J. PERVASIVE COMPUT. & COMM. 1 (1), MARCH 2005. ©TROUBADOR PUBLISHING LTD)

Development and evaluation of a context-driven, mobile tourist guide

Ronny Kramer, Marko Modsching, Klaus ten Hagen
{RKramer, MModsching, K.tenHagen}@HS-ZiGr.de
University of Applied Sciences Zittau-Goerlitz, Brueckenstr. 1, D-02826 Goerlitz, Germany

Received: August 01 2005; revised: December 02 2005

***Abstract*— The behavior of tourists strongly depends on the availability and quality of information. Little information as well as a flood can be disorienting and forces many tourists to join the majority visiting major sights. This causes a few crowded places in contrast to many under-utilized. A Destination Management Organization (DMO) has the goal to spread the tourists more evenly, whereas the tourists would like to enjoy the destination to its full potential according to their personal interests. The target of the Dynamic Tour Guide (DTG) is supporting both goals by means of pervasive computing based on the actual context which is defined by personal interests, location and schedule of a tourist. It enables a personalized, spontaneous and guided tour. A field trial was conducted in the summer of 2005 to study the following questions as a precondition for the development: (1) Is it possible to seed generic interest profiles in the mobile context that allow the accurate prediction of actual rankings? (2) Are the interest profiles sufficiently diverse to base personalized tours on individual interest profiles instead of interest prototypes? (3) How do personalized tours affect the spatial behavior of tourist? Three methods to elicit the generic preferences of tourist in the mobile context are compared with actual rankings using Spearman's rank order coefficient. The diversity of the interest profiles is analyzed in various ways leading to the conclusion that personalized interest profiles are necessary. For the gathered profiles tours are being computed and simulated in order to gain a first insight into the effect on the spatial behavior of tourists.**

***Index Terms*— context, mobile computing, dynamic tour guide, ontology, semantic matching, personalized tour**

I. INTRODUCTION

As human tour guides generally serve groups of tourists they follow predetermined routes to the major sights. Even individual tourists generally lacking detailed information often decide to follow groups in order to get to interesting locations. Therefore the majority of the tourists end-up on the beaten tracks. Interesting sights just a couple of hundred yards off the main tourist arteries are rarely visited. This thesis is supported by perceptions gained during studies in various tourist destinations (see Section V) and a tracking experiment in the city of Goerlitz. In this experiment GPS receivers are handed out to tourists discovering the city. After return the log of the positions is extracted and analysed. In order to visualize the spatial distribution of the tourists the number of visitors to each grid cell is counted and color coded in order to create the map shown in Fig. 1. Most tourists move within a limited area and very attractive sights are visited only by

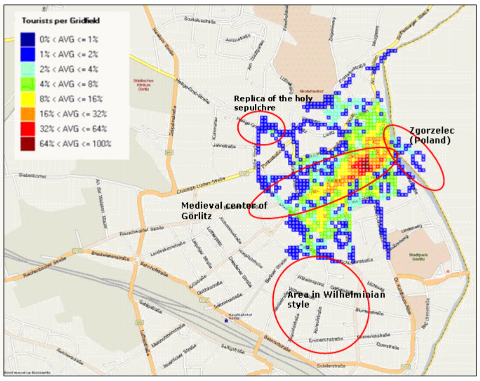
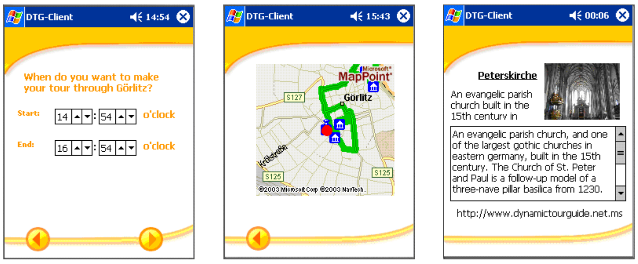


Fig. 1. Distribution of tourists in the city of Goerlitz

few. Important architectural attractions are marked by circles in Fig. 1. Two of them, first a large and consistent ensemble of buildings in Wilhelminian style and second a replica of the Holy Sepulchre, are rarely visited even by architecturally interested visitors. This situation might easily be improved by creating personalized tours based on individual generic preferences and contextual information in order to enable the tourists to enjoy the destination to is full potential.

