2008

Using location-based tracking data to analyze the movements of city tourists

Modsching Marko
University of Applied Sciences Zittau-Gorlitz

Kramer Ronny
University of Applied Sciences Zittau-Gorlitz

Hagen Klaus Ten
University of Applied Sciences Zittau-Gorlitz

Ulrike Gretzel
Texas A&M University, ugretzel@uow.edu.au

Using location-based tracking data to analyze the movements of city tourists

Abstract
This article presents a methodology to analyze the spatial behavior of tourists based on tracking data. This method was applied during a field study in the city of Görlitz at the east border of Germany. Based on Global Positioning System (GPS) logs the spatial distribution of visitors in various areas is visualized and analyzed. Using the bimodality of the distribution of walking speeds, areas of slowdown are identified and subsequently clustered into activity areas. Using the activity areas, the amount of time tourists allocate to various activity categories is computed. Furthermore, a subsequent analysis of the activity behavior is used to identify the current visiting pattern of tourists and a network analysis of the identified activity areas is used to locate hubs. The network analysis highlights sequences of sights used very often and therefore identifies the beaten paths.

Keywords
Using, location, based, tracking, data, analyze, movements, city, tourists

Disciplines
Business | Social and Behavioral Sciences

Publication Details
Modsching, M., Kramer, R., Hagen, K. & Gretzel, U. (2008). Using location-based tracking data to analyze the movements of city tourists. Information Technology & Tourism, 10 (1), 31-42.

Information Technology & Tourism, Vol. 10 pp. 000–000
Printed in the USA. All rights reserved.

1098-3058/08 $60.00 + .00

www.cognizantcommunication.com

USING LOCATION-BASED TRACKING DATA TO ANALYZE THE MOVEMENTS OF CITY TOURISTS

MARKO MODSCHING,* RONNY KRAMER,* KLAUS TEN HAGEN,* and ULRIKE GRETZEL†

*University of Applied Sciences Zittau-Görlitz, Gölitz, Germany
†Laboratory for Intelligent Systems in Tourism, Texas A&M University, USA

This article presents a methodology to analyze the spatial behavior of tourists based on tracking data. This method was applied during a field study in the city of Görlitz at the east border of Germany. Based on Global Position System (GPS) logs the spatial distribution of visitors in various areas is visualized and analyzed. Using the bimodality of the distribution of walking speeds, areas of slowdown are identified and subsequently clustered into activity areas. Using the activity areas, the amount of time tourists allocate to various activity categories is computed. Furthermore, a subsequent analysis of the activity behavior is used to identify the current visiting pattern of tourists and a network analysis of the identified activity areas is used to locate hubs. The network analysis highlights sequences of sights used very often and therefore identifies the beaten paths.

Key words: Spatial behavior; Activity analysis; GPS logging; City tourism; Network analysis

Introduction

It is essential for the tourism industry to know the places (which sights, shops, restaurants, events, etc.) and times (at which daytime, in which season, etc.) tourists visit. Restaurants use this information to find locations that are most frequently seen by tourists. Destination management tries to direct tourist flows to avoid overcrowding at single places and to enable the tourists to enjoy a destination to its full potential. Unfortunately, the only tourist-related information destination management organizations typically have is the total number of overnight stays whereas little is known about tourists' actual behaviors in terms of activities and specific locations visited. Approaches used to overcome the lack of data, like the simple capturing of pictures and counting of tourists, do not solve the problem because: 1) it is hard to distinguish between a tourist and a local inhabitant, and 2) data are only collected for a specific location at a specific time and, thus, do not allow for conclusions regarding order of visitation and the way certain attractions are combined. But with wearable GPS receivers it is possible to track the paths tourists take. The obtained data can be evaluated in different ways. The most obvious uses of the data are of course the visualization of the track of the tour in a map and the indication of the places visited by tourists. However, there is a lot more

Address correspondence to Klaus ten Hagen, University of Applied Sciences Zittau-Görlitz, Brückenstr. 1, D-02826 Gölitz, Germany. Tel: +49 (3581) 48 28 265; E-mail: K.tenHagen@HS-ZiGr.de

that can be gained from analyzing the logged data. This article presents an approach for analyzing the complex spatial behavior of tourists and for pointing out the actual visitation of different Areas of Interest (AoI). The proposed measures can be used to evaluate the success of different marketing actions quantitatively. At present city councils spend a lot of money on tourist information provision and marketing campaigns without having any information about their success. This article illustrates how spatial behavior data can be translated into useful information that can help gauge the impact of marketing and management efforts.

In the next section the existing research related to analyzing spatial behavior in various contexts will be discussed. The third section will introduce the theoretical background and methodological implications for an analysis of activities and spatial movement. The proposed methodology was applied in a field trial in Görlitz described in the fourth section. Section five discusses the results of the experiment. The article concludes with a section on limitations and future work as well as implications of the study findings.

Related Work

A study by Freytag (2003) showed that the spatial behavior of tourists to Heidelberg is very concentrated, with most tourists visiting the Old Town and some attractions receiving very little attention. Kempermann, Joh, and Timmermans (2004) tracked visitor behavior at a theme park and found that significant differences exist between first-time and repeat visitors: First timers visit a large number of attractions while repeat visitors are much more selective. Hwang, Gretzel, and Fesenmaier (2006) analyzed the spatial behavior of international tourists to US cities and found that trip patterns have important implications for destination bundling and cooperative destination marketing efforts. Nagao, Kawamura, Yamamoto, and Ohuchi (2006) analyzed circular tour activity of rental car tourists in Hokkaido. They found out that some tourists use particularly attractive cities as hubs to get to other locations on the island. These articles illustrate the practical importance of capturing the spatial distribution of tourists at destinations.

