the current cell is increased with each pair of consequent play actions both originating and ending in this cell.

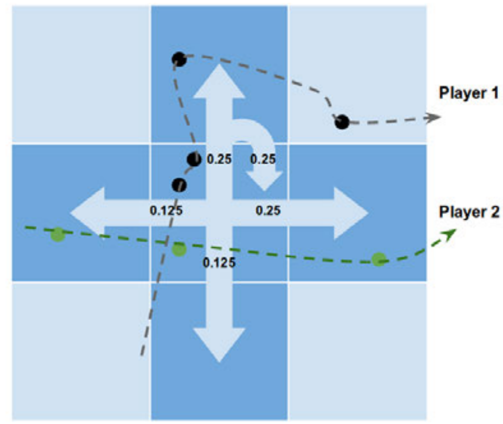

Figure 4.1 Distribution of the movement probabilities in a sample cell

To demonstrate the calculation of probabilities consider the following example. Player 1 collected four eggs moving from the middle cell in a northeast direction. Player 2 moved from west to east and collected three eggs (see Figure 4.1). The middle cell has 1 pair of actions starting and ending in this cell; 1 pair of actions starting in this cell and ending in the northern neighbor and 1 pair of actions starting in this cell and ending in the eastern neighbor. The distribution of pairs is therefore: self – 1, north – 1, east – 1, south – 0, west – 0. Based on this distribution the probabilities of staying in cell, moving north or east increase from 0.2 to 0.25, whereas the probabilities of moving south or west decrease from 0.2 to 0.125.

In the final step of the first phase the generated cells and the movement probabilities are used to form a graph. The cells become the graph vertices. The edges are constructed based on movement model described earlier. Each vertex is linked to itself and its direct neighbors (in the grid) on the north, east, south and west. All middle cells become vertices with 5 outgoing edges; corner cells become vertices have 3 outgoing edges; border cells become vertices with 4 outgoing edges. The edges are weighted according to the movement probability. For example, the probability of moving north out of a given cell becomes the weight of the edge connecting the vertex of this cell to the vertex of the neighbor cell on the south.

4.2 Calculating the structural salience

The structural salience is computed using the movement graph build in the previous steps (see Section 4.1). According to the classification introduced by Sorrows and Hirtle (see Section 2), structural salience is a characteristic of a landmark defined by the prominence of its spatial position. One quality that influences the prominence of a spatial position is its accessibility, or a measure of how easy it is for a person to reach a certain location. We define accessibility following this intuition. The accessibility of a node is a probability for an agent to land on this node, after being placed at a random node and following the outgoing links according to the movement model and the distribution of the movement probabilities. The accessibility of a location is high if the likelihood of encountering this location is high. Such definition of accessibility is very close to the definition of the PageRank value (see Section 2). We therefore use a value assigned by the PageRank algorithm to a node as a measure of its structural salience.

We apply PageRank to calculate the rank of each vertex in the movement graph. Following the analogy of a randomly clicking web user described by Page et al., the intuition of the PageRank is as follows. A person moves along the graph starting at a random node. The person follows the rules of the movement model discussed earlier. However, at every node the movement-session ends with a probability of (*1-d)*. If the session ends the person starts a new one beginning at a random node in the graph. The PageRank value of a node models the chance that this person resides at that node at a random point in time.

The calculation of the PageRank values is best explained through the pseudo code found below.

function $PageRank(G)$

$$R=\left(\frac{1}{N}\right)_{(0\leqslant i\leqslant N)}$$

do

$$temp=R$$

$$PR_i=\frac{1-d}{N}+dx\left(\sum_{i\leqslant N} PR_i\times p_{ji}\right)$$

while ($distance(R, temp)>\delta$)

return R

Where N is the number of cells; PR_i the PageRank of the i -th cell; $R=\left(\frac{1}{N}\right)_{(0\leqslant i\leqslant N)}$ is the initial PageRank value; p_{ji} is the predicted chance of movement from cell i to cell j ; d is the chance that the random movement does not stop after the current cell is visited; δ *i*s a threshold controlling the level of accuracy.

In final step we extract the cells that are local maxima regarding the value assigned by the PageRank. This step is useful, since navigational landmarks are local phenomena, which will be identified because they have some outstanding feature in their greater surroundings (see Section 2). If the PageRank value of a cell is higher than those of its neighbors, it indicates, that it does have some attracting feature in it or is highly accessible.

5. LANDMARK IDENTIFICATION IN A PARK

In order to test the possibility of using data collected with Ostereiersuche for identification of landmarks, we apply the method presented in the previous chapter to the data collected over Easter in 2011 and 2012. In the following we first describe the collected data. Then, we describe and discuss the identification results.