Destination management organizations (DMO) like to have tourists spread over a wider area rather than having them concentrated at certain points. This improves the experience for individual tourists, provides exposure to a wider set of services and projects a more varied image of the destination, which will attract more tourists, motivate them to stay longer or come back. The ideal is to have a local guide, who understands the individual interests and timeframe, knows the local situation and gives a personal tour to each tourist, and which additionally fits into a pocket. This is the objective of the Dynamic Tour Guide (DTG). The purpose is to devise a tour, just like an expert guidance would do after getting to know a tourist's preferences, by means of new technologies like mobile applications and context aware computing. The first sections introduces the scenario and derives an architectural view planned for the DTG. Subsequently related projects are considered for comparison and to frame the scientific challenges. The computation of an individual tour by means of semantic matching and a discussion of context driven interpretation can be found in [26] and [28]. The main part of



(a) Setting of time (b) Navigation (c) Information

Fig. 2. Screens of prototype

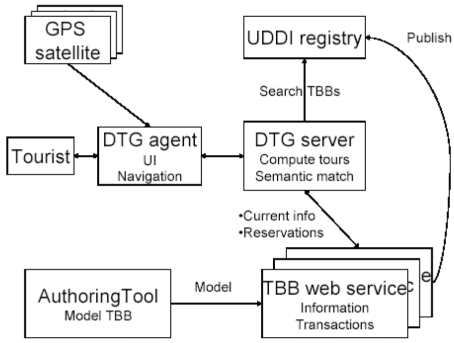


Fig. 3. DTG system architecture

this article deals with the evaluation of three different methods of eliciting one's preferences in a field study. The impact of personalized tours on the spatial distribution are assessed using a simulation based on the gathered generic interest profiles. The article closes with an outline of future research.

II. Scenario

Expectedly most people will own a mobile device in the next couple of years, cities will be covered with WLAN access points and DGPS with local augmentation will provide localization with a precision down to 1 m. These are the preconditions to develop a Dynamic Tour Guide. The following scenario describes its functionality best: "A businessman has an appointment in a foreign city in the evening at 2pm. After arrival at his destination in the morning at 10 o'clock, he has some time left and would like to get to know the city. He starts the DTG which is installed on his mobile device. Furthermore, the mobile device is aware of its position via e.g. the Global Positioning System (GPS-WAAS) and it also maintains a personal interest profile. Setting the available time period to 4 hours will start a tour request. The DTG automatically discovers the sights and services at this destination, interrogates the corresponding web services to update the current information and then computes potential tours by selecting attractions according to his personal interests. As the tour will include noon, a lunch-break is integrated. A table in a suitable restaurant is booked for 12 o'clock. After selection of the tour, the DTG will visualize it on a map, giving the tourist the option to modify it. Then the tourist starts the tour. A standard pedestrian navigator integrated into the DTG guides him via audio information to the first attraction which is a church. Noticing the tourists approach, the DTG draws his attention to it by giving audio information about the architecture style and history of it. The tourist listens and watches carefully. As he spends more time at the attractions as the DTG had planned, the next attraction is left and he is directly guided to the restaurant where he must be at 12 o'clock. After lunch and on his way to his appointment location, the DTG realizes that there is some time left and leads him to another monument, again presenting audiovisual information. It gives a warning signal to let the tourist know it's time to leave. It leads him straight to the office building so he makes it to his appointment in time." Screenshots illustrating this scenario are shown in Fig. 2.

III. Architecture

Each tourist has a mobile device using e.g. GPS to determine its location. The mobile device is connected to the internet either via GPRS or UMTS. Each sight, as a possible component of the tour (TBB = Tour Building Block), is semantically modeled by a content provider using an AuthoringTool. This model contains address, interest coverage, descriptive text modules, various pictures, audio files and general information. Each TBB will have its own web service (WS) to store and provide these data. A service provider like a restaurant will wrap the local restaurant management system by a WS to grant public access to the semantic model, current information, e.g. opening hours, and a transactional interface to e.g. reserve a table. The WSs of the TBBs are registered at a UDDI registry. The DTG server is executing a semantic match algorithm to rank the sights for a specific tourist. A computationally more demanding task for the DTG server is the computation of a tour as a sequence of TBBs. Audio hints and a map for navigation are provided by standard navigation software installed on the mobile device to guide the tourist to the next TBB [20]. The DTG provides information about a TBB as the tourist approaches it depending on the direction. Furthermore it adapts the higher-level plan for the remaining time to the actual walking speed and the actual time spent at each TBB. The standard navigation software will try to get a tourist back on-track to the next TBB. After some time limit the DTG will interpret the continued movement of the tourist as a decision and adapt the tour by computing a new one starting from the current position.