Traditional ways of measuring tourists' spatial behavior rely on diary data completed during a visit or survey questionnaires completed after the actual tour or trip (Freytag, 2003; Kempermann et al., 2004). The problem with the first method is that it is highly intrusive, whereas the latter relies on the honesty and memory of people when providing their information. It is quite uncertain how accurate spatial behavior data are when collected using these traditional approaches. The ideal way of logging would be to log the movement of a tourist and to measure the time without letting the tourist take note of it. Several such methods have been implemented in the context of transportation and retail studies:

- Dijkstra, Jessurun, and Timmermans (2001) implemented a model that simulates the movement of pedestrians by agents. Because of defined rules, the agents either move or wait within different cells. They visualize possible interactions of pedestrians in crowded areas.
- Shoval and Isaacson (2005) compared geographic information systems like GPS to land-based tracking systems; these are units sending signals to antenna stations that calculate the position, by measuring the movement of pedestrians. GPS uses the time of arrival of the signal to estimate the current position. The main advantages of GPS are the worldwide availability, little cost and exacter positions, whereas land-based tracking systems have the advantages of being unaffected by weather and work also well in urban regions and indoors.
- Larson, Bradlow, and Fader (2005) analyzed the paths of shoppers in a supermarket with Radio Frequency Identification (RFID) tags located on their shopping carts. RFID is an automatic identification method, relying on storing and remotely retrieving data using devices called RFID tags or transponders. The tracked pathways were clustered to find out typical routes through a grocery store.

The methodology used for studying shopping activities could provide important insights regarding tourist behaviors if it is expanded to an urban destination. However, RFID tags are not suitable for tracking tourists' movements in a city because in portable hardware their range is limited to a couple of centimeters. There are of course RFID devices with ranges of several meters but currently the size of the hardware is growing with the range of the signal. Instead, the worldwide availability of GPS signals makes the small GPS receivers an attractive method in order to track changes in tourists' positions together with a timestamp. The stored position data can be mapped and used to analyze the aggregated spatial behavior of tourists. This analysis indicates which attractions or services are visible to the tourists and where information systems might help in diversifying spatial behavior and redirecting tourists to certain attractions that might be of greater interest to them than the most obvious options. In addition, spatial data enriched with timestamps provides important information about tourists' time allocations over the course of a visit.

Analysis Methodologies

Several types of analyses are possible for data that results from a GPS tracking study and can be summarized into two broad categories: 1) analyses using spatial maps, and 2) activity analysis.

Spatial Maps

Most tourists tend to stay on the beaten tracks when visiting urban destinations (Freytag, 2003). Mobile or web-based information systems are built to enable tourists to discover sights or activities that suit their personal tastes. In order to assess the effectiveness of these emerging technologies and other more traditional marketing measures, spatial distribution metrics can be used. A density map provides insight into the spatial distribution of tourists. In order to compute a density map the map is divided using an even grid. If a track crosses a cell the number of visitors for that cell is incremented. After all tracks have been analyzed the number of visitors to a single cell is divided by the total number of visits to all cells in order to compute the relative number of visitors to each cell.

For a certain time period the relative number of visitors (RNoV) to grid cell (i,j) can be defined as:

$$\mathrm{RNoV}(i,j) = \frac{\mathrm{NoV}(i,j)}{\mathrm{TNoV}} \tag{1}$$

with $\mathrm{NoV}(i,j)$ the number of individual visitors to cell (i,j) and TNoV the total number of visits to cells being tracked in this time period. Obviously formula (2) is valid.

$$0 \leq \mathrm{RNoV}(i,j) \leq 1 \tag{2}$$

Shannon (1948) has developed a formula to calculate the amount of disarrangement in a system—the so called entropy. This formula was adapted for the purpose of spatial measurement by replacing the probabilities through the RNoV values of each cell. As a result the spatial distribution metric (SDM) for a given time period, a destination, a grid, and a set of tracked tourists can be defined:

$$\mathrm{SDM} = \sum_{\forall i,j} \begin{cases} \mathrm{RNoV}(i,j) = 0 \Rightarrow 0 \\ \mathrm{RNoV}(i,j) > 0 \Rightarrow \mathrm{RNoV}(i,j) \\ \quad \log_2(\mathrm{RNoV}(i,j)) \end{cases} \tag{3}$$

SDM reaches its maximum if the RNoV values of all cells have an equal number. That maximum is determined by equation (4) with I as the number of rows and J the number of columns in the grid.

$$\log_2(I^*J) \tag{4}$$

A system is situated optimal if all grids have an equal amount of RNoV. In order to indicate how close the SDM approximates the optimum, absolute values need to be divided by the maximal value to receive the Relative Spatial Distribution Metric (RSDM) shown in equation (5).

$$\mathrm{RSDM} = \frac{\mathrm{SDM}}{\log_2(I^*J)} \tag{5}$$

The result set of the RSDM value is shown in equation (6) where 0 indicates a very high concentration and 1 certifies that the tourists are spread equally over all cells.

$$0 \geq \mathrm{RSDM} \leq 1 \tag{6}$$

Figure 1 exemplifies some possible distributions for a grid of four cells and the resulting RSDM values. It clearly illustrates that RSDM is a suitable metric to measure the actual state of spatial distribution.