5.1 Player-generated data

As Easter is an annual event, Ostereiersuche is officially played only two days in a year during Easter Sunday and Easter Monday. By the moment of writing the game was staged on April 24th and 25th in 2011, and April 8th and 9th in 2012. In 2011 it was played across all public green areas in Bremen, Germany. In 2012 the area scaled up to include parks in 16 major cities in Germany. Table 1 gives a general overview of the difference in collected data between 2011 and 2012. The area of Bürgerpark (the city park in Bremen) stands out in both years with the number of recorded play actions. We therefore chose this area for application of the method discussed above.

Figure 5.1 shows the locations of the eggs hidden in the Bürgerpark area. 1983 eggs were distributed in Bürgerpark using the algorithm described earlier (see Section 3). In two consequent play events in 2011 and 2012 58 players collected 792 eggs performing 980 play actions. The information about these play actions was recorded in a database. The database management system supported spatial data types and queries. Each record contains information about: 1) a type of the play action, 2) an identification number (id) of a player who performed the action, 3) a timestamp and 4) geographical position of the user in the moment of performing action.

Table 5.1 Play actions recorded with Ostereiersuche in 2011 and 2012.

Parameter	2011 in Bremen	2012 in 16 cities	Both years in Bürgerpark
Total number of play actions	1,390	7,020	980
Total number of players	127	595	71
Total number of players collected at least one egg (active players)	77	243	58
Total number of eggs	2,518	47,054	1983
Total number of collected eggs	580	4,695	792

Figure 5.1 Location of play actions (red dots) alongside with hidden eggs (blue dots) in the south part of the Bürgerpark

Figure 5.1 shows positions of players while performing a play action (red dots). The small blue dots show the positions of the hidden eggs. The positions of the players were recorded using GPS sensors built into the smartphones. In 2011 the game was available only for iOS. In 2012 an Android version was additionally offered. The information about the device model is unavailable in the dataset; therefore it is impossible to justify the accuracy of player positions.

The method described in the previous section was applied to this data with the following modification. The size of grid cells was experimentally chosen to be 2500 square meters (50m x 50m). For the selected area and the data set this size appeared to yield to most meaningful results. Partitioning the area of Bürgerpark using cells of this size generated 3015 cells arranged in 67 rows and 45 columns. 2436 cells contain no play actions; 579 cells contain between 1 and 9 actions. Figure 5.2 displays the southern part of Bürgerpark partitioned in this fashion. Also refer to Figure 5.3 to get the intuition on the distribution of play actions among the cells. More than a half of such cells contain only one action.

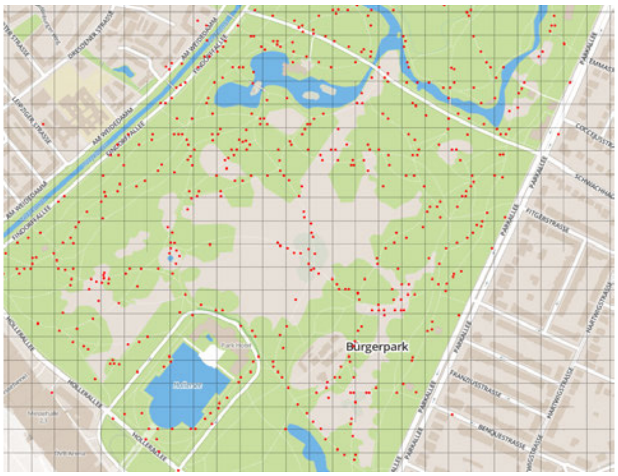

Figure 5.2 The southern part of Bürgerpark partitioned into 50 to 50 meter cells

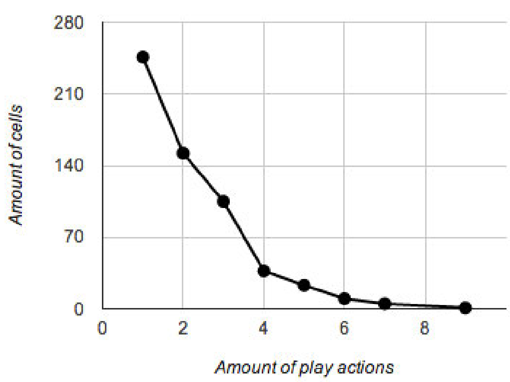

Figure 5.3 Distribution of play actions between cells in Bürgerpark

5.2 Results

The application of the method described in section 4 to the data described in section 5 allowed us to calculate ranking of cells in Bürgerpark. In accordance with the last step of the identification method, among all cells we manually selected those, which have the highest local value of the rank. We then mapped these cells onto a map rendered from the openstreetmap data for further inspection. These 24 manually selected locations are highlighted in the Figure 5.5. The number in the bottom-right corner of each highlighted location represents the sequential number of the identified location. We numbered the cells manually to be able to reference them from the text.