IV. Challenges

Tour Guides have always been an important research topic. The following projects summarize the current state of the art in this area:

- GUIDE [3] is a mobile tour guide which concepts are most related to the DTG. The visitor chooses attractions from various categories. These attractions are then sequenced by the GUIDE taking into account opening hours, best time to visit and the distance between attractions. The sequence can be modified manually. Navigation is achieved by a map and a list of instructions. Reaching a point of interest (POI), context-sensitive information is provided. Differences are the use of cell based positioning instead of GPS and the selection of concrete sights to visit by the tourist him/herself instead of using generic preferences to compute a ranking which then drives the computation of the initial tour plan. The DTG also adapts to the actual behaviour of the tourist by recomputing the tour for the remaining amount of time. Lacking a ranking the GUIDE re-arranges the sequence of initally selected attractions.

- Cyberguide [1] was one of the first mobile tour guides. It works outdoor with GPS and indoor with infrared to determine context information like users' position and orientation. Personal preferences are not analyzed to compute a tour plan, but the user can receive information about anything he/she sees, wherever he/she is. Requesting a route to a desired POI is possible too. In addition it provides the option to create a kind of diary about the whole tour.
- The Crumpet project [21] enables a mobile agent to find certain sights, to present them on a map and to calculate a route to a selected one.
- The software developed by eNarro [7] presenting the most important sights along predetermined routes in many big cities all over the world. The tourist needs a PDA with a special player loaded with the content for the particular tour. She/he also has to have navigation software which will lead her/him to the different places. The attractions are then presented using audiovisual information.
- The Deep Map project [19] presents a tourist guide that is accessable by voice, provides domain knowledge in a database and has a geographical information system integrated. But the user has to plan the tour her/himself. Virtual tours on the screen are possible as well. The paper also describes the challenges of creating personalized tours, while this paper provides a possible solution based on empirical studies.

In contrast to existing tour guides the DTG computes an individual tour in real-time by considering available context information like personal interests and location based services. The development addresses the following challenges:

- Elicitation of generic interests of a tourist in a mobile context to seed the profile
- Ranking of Tour Building Blocks (TBB) by semantic matching
- Computation of an individual tour plan in less than 5 seconds
- Context aware interpretation of the environment
- Tour tracking and adaptation

Especially the elicitation of preferences in mobile context is known little about. This paper is aimed at that challenge. As the city Goerlitz is an important target for tourists, a field trial should help to clarify basic methods.

V. Field study

In order to check the ability to capture individual generic preferences and to rank attractions based on it by the designed semantic matching technology, a field study was conducted in Goerlitz in June/July 2005. The field study was designed to answer the following questions:

1) The system described above computes an optimal tour according to the interest profile of a tourist. Therefore the most fundamental question is: Is it possible to build a system that collects information from the tourist that is indeed suitable to select attractions? Such a system will have to rely on a mobile device; since that's the only device a tourist arriving at a destination has access to.
2) In case an effective mobile interest gathering capability can be built, the next question is: Do individual interest profiles exist? Or are there only 2-3 prototypical interest profiles for which standard tours are sufficient?
3) The last and most important question for any form of pervasive computing or ambient intelligence is: Does the additional contextual information affect the spatial behavior of tourists or does the DTG merely increase the ambient noise? Are the interest profiles so similar anyhow that the resulting tours hardly differ and thus the tourists are best served by following the beaten tracks?