NoV(*i,j*)		RSDM	NoV(*i,j*)		RSDM
10	10	**1**	10	0	**0**
10	10		0	0	
10	1	**0.41**	10	5	**0.75**
1	0		5	0	
10	7	**0.96**	10	7	**0.98**
5	4		6	5	

Figure 1. RSDM calculation examples.

Activities

Tracked positions and timestamps can be used to examine the activities that tourists perform at the destination. Activities can be extracted from the tracking logs using two approaches: 1) Hot Area Analysis, and 2) Walking Speed Analysis.

Hot Area Analysis. Different regions with a geographic reference and an associated category (restaurant, shop, museum, etc.) are modeled in advance. The time a tourist is located in the Hot Area is allocated to the associated activity.

Walking Speed Analysis. The trajectory speed of the tourists has two modes: either walking between sights or walking very slowly or even standing to explore a sight, to shop or to have a meal. Using the walking speed analysis, points of slowdown can be identified for each tourist. The points of slowdown for all tourists can then be clustered, because most tourists slow down in the same area. The clusters of "slowdown" points are called an "Area of Interest" (AoI). Using local domain expertise each AoI can be associated with one or multiple concrete activities. The time spent in such an AoI can subsequently be allocated to the time budget of each activity category. Using the AoIs as nodes, a network graph can be constructed to analyze the flow of visitors through the city.

Field Study Design

All together 15 mobile devices were used for the experiment. The experiment took place in the city center of Görlitz for about a month in the summer of 2005. Students and scientific assistants handed out the mobile devices every morning together with a GPS receiver and an external antenna. The GPS antenna had to be put onto the shoulder; the rest of the equipment was to be put into a pocket. The tourists were promised a gift when returning in the afternoon. The starting point was situated at a central point in Görlitz. After receiving the device, tourists were asked to go about their tour as they pleased.

The mobile digital assistant (MDA), a handheld device with an integrated mobile phone, was connected to the GPS receiver via Bluetooth. On the mobile device an application ran with all buttons disabled so that the tourists could not stop the application or start any other. This application constantly logged the positions delivered by the GPS receiver. When the tourists returned the mobile device, the application was stopped by an assistant, the mobile device was connected to a PC workstation, and the data were stored in a database. A PC application then read the data from the database and generated a map with the routes and the current allocation of tourists. Furthermore, specific tour characteristics (e.g., the distribution of waking speeds) were computed.

This logging and analyzing of data touches an important privacy issue. It had to be guaranteed that the gathered information could not be connected to the personal information of the attendees. On the other side, personal information was necessary to ensure that the device was given back after the tour. To facilitate this all the different information (personal, device, survey, and spatial data) was connected by a unique identifier. After the device retraction the ID and personal data were deleted in the presence of the tourist. However, to have an official authorization of logging spatial data the user had to be informed about what data would be stored. All participants had to read and sign a legal assessment and explicitly had to give their permission.

Results

The basic demographic data are shown in Table 1 and indicates that the majority of the people was male and visiting for the first time in Görlitz.

Table 1
Demographics

Key	Value
Number	65
Median	49
Mean	46
irst visit	62%
Male	65%

Additionally, Figure 2 shows the age distribution of the probands. It emphasizes that the field trial attendees were mainly older persons, just like the typical tourists in the city of Görlitz.

Spatial Distribution of Tourists

The number of tourists who visited a certain grid cell was calculated and the specific density level color-coded to map different levels of concentration. The result is displayed in Figure 3. The map indicates that tourists' spatial behavior is highly concentrated within the medieval city center and that attractions such as the Replica of the Holy Sepulchre and the Wilhelminian Style Area are hardly frequented at all. Further, the RSDM of 0.6 calculated from the spatial distribution data confirms the high concentration of tourist flows around certain attractions within the city. This indicates a need for marketing (e.g., creating awareness) and management (e.g., better signage) to diversify tourist flows at the destination. There are a lot of unique sights available in Görlitz that would surely be better visited by tourists if they had more information regarding these attractions.

Results Regarding Activities

Activities Discovered by Hot Areas. Ten Hagen, Kramer, Modsching, Schulze, and Hermkes (2005) illustrate that virtual areas that are modeled onto a geographic map can be used to trigger certain actions, like presenting location-relevant information. These areas can also be used to analyze the activities of tourists. Each time a tourist enters and stops inside such a hot area the time spent for this activity is increased appropriately. These data can be used to analyze the distribution of time tourists spend engaging in different activities. Because each activity belongs to a category, the total time spent for various activities can be aggregated and compared to other activity categories.

The data collected during the field trial suggest that tourists spend more time at restaurants than at attractions and confirm the results of Schmidt-Belz, and Posland (2003) and Schmidt-Belz, Laamanen, Posland, and Zipf (2003) regarding the importance of restaurants in tourists' needs and time budgets. Figure 4 displays the average time tourists spent on certain activities.