From 3015 cells remained only those that have maximal local value calculated with PageRank. Even though rank values may differ on the remaining cells, each one has a high environmental meaning to its surroundings. Only 24 cells stand out as local maxima. On the first sight readers familiar with Bürgerpark Bremen can qualitatively validate, that the most famous points of interest are marked - i.e. Coffeehouse Emma am See (cell 4), Parkhotel (cell 18) with Hollersee (cell 21, 24), Marcusbrunnen and Hollerbank (cell 13), Dyckhoffpavillion (cell 11), entry to Tiergehege (cell 1), Remmersbank (cell 15), park administration (cell 23) - important crossings (cell 19), especially near entries (cell 3, 12, 17) and between points of interest (cell 22) are marked as well. Places that are especially interesting for the expected target group - i.e. playgrounds (cell 8, 9, 16, 20) - are highlighted too.

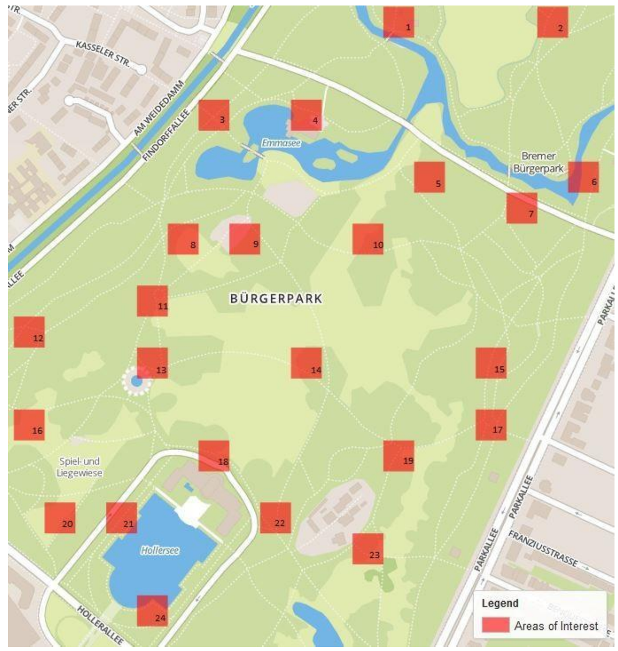

Figure 5.5 Identified significant locations in the southern part of Bürgerpark

5.3 Discussion

Figure 5.1 demonstrates that the distribution of eggs in the area of Bürgerpark was relatively even. In contrast the distribution of play actions is not (see Figure 5.2). Some parts of the park were more explored by the players than the others. This shows that constrains other than game rules direct player movement. In many cases the locations of the play actions map to the walking paths. Despite it might cost more walking, players prefer staying on the path rather than entering a lane. The players prefer convenience for efficiency in the game. This fact proves the assumption that this game does not interfere with usual movement of the players within the park (see Section 3). The game does not dictate players where to go. In contrast, the spatial structure of the park seems to have high impact on the distribution of the play actions. Obviously, players follow the walking paths. This confirms the results of Matyas's studies (see Section 3) that LBGs can be used for collecting information about the spatial structure.

Figure 5.5 shows the locations of the cells with the highest local value of PageRank. Cells number 2, 3, 4, 5, 7, 8, 11, 12, 13, 14, 15, 16, 17, 19, 22, 23 and 24 either themselves contain a path intersection or one of their direct neighbors do. It demonstrates that even application of a simple ranking method (such as the one we offered in Section 4) allows identification of some structurally significant nodes.

There is however significant evidence to the inaccuracy of the methods applied. Cells number 5 and 10 seem to have unreasonably high ranking. And further there are intersections that were not identified. For example, the space between cells 7, 10 and 15 has several of intersections, which is clearly seen on the Figure 5.5. Figure 5.4 shows that user actions for this part of the park were recorded. It did not though result in high ranking for the corresponding cells. This is a sign of problems in the chosen methods.

The limitations of the method also become visible in the identification of bridges. The cell number 1 contains a bridge leading to the zoo. The zoo is, no doubt, a significant location for parents with children, who are the major target group of Ostereiersuche (see Section 3). There is, though, another bridge between cells number 1, 4 and 5, which was not ranked high by the algorithm. This bridge is a major structural landmark as it connects two parts of the widest street in the park. According to the map it is also accessible from multiple locations and there were play actions recorded (see Figure 5.3). These facts demonstrate a need to revise the identification method and the correctness of its implementation. The simplicity of our movement model might also lead to producing artifacts. Limiting movement to only 5 artificial directions is certainly very restrictive and roughly models actual movement of players. Instead of the artificial movement graph one should consider a "natural" graph, which reflects crossings as nodes and natural paths as edges.