A. Related studies

The primary step towards a solution was the analysis of the current spatial distribution of tourists using GPS tracking. Related examinations that have been done in tourism sector, among others in theme parks, are to follow. They identified the same problems and helped to design the methodology of the experiment presented in the following section V-B

- During a survey of tourists in Heidelberg [8] 1500 tourists were asked about their activities during their visit of the city in 2003. The first important fact to mention is that most tourists explore the city by foot and on their own. Only 7% decide for a guided tour. There aren't any possible reasons discussed, but as the DTG is targeted at individual tourists it has very good chances for acceptance among the majority of tourists. The second finding indicates that most tourists move within a very limited area around the Old Town. Almost anybody visits the castle while all other sights receive less attention; some even less than 5%. This implies that most tourists gather at a few places which might be an effect of missing contextual information. One can predict that some tourists would visit other attractions too if they knew about them.
- In chapter 9 of Kempermann et.al [15] an examination of the different behaviour of first-time and repeat tourists at theme park destinations is presented. The visitors were given questionnaires afterwards to specify the attended places, the time spend there and the reasons for that. It is outlined that first-time visitors have less information about a destination and try to visit as many attractions as possible, whereas repeat visitors select the attractions they attend more properly because they already know what to expect. Tourists are clustered using the sequence alignment method. In this case, similar activity patterns of tourists are grouped together and result in clusters. The DTG shall help tourists being able to pick out the

sights they are most interested in for a visit, because the DTG has all the information that are invisible or at least inconvenient to access for a mobile tourist.

- Kempermann et.al [14] did further studies on the time tourists spent for certain activities or at certain sights. Tourists specified the time spent for waiting, eating and acting in a questionnaire. E.g. it was found out that tourists spend more time on activities when the location offers food. Both these approaches relied on the honesty and capacity of peoples' memory when giving their information. It is quite unsure how credible these data are. A better way would be to log the movement of a tourist and to measure the time, without letting the tourist take note of it.
- Dijkstra [6] 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 [25] compared localisation systems like GPS to land-based tracking systems; these are units sending signals to antenna stations that calculate the position. The main advantages of GPS are the worldwide ability, no costs and exacter positions, whereas land-based tracking systems have the advantages of being unaffected by the weather and work also well in urban regions and indoors.

The next step is to find a way to get to know a tourist's interests.

- Schmidt-Belz [24], [23] made a study in the city of Heidelberg about the general information needs of tourists visiting a destination. Tourists were asked at a central place and mentioned restaurants most often. Sights were only third place. This paper intends to go one step further and to capture the special kinds of interests towards restaurants and sights.
- If tourists are asked for their interests, many probably won't have concrete ideas about it. But Gretzel/Fesenmeier [11] showed that tourists need to be inspired by suggestions to select things and get aware of their own interests. This is called elicitation of preferences as the persuasive component of a recommendation system is mentioned as well. Of course a precondition is that the tourists are willing to reveal their personal interests.
- Fink and Kobsa [4] investigated the elicitation of preferences in order to personalize a tour. They also propose to observe the behaviour of the tourist, generalize the observations based on "stereotypes" and then predict interests in certain concrete items. This approach presumes a central server to aggregate and mine observations. In order to bootstrap this bottom-up recommender a certain amount of observations needs to be gathered prior to derive stereotypes and then recommendations. The DTG approach intends to develop and validate methods to gather a personal interest profile. This generic interest profile is then used to derive rankings on concrete TBBs by semantic matching based on a common public ontology of the destination. The top-down DTG recommender gathers personal data using a mobile device owned by the user. Importantly, personal information does not leave the boundary of the personal computing device.
- Eliciting somebody's preferences is a significant challenge especially in a mobile context as found by Nguyen, Cavada & Ricci [5]. Solving this problem may lead to fundamental improvements as more personalized information provision enables tourists to enjoy a destination to its full potential.