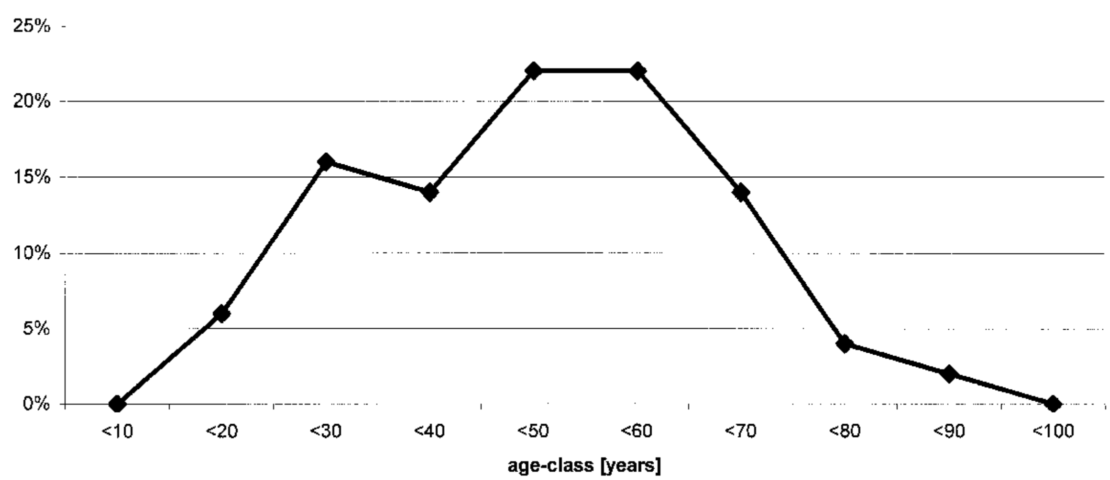

Figure 2. Age distribution of tourists.

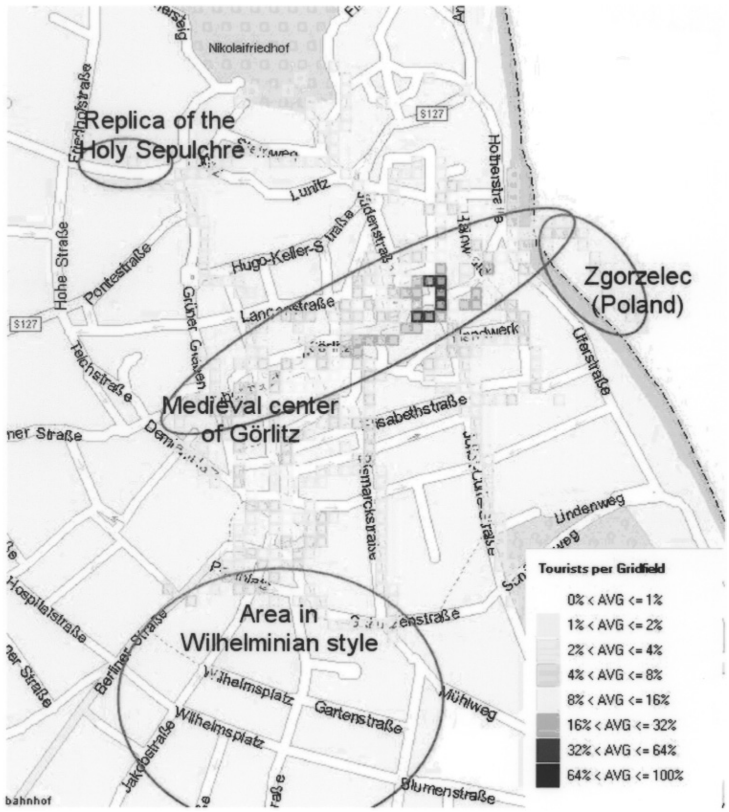

Figure 3. Spatial distribution of tourists.

With the presented hot area method special evaluations for different sights can be used to evaluate how effectively these points of interest are used by tourists. As an example, the evaluation of the "Vierradenmühle," which is located in Görlitz, shows that tourists stay there on average for only 2.3 minutes. Tourists who only take a look will need less time and tourists who eat there will need much more time. This indicates that most tourists did not frequent the restaurant; as a matter of fact, only two tourists decided to become patrons of the "Vierradenmühle."

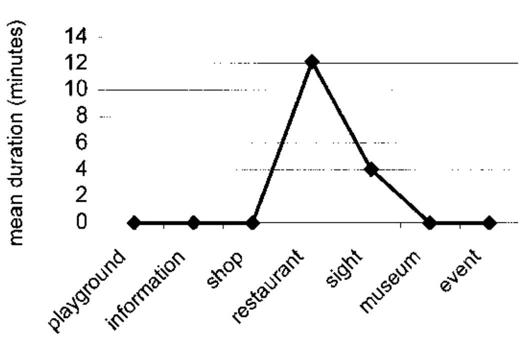

Figure 4. Time distribution for different activities.