As we have discussed earlier the limited amount of data bears the risk to highlight places that do not seem to have a magnifying feature to the general public. Highlighted places could contain personal landmarks that cannot be discovered computationally. The cells 5, 10 might contain such landmarks or they could just be highlighted by chance. After all, we cannot be sure, that all the previously mentioned landmarks were influencing the movement of players. Players could have had other individual intentions that led their movement. Only a larger datasets with more different players will assure which places stand out in regards of accessibility and attractiveness.

Based on the obtained results it is rather hard to draw any certain conclusion. The application of PageRank to the movement model constructed from the play actions did produce structurally significant locations. There is however a range of areas ranked low by PageRank that have both play-actions and structurally salient features (like intersections or bridges). It remains therefore uncertain if the play actions recorded in a location-based game provide a reliable source for improvement to existing landmark identification methods. There exists however a strong theoretical evidence for such a possibility (see Sections 2 and 3). Another study with a bigger dataset and a stronger focus on the quality of the analytical methods might therefore be reasonable.

5.4 Future work

As suggested in the previous section, any consequent attempts of landmark identification with Ostereiersuche must start from revising the method for identification of structural importance. Andrienko et al. (Andrienko et al., 2012) suggest that tessellation might hinder extracting significant places as they can have "arbitrary shapes and sizes and irregular spatial distribution". They developed a method that does not require partitioning. Andrienko et al. also suggests using density clustering for eliminating noise data. Applying these ideas can make results more accurate since there would be no division of the area into cells without preliminary knowledge about the areas structure and the player's movement.

Then, obviously, more reliable results are produced if more actions can be taken into consideration. Considering semantic, dynamic and systemic attributes in landmark identification requires more instances of recorded interaction than collected with Ostereiersuche in two years. The solution here is to include the region, for which the landmarks should be identified into multiple games. This step should ensure a continuous flow of play actions for the identification procedure. We plan to establish such flow for the area of Ahaus, Germany. For this reason we build a local instance of Mobile Game Lab in cooperation with "Ahaus Marketing und Touristik" GmbH[5]. We plan to make a new iteration in the development of the landmark management system, which improves the identification results.

A future development step of the method could automatically retrieve semantic information about the cells. Ying et al. (Ying et al., 2011) provide a guideline for a framework that assigns a geospatial cell to landmarks by analyzing a geographic semantic information database. In their framework Ying et al. assume, that each cell can be assigned to only one landmark, but they do not provide a guideline in case unambiguous assignments are not possible. Elias (Elias, 2003) proposes a formalism to decide which objects in a certain radius of a point of view can be considered landmarks. In her studies she focused on databases of buildings. Sadeghian et al. (Sadeghian et al., 2008) suggest how this formalism could be altered to include different object types and add semantic and dynamic information about the objects. By preprocessing a geographic semantic information database this idea can be embedded into the suggested framework.

6. SUMMARY AND CONCLUSION

Using Ostereiersuche this paper explored the possibility to identify structural landmarks using movement data collected in a location-based game. Despite continuous advancement, landmark identification remains a difficult computational task for GIS. As Sadeghian pointed out, partially it is due to the underestimation of the importance that actual interaction of people with space has. The observation of how people use places may be used to reason about their significance. Using tracks of human movement should therefore improve existing landmark identification systems. The design of Ostereiersuche allows reconstruct movement of players without continuous tracking of their location. The game mechanics put minimal constraints on navigation.

In order to test how applicable Ostereiersuche is for identification of structurally salient landmarks, we developed a simple identification method based on Markov chains and PageRank. We applied this method to the data collected with Ostereiersuche in a city park in Bremen, Germany. The application revealed indefinite results. On one hand they demonstrate that Ostereiersuche has a potential for landmark identification. The most significant cells were often included paths intersections or meaningful places in park. On the other hand the results showed flaws in the chosen method. It is sensitive to the quantity of data and might lack precision due to tessellation as argued by Andrienko et al.

In the future iterations of the landmark management system we plan to address all revealed issues. We will reconsider the use of naive movement model and the application of PageRank, as this

[5] „Ahaus Marketing und Touristik" GmbH: http://www.ahaus.de/ahausmarketingtouristik.0.html

seems to cause many artifacts. We plan to abandon tessellation and include filtering out of noise as suggested by Andrienko. We expect to establish a continuous flow of play actions through a local instance of the Mobile Game Lab in Ahaus.

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