The challenge then is to find out the quickest and most effective way to elicit the preferences of a tourist in regard to selecting attractions for a tour. There have been studies on websites in order to recommend travel destinations (e.g. Collaborative browsing by Ricci et. al [22]) and resulted different ideas. The provision of several options is the most obvious way. More effective is to offer these options in form of suggestions. The assumption here is that the results of such a selection process will strongly depend on the way the options are presented. The problem herein is that too many options will discourage the tourist to select the right ones and missing options will have a fatal effect and maybe cause wrong recommendations. Another way is to ask the tourist some questions whereas the answers will allow guessing his/her interests. Therefore clusters of interest groups will have to be created and tourists will be related to them. These cluster formation can also be used to decide about the degree of diversity among the single interest profiles and thus about the need for individualized tours. This is discussed in more detail in section V-G. However, the difference in contrast to websites is that in mobile context time and pixel space are much more limited, as many environmental influences distract the tourist and the display of a mobile device only provides a resolution of about 320*240 pixels. 320*240 pixels is less than 4% of the pixels available at contemporary laptops. All these criterions were considered when developing three different ways of presenting interest categories as described in section V-B. Furthermore a systematic experiment was conducted to find the most effective way to elicit the preferences of tourists with a mobile device using the spearman rank order correlation coefficient as a metric. In order to assess if the contextual information the DTG provides is truly information and not ambient noise the current spatial behavior of the tourist in Goerlitz needs to be compared to the behavior after the DTG provided appropriate contextual information. In order to get a first assessment, tours for various durations were computed based on the gathered interest profiles and 80 TBBs modeled for this first field study. The simulated spatial behavior of the tourist is compared to the observed spatial behavior in section V-H. Analysis shows that the tourists supported by contextual information were indeed covering a much broader area of the destination. A single metric called the spatial entropy [27] is used to measure the greater diversity of the spatial behavior.

B. Methodology

For a timeframe of about 4 weeks in June/July 2005, 235 tourists could be involved in the following study in the city of Goerlitz.

1) Preparation: Before the experiment could start, 80 sights of the city Goerlitz were modeled semantically, which means that they had to be assigned to classes of the ontology. The ontology is a classification of all tourist attractions which was designed in advance and offers the five top-level categories architecture, landmarks, art & culture, nature and celebrities. It can be visualized as a hierarchy and also serves to provide selectable options for the tourists' generic interests. Additionally for each sight pictures and describing text were collected for visualization on a PC in order to provide fair means for the tourists to rank concrete sights during the experiment. The tourists were given an MDA, which is a PDA type mobile device with an integrated mobile phone to fulfill the following tasks.

2) Questionnaire: The questionnaire served to collect general demographic data about the tourists which are not connected to any personal information. This was already done on the mobile device in order to familiarize the tourist with the MDA device:

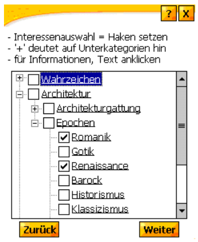
- Specification of age, from 0 to 99
- Gender, male or female
- Computer literacy by categorizing their usage into "often, seldom or never" to the following devices:
  - PC
  - Handy
  - Internet
  - Mobile devices (PDA/MDA)

These data is mainly used to find correlations between the kind of interests specified towards age, gender and computer literacy.

3) Specification of interests: Second the tourists use the MDA to specify their interests by one of three possible ways listed in TABLE I. These methods have been developed together with psychologists and tested qualitatively in advance. The main difficulties were the selections of well-known terms and the design of an intuitive graphical user interface (GUI) despite of the limited pixel space.

4) Ranking of sights: Third, the mobile device was connected to a PC, copying the interest profile automatically. The application running on that PC suggested six sights to the tourist as depicted in the left side of the screen in Fig. 4. In the background, the Semantic Matching algorithm [26] has already rated each available sight because of the specified interests and created a ranking. Depending on the fields of interest each sight was assigned to compared to the fields of interest a tourist chose, they receive a certain amount of points which determines their position within the rank order. The six sights presented to the tourist are two high rated, two medium rated and two low rated ones in random order. The tourist was then asked to sort them based on which one he/she is interested in most and which one least. Therefore he/she can look at additional information and pictures of each sight to be able to decide whether he/she likes it or not. Please see the right part of Fig. 4. The purpose was to find out the method that was able to predict the behavior of the tourist in ranking the concrete sights.

TABLE I
INTEREST SPECIFICATION METHODS

Hierarchical browser	
	The hierarchical structure of the ontology is visualized by a tree view element. The user can select any category she/he is interested in by checking the boxes. The advantage is that everything can be displayed on a single screen which turns into a disadvantage at the same time as small fonts have to be used and scrolling becomes necessary when expanding the tree.
Inspirational images	
	The hierarchy is presented by iconic images for each level. These images shall inspire associations causing positive or negative feelings with each term. The pictures can be maximized and information for each term is offered too. The advantage here is the visualization by pictures and symbols which clearly emphasizes the recommendation aspect. However to proper presentation on a mobile device requires several screens, which makes the orientation difficult.
Main categories	
	Only the main categories are provided for selection. Selecting one category will open a pop-up window to give a percentage value to express the intensity of the interest displayed by a certain amount of colored stars.