Automatic Discovery of Activity Areas by Walking Speed. Because the analysis using hot areas depends on the quality of the localization technology (e.g., GPS), another more robust method had to be found for analyzing activities. The locations of the activities might also be discovered automatically considering different walking speeds. Figure 5 shows a typical walking speed distribution for a single tourist. There the distribution is clearly bimodal, representing two different states the tourist had (walking and slowdown). This is similar to most of the other speed histograms collected during the field trial. Every movement below a cer-

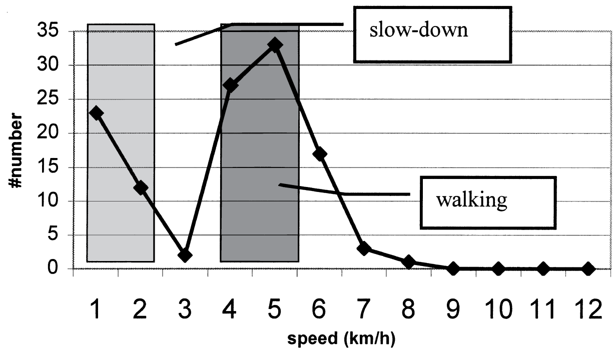

Figure 5. A typical walking speed histogram.

tain threshold could be interpreted as being in "slowdown" or being attracted. All other points of the track with a speed above that value are interpreted as "walking between activities." For the histogram illustrated in Figure 5 this threshold is 3 km/h but could certainly vary for other people. The low point of the distribution as the threshold has to be calculated individually for every tourist.

Figure 5 also shows some of the measured points have speeds of more than 6 km/h. It is unlikely that the tourist really had such a high spatial progress during his/her sightseeing tour. These values might be measurement errors because the positioning starts jumping around the actual position just before the signal breaks down or becomes too weak (Modsching, Kramer, & ten Hagen, 2006). The jumps can have high distances to the previously measured points and therefore cause higher speed calculations. However, a way of compensating for this error is to filter out all speed values over a special threshold, which was 8 km/h for the data presented in Figure 5.

The positions at which the tourists stopped were identified based on individual walking speed thresholds and subsequently mapped. Because a number of tourists stop at the same locations, many point agglomerations became visible on the map. To get a clear impression regarding the centroids of these crowds, the points were clustered by a k-means algorithm shown in Lingras and West (2004). The initial positions and the number of the clusters were adjusted and optimized by reducing the Sum of Squared Error (SSE).

$$\mathrm{SSE} = \sum_{i=1}^{K} \sum_{x \in C_i} \mathrm{dist}^2(m_i, x) \qquad (7)$$

The SSE squares the distance of each point to the center of its associated cluster (C) and sums up the squared errors for all clusters. Obviously this value decreases with an increasing number of clusters (K). Thus, a constellation with lower numbers of clusters but with a somewhat higher SSE might be the better choice.

The map shown in Figure 6 was produced using this clustering algorithm. The optimal cluster count of 20 clusters from different categories emphasizes the high concentration of tourist stops at a small number of specific places within the city. The location of the circles represents the position of the activities. The darker the circle the longer the tourists attended the attraction and the greater the circle the more tourists stopped there. This map illustrates that by analyzing the walking speed, the system can identify popular AoIs. After the automatic discovery process, human expert knowledge was used to associate the areas of interest with an activity, like a sight or a restaurant. Thus, the automatic discovery process proceeds in the following steps:

1. Determine the thresholds for walking and slowdown for each tourist.
2. Identify the points of slowdown.
3. Cluster the points of slowdown of all tourists.

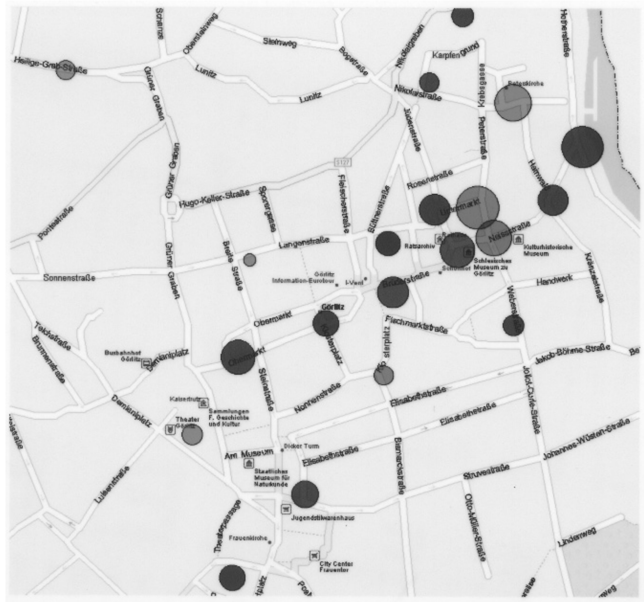

Figure 6. Automatically discovered activity areas.

4. Compute SSE for that constellation and compare to previous values.
5. Repeat steps 3 and 4 to optimize.
6. Compute duration distributions for the discovered AoI.
7. Visualization: Draw a circle for each AoI with the number of tourists indicated by the size and the average duration by the color/shade.

The walking speed analysis method is much more robust to location errors because of the following reasons:

1. In case of a GPS position between two streets the navigator might correct the position to one of them (Modsching et al., 2006). This leads to high-speed jumps during the correction process, which are filtered out.
2. Systematic and even location dependent errors of the GPS position are easily dealt by a human, who assigns clusters to activities, because these errors are too small to cause an association with an adjacent activity.
3. There is averaging in associating a sequence of slow speed positions with an AoI. There is also averaging when AoIs are clustered together. These two steps remove a significant amount of spatial noise in the location measurement.