5) Architecture: The architecture of the system consists of a server hosting the database where all data is stored. This includes the selected interests, the anonymous answers of the questionnaire, the list of sights ordered by the tourist and the click events he/she caused while using the application. The data is sent from the mobile device to the PC via the docking station.

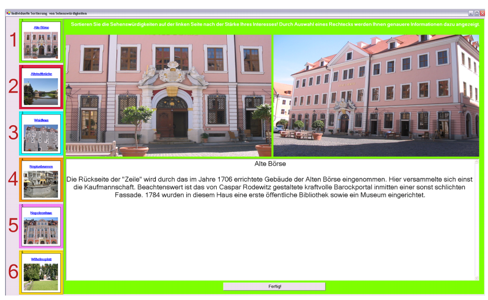


Fig. 4. PC application

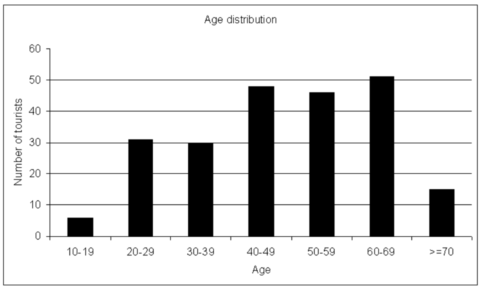


Fig. 5. Age pattern of the tourists

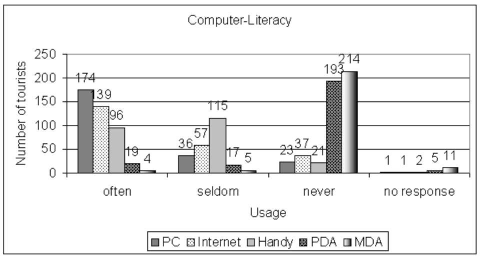


Fig. 6. Computer literacy

C. Results

60% of the tourists that took part in the field study were male. Their age ranged from 13 to 78, while the average age was 47 years. However, the modal age was 60 and 63 what gives a better impression on the actual age pattern which is displayed in Fig. 5.

The computer-literacy results in Fig. 6 show that most of the tourists, more than 2/3, stated a regular use of the PC. Still more than 1/3 often worked with the internet and a handy, while almost nobody uses an MDA. Only 10% don't owe a PC or a handy.

Evaluating the originated interest profiles from the tourists allowed an insight into their selection behavior. Conditional on the method, Fig. 7 shows the number of selections within the main categories or of the category itself. In every method the category architecture or its subcategories have been chosen most often. That was expected since Goerlitz offers many architectural sights that most tourists come there for. Landmarks have been selected very often too, which is a good choice for tourists not knowing anything about the destination.

The diagram in Fig. 8 displays the complexity or range of interests. Here a big difference between the methods of preference elicitation becomes obvious. The majority of tourists using the main category method specified interests from all five categories (what means they set the percentage value higher than zero), while they only specified three for the image version and two for the tree explorer.

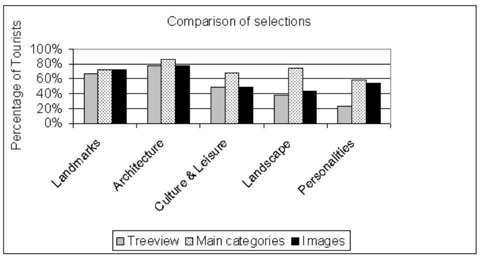


Fig. 7. Comparison of selected categories

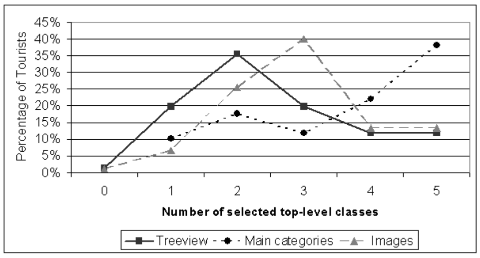


Fig. 8. Complexity of interest selections

TABLE II shows the interaction of the tourists with the system for the main category method. Each group of columns represents a level of panels in the software application. In the second column the number of visits to the top-level panel is given. All tourists exited the application properly. Five tourists returned to the overview panel twice. The number of tourists using the main category application is used as a base for the percentages in the fourth column. An interesting fact is that many tourists returning to the main categories more than once either to have a closer look or to change settings. The right most column lists the likelihood that a visit to a main category leads to a request of more detailed information about this category. These rather small percentages are in line with 10% chances of a tourist using the help page leading to the conclusion that the main category is intuitive for most tourists.

Comparing the two rank orders of the sights first sorted automatically by the semantic matching algorithm and second sorted manually by the tourist returns a correlation value. This value expresses how similar the tourists rated the sights in contrast to the algorithm. The best result is an identical ranking, the worst one is a reverse order. The correlation value is determined by the formula of Spearman which compares two ranked lists [17].

$$r_s = 1 - \frac{6 \times \sum_{i-1}^{n} d_i^2}{n \times (n^2 - 1)} \tag{1}$$

n = number of elements, d= difference of the element positions, i = index

The difference of the positions of each sight in both lists is calculated and squared. The condition is that the elements must be ordered ordinal. That means that there is a significant

TABLE II

INTERACTION FOR MAIN CATEGORY METHOD

1st level	#	2nd level	%	3rd level	%
Welcome	67	Architecture	157	Info	28.6
Overview	72	Landmarks	112	Info	22.7
Thanks	67	Landscape	96	Info	9.4
		Culture and Leisure	93	Info	16.1
		Celebrities	73	Info	10.2

TABLE III

CALCULATION OF CORRELATION

Predicted ranking r_p	**Tourist ranking r_t**	$(r_p - r_t)^2$	r_s
Sight 1	Sight 2	1	
Sight 2	Sight 4	4	
Sight 3	Sight 1	4	
Sight 4	Sight 3	1	
Sight 5	Sight 5	0	
Sight 6	Sight 6	0	0.714

TABLE IV

COMPARISON OF THE PREFERENCE ELICITATION METHODS

Method		**Tree**	**Images**	**Categories**
r_s coefficient	Mean	0.47	0.48	0.52
	Median	0.54	0.6	0.6
Time in min	Mean	2.03	2.12	2.03
	Median	1.44	1.28	1.50
Clicks	Mean	16	29	21
	Median	12	13.5	19

difference between the first and second element and so on. In this case there might be sights at adjacent positions having received the same amount of points. Then the difference is set to 0, where else it is 1. The best possible result is value 1 then both lists are identical. If the value of this coefficient is 0 then there is no correlation recognizable. A value of -1 means a negative correlation. The example in TABLE III shall demonstrate this:

The result 0.714 is closer to 1 than to 0, which means a good correlation. As the distribution of the rank order correlation values in Fig. 9 clearly shows, more than half of all tourists have reached a correlation higher than 0.6 what means that for the majority of the tourists the recommendations are pretty good. Only very few reached a negative correlation. As a result the first question about the possibility to build a mobile application collecting a generic interest profile and then selecting suitable attractions can be answered positively.

The correlation results, durations of the preference elicitation process and the number of clicks for all three methods are listed in TABLE IV. From a correlation perspective the median correlation for the relatively simple method using five main categories and the imaginative method using pictures are equal and higher than the method using a Windows Explorer style hierarchy browser which in strict sense is the method the tourists spent least time with. But considered duration and amount of clicks all three methods only show few differences consuming about 2 minutes and about 20 clicks. These results seem to indicate that a more detailed hierarchy of interests might not be necessary in order to receive exacter preferences and be able to make better recommendations.