Activity Behavior Analysis. With the automatic activity discovery methodology it is possible to identify areas in the city that impress the tourists most, thus leading to smaller spatial progress. These areas were used for a deeper analysis to find the typical activity pattern of tourists for the specific destination. The chart in Figure 7 visualizes how many tourists were attracted (decreased their walking speed) at how many places. The average number of visited sights of all tourists is 3.5 of more than 200 densely packed sights, whereas a typical guided tour in Görlitz by a human leader contains about 13 sights (http://www.goerlitz.de). Furthermore, the city contains one of the biggest coherent Wilhelminian style quarters and a lot of other worth-seeing sights. This shows that most tourists do not recognize the broadness and the richness of available sights in the city. Even the medieval center of Görlitz, with its many beautiful houses, is very often discovered just by passing through. A lot of interesting stories and legends exist for most of the sights tyat definitely would grab more of a tourist's attention and lead to longer durations at the front of the houses, but obviously tourists lack necessary information that would encourage stops. The duration statistic of the current state is a mean duration of 10 minutes for all discovered activity areas, with values ranging from 3 seconds to 68 minutes for a single attraction. These values could surely be extended by better information offerings (e.g., through a location-aware mobile tour guide) (ten Hagen et al., 2005).

Flow Between AoIs. The data collected by the automatic discovery approach was exported to the social network analysis application NetDraw (Borgatti, 2002). This program enables the visualization of nodes and the ties among them to understand how different sights are combined within individual tours and to visualize the main areas of tourist visitation and paths of interest. Figure 8 is a weighted directional graph showing a subgroup of nodes and the strength of their relationships. The categories are visualized by the type of the shape (here square for a restaurant, circle for a sight) and the duration of staying time is indicated by the size of the node. The thickness of a line visualizes the number of tourists that moved between these AoIs. Arrows indicate the sequence in which the attractions were visited. The center of the graph shows the sights "Schönhof," "Untermarkt," "Biblisches Haus," and "Rathaus," which are densely connected by thick lines. Geographically these sights are at close quarters in the medieval center of Görlitz. This high concentration of sights could be a reason for the comparatively short stay at these attractions, indicated by the small size of the nodes. The tourists seem to be distracted while enjoying one sight due to other sights being visible.

The graph as a whole is densely connected, meaning that most sights have a direct tie to other attractions. This implies that, although the total number of attractions visited is highly concentrated, tourists seem to combine the attractions in many ways, leading to very idiosyncratic tours of the city that also involve stops at various restaurants between visiting different attractions. In addition, it is an indication of strolling rather than goal-directed behavior that leads to crisscross movements between attractions rather than clear directional paths through the city center.

Additional information can be derived from the strength of ties and cluster membership of the different attractions. The NetDraw application enables a k-core clustering algorithm to be performed that can identify nodes with and without strong relations to other nodes. Several attractions were identified as not having a high connectivity to the rest of the attractions, meaning that they are only visited in conjunction with a limited number of other attractions. These attractions (Postplatz, Zum Flyns, Heiliges Grab, Zwinger, and Destille)

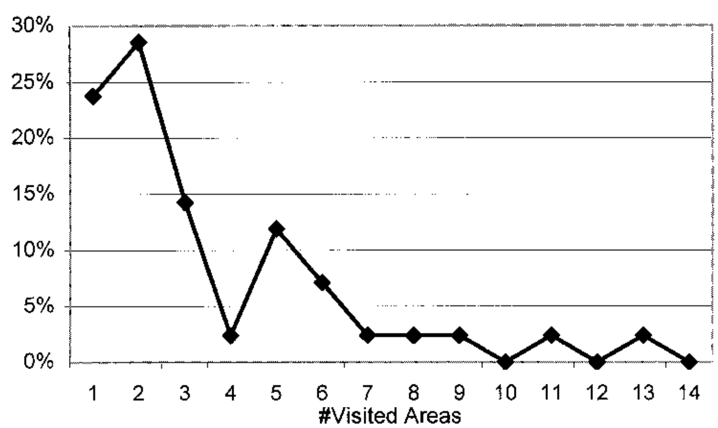

Figure 7. Visiting pattern of tourists.

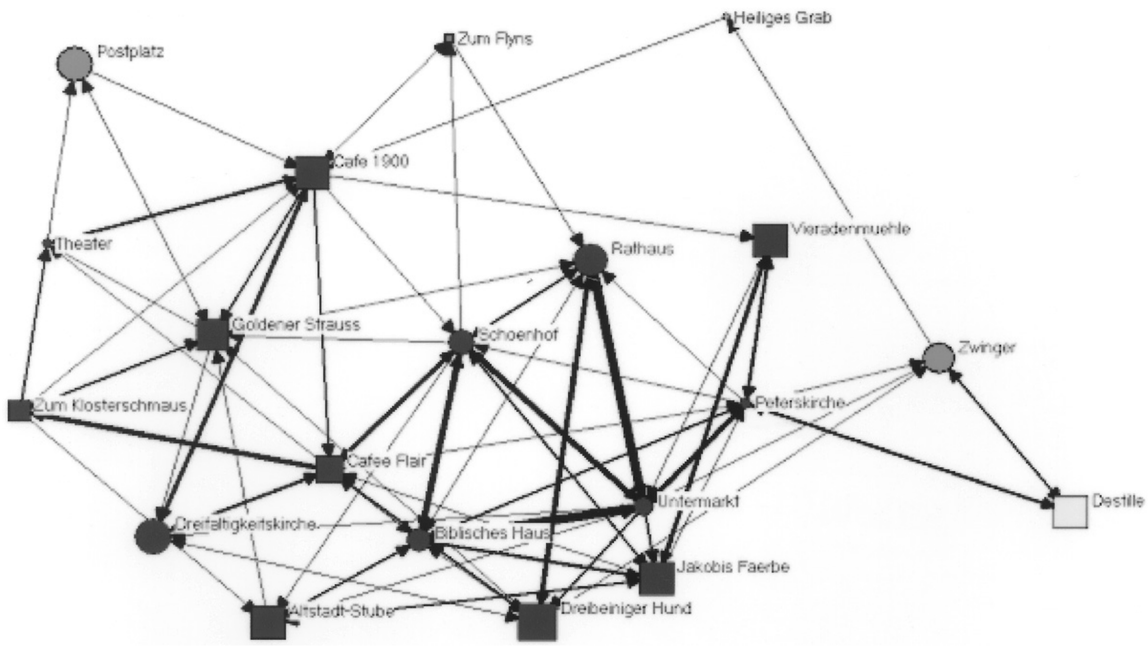

Figure 8. Network of activity areas.

appear on the outside of the graph, representing distance to the closely connected core of attractions. The sight "Heiliges Grab," for instance, is only visited after the sight "Zwinger" was visited and the restaurant "Destille" is only frequented in conjunction with visiting the "Zwinger" or the "Peterskirche."

Limitations and Future Research

Several things can happen during a tour that can cause a misinterpretation of the gathered data with the hot area method. For instance, stops for meeting friends or orientation might be considered as sightseeing. Human expert knowledge is crucial in determining whether a stop occurred in conjunction with an attraction or not. However, there will always be a certain extent of noise in the data that will vary depending on the density and types of attractions available at the destination. Also, the study methodology might have encouraged a self-selection process because the sample contained more males than the general population of visitors to Görlitz. It could be that the prospect of having to use a mobile technology or privacy concerns discouraged some individuals from participating in the study. The knowledge of the users that all of their movements are logged might also have an indirect influence on the actual behavior of the tourists. The setup for future studies should be changed to a single blind distribution of two different kinds of devices, whereas only one of them really logs the data. This will require a larger sample size of probands but will probably avoid an artificial change of the real behavior due to the personal feeling of being observed. Also, simplification of the technological setup is needed to gain a more representative sample. A major factor will be incentives that could help overcome participation barriers.

The position data in the field trial was collected by a combination of an MDA and Bluetooth GPS receiver. This combination is prone to errors because the Bluetooth connection or the operating system may break down. New studies of spatial behavior should be conducted with stand-alone GPS loggers. These loggers should be handed out at various points within the destination to reduce potential bias in the data and make sure that tourists are being tracked from the very beginning of their tour. Also, there need to be a sufficient amount of dropoff points (e.g., hotel receptions) to ensure that the data collection methodology does not interfere with the actual tourist behavior. Recommender systems have been proposed as tools to influence tourist behavior by providing specific suggestions tailored to the preferences of the particular user (Nguyen, Cavada, & Ricci, 2004). The methodology presented in this article can not only be used as input for the generation of tours but also as a tool to evaluate whether the provision of attraction-related information has an impact on tourists' actual behavior when touring a city destination. Future research in this area will provide important input regarding drivers of tourist spatial behavior and will also offer valuable insights regarding the design of tourist information systems.

Conclusion

The main contribution of this article is to devise a first method to depict and quantitatively analyze the spatial behavior of tourists in a city and discuss the results of a first application. The data collected in this field trial is of course too little and to biased through GPS inaccuracies to derive some managerial implications or suggestions. But it is crucial for the destination management organization as well as business owners to know where tourists really go and what activities they engage in. The steadily decreasing cost of mobile devices and GPS tracking devices will make this methodology ever more affordable and will hopefully also increase its actual use for research purposes. Also, the progress of the positioning technology forces the opportunity to generate soon a commercial service for destination management organizations. The presented analysis methodology allows for input in planning processes but can also be used to evaluate the implementation of certain measures such as specific marketing campaigns by comparing preimplementation data with spatial behavior after the measure was introduced. The steadily decreasing cost of mobile devices and GPS tracking devices will make this methodology ever more affordable and will hopefully also increase its actual use for research purposes.

Acknowledgments

This work is part of the IKAROS project funded by the federal ministry for education and research (BMFT) and part of the VESUV project in cooperation with Siemens AG, Microsoft's European Innovation Center (EMIC), the city of Görlitz, and Fraunhofer Institute IGD. VESUV is supported by the Federal Ministry for Economics and Labour (BMWA).

Biographical Notes

Dipl.-Inf. Marko Modsching was born 1980 in Hoyerswerda (Saxony), where he did his A-levels in 1999. After his military service in 2000 he studied computer science at the University of Applied Sciences in Zittau-Görlitz. During his study he did some research together with Prof. Dr. Joerg Schulze. There he developed a concept for a new eLearning platform called TaskTrainer. The outcome of this work was an application which is currently being used at the University of Applied Sciences Zittau-Görlitz. As his diploma he researched for an additional TaskTrainer-module called TaskExaminator to perform software-based exams. Since November of 2004 he has been working as a research assistant at the university for the projects IKAROS (www.ikaros-projekt.de) and VESUV (www.vesuv-projekt.de). The main focus of both projects is the development of context-aware software agents and services for mobile collaborative networks.

Prof. Dr.-Ing. Klaus ten Hagen studied EE/CS from 1983 to 1987 at the Technical University of Aachen (RWTH). He started as a developer of hardware and real-time software at the Institute for Plastics Processing (IKV). From 1988 to 1994 he was a research assistant at the Institute for Integrated Systems (ISS). His research area was hardware–software co-design. One outcome of his work was the HW/SW cosimulation capability in the system simulator COS SAP. (COSSAP was productized by CADIS. CADIS was acquired by Synopsys in 1994.) Prof. ten Hagen is the author of the book *Abstract Modeling of Digital Circuits* published by Springer. In 1995 he worked as a consultant for high-level design methodology. From 1995 to 2000 he held various management positions at Synopsys in the Silicon Valley. From 2000 to 2001 he was Director of Design Planning with eSilicon and from 2001 to 2003 VP of Engineering at SigmaQuest. Since March 2003 he has been a professor at the University of Zittau-Görlitz. Prof. ten Hagen is the author of numerous publications and two US patents.

Dipl.-Inf. Ronny Kramer was born 1981 in Bad Muskau, but lived and went to school in Weisswasser (Saxony) where he did his A-levels in 1999. From 2000 until 2004 he studied computer science at the University of Applied Sciences in Zittau-Görlitz. For his diploma he researched the matchmaking of interests in eTourism applications, which also resulted in a publication. Since November of 2004 he has been working as a research assistant at this university. His current work concentrates on the VESUV project (www.vesuv-projekt.de) developing software agents for secure delegation in mobile collaborative applications.

Dr. Ulrike Gretzel is an Assistant Professor at the Department of Recreation, Park & Tourism Sciences at Texas A&M University and Director of the Laboratory for Intelligent Systems in Tourism. She received her Ph.D. in Communications from the University of Illinois in Urbana-Champaign and holds a master's degree in International Business from the Vienna University of Economics and Business Administration. Her research focuses on persuasion in human–technology interaction, the representation of sensory and emotional aspects of tourism experiences, and issues related to the development and use of intelligent systems in tourism.

References

Borgatti, S. P. (2002). *NetDraw1.0. graph visualization software*. Harvard: Analytic Technologies.

Djikstra, J., Jessurun, J., & Timmermans, H. (2001). A multi-agent cellular automata model of pedestrian movement. In M. Schreckenberg & S. D. Sharma (Eds.), *Pedestrian and evacuation dynamics* (pp. 173–180). Berlin: Springer Verlag.

Freytag, T. (2003). *Städtetourismus in Heidelberg—Ergebnisbericht zur Gästebefragung 2003*. Heidelberg: Geographisches Institut der Universität Heidelberg.

Hwang, Y. H., Gretzel, U., & Fesenmaier, D. R. (2006). Multi-city trip patterns: International tourists to the U.S. *Annals of Tourism Research, 33*(4).

Larson, J. S., Bradlow, E. T., & Fader, P. S. (2005). An exploratory look at supermarket shopping paths. *International Journal of Research in Marketing, 22*(4), 395–414.

Kempermann, A., Joh, C-H., & Timmermans, H. (2004). Comparing first-time and repeat visitors' activity patterns in a tourism environment. In G. I. Crouch, R. R. Perdue, H. Timmermans, & M. Uysal (Eds.), *Consumer psychology of tourism, hospitality and leisure* (Vol. 3, pp. 103–120). Cambridge, MA: CABI Publishing.

Modsching, M., Kramer, R., & ten Hagen, K. (2006, March 16). Field trial on GPS accuracy in a medium size city: The influence of built-up. In *3rd Workshop on Positioning, Navigation and Communication 2006 (WPNC'06)*, Hannover.

Nagao, M., Kawamura, H., Yamamoto, M., & Ohuchi, A. (2006). Analysis of circular tour activity based on GPS Log. In M. Hitz, M. Sigala, & J. Murphy (Eds.), *Information and communication technologies in tourism 2006* (pp. 87–98). Vienna, Austria: Springer.

Nguyen, Q. N., Cavada, D., & Ricci, F. (2004). On-tour interactive travel recommendations. In A. Frew (Ed.), *Information and communication technologies in tourism 2004* (pp. 259–270). Vienna, Austria: Springer.

Lingras, P., & West, C. (2004). Interval set clustering of web users with rough K-means. *Journal of Intelligent Information Systems, 23*(1), 5–16.

Schmidt-Belz, B., & Posland, S. (2003). *User validation of a mobile tourism service*. Paper presented at the Workshop on HCI Mobile Guides, Udine (Italy).

Schmidt-Belz, B., Laamanen, H., Posland, S., & Zipf, A. (2003). Location-based mobile tourist services—first user interaction. In A. Frew, M. Hitz, & P. O'Conner (Eds.), *Information and communication technologies in tourism 2003* (pp. 115–123). Vienna, Austria: Springer Computer Science.

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal, 27*, 379/n/423, 623–656.

Shoval, N., & Isaacson, M. (2005). The application of tracking technologies to the study of pedestrian spatial behaviour. *The Professional Geographer, 58*, 172–201.

ten Hagen, K., Kramer, R., Modsching, M., Schulze, J., & Hermkes, M. (2005, May 9). *Context driven adaptive tour computation and information presentation*. Paper presented at the First International Workshop on Managing Context Information in Mobile and Pervasive Environments, Ayia Napa, Cyprus.