The low mean correlation for the method using images was a surprise, given that the imaginative method works on the web, where admittedly a 25 times higher amount

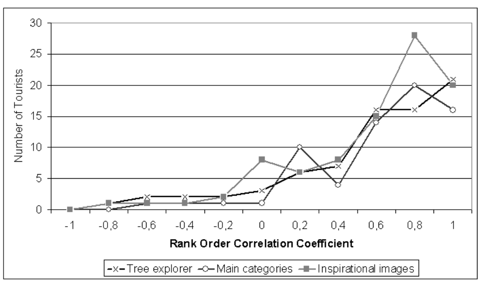


Fig. 9. Distribution of correlations

of pixels provides space to visualize the hierarchy traversal much more efficient. One reason might be that the hierarchical structure of the classification of interests was too complex and hardly understandable displayed by images, while the simple version using main categories caused the fewest problems. Furthermore in order to provide a choice with limited scrolling four images were put on a single screen. This might have created problems with recognizing the concepts represented by the images, whereas the problem with the tree view might be the missing inspiration for certain highly specialized terms. The actual reasons are discussed in section V-D.

TABLE V shows the correlation of the rank order correlation coefficient with age and computer literacy. It was strongly expected that the ability to express ones interests using a mobile device would increase with prior experience using computing or communication devices. However the data indicates that for the tourists who participated in the field study neither age nor computer literacy had a significant influence on quality of the interest profile. This is interpreted as an indication that the mobile application is self-describing and user-friendly.

TABLE V

CORRELATION OF THE RANK ORDER CORRELATION COEFFICIENT

Method	**Correlation**	
	Age	Computer Literacy
Tree	0.18	0.04
Images	0.08	-0.16
Categories	-0.08	-0.01

D. Evaluation

The evaluation of the interest data gathered through inspirational images organized in a hierarchical structure shows that about half of all tourists using the inspirational method didn't specify interests in any deeper level than the first (see Fig. 10). It has to be mentioned that some categories only consist of two levels but still they haven't been used very often neither. In contrast the third level was used most often from tourists working with the tree explorer. The usage pattern of the inspirational method was thus very similar to the much simpler method using main categories as they mainly selected top-level categories. The similarities in the usage pattern might be the reason why the time duration was very similar too.

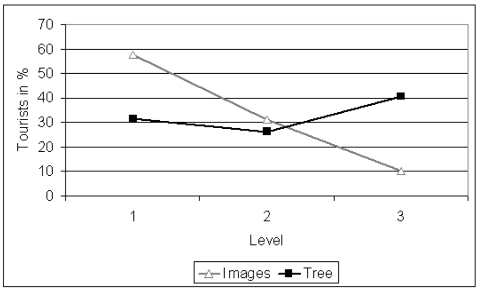


Fig. 10. Interest selection per level

The evaluation of the screen shots indicates that many tourists didn't understand the hierarchical structure of the classification of interests in the method using images, while the version using main categories caused the fewest problems. The additional levels (for those who found them) obviously confused many what might explain that this method gave a worse correlation than the main category method. Images are only displayed from the second level downwards; the top level categories are symbolized by an icon and can be selected by a checkbox. The problem is that most tourists didn't realize that clicking on a category name or its icon reveals subcategories displayed by concrete images, though it was mentioned on the screen. A reason might be they didn't read, either because the font was simply too small or they couldnt see the text on the screen due to reflecting sunlight. This is a GUI deficit that has to be improved immediately. Furthermore this version has to be tested on the web where the images and visual clues can be presented more effectively, to see whether more tourists make use of the possibility to express their preferences in more detail. According to the questionnaire the tourists felt very comfortable with the GUI in general (see Fig. 11). Having asked the tourists to judge the application concerning self description, expectation conformity or controllability almost always produced very positive feedback. All answers were grouped together. As the diagram in Fig. 11 shows, 3/4 of the tourists at least agreed. So the tourists thought of themselves to have understood the functions of the application correctly which isn't true in the case of the image version.

Another reason may be they didn't intend to go into more detail, e.g. because they didn't want to spend more time on it. One finding was that the interest selection takes less than two minutes, and going into more detail is much more time consuming. The results of this field study might be affected by the following sources of errors: The first source of misinterpretations is the terms used to describe the different categories of interest. If the tourist associates other things with the proposed interests then he/she will probably select other sights. There is a help providing information for each term so that the meaning should be clear, but as expected help wasn't used by most people. The ranking of the sights done by the tourist strongly depends on the quality of the pictures and texts which are presented. The tourist might favor a sight regardless of his/her interests if it is displayed in a very nice shot on a sunny day with blue sky and in contrast dislike a sight exactly matching his interests because of being displayed on a dark cloudy autumn day. The selection of prototypical sights is a challenge, since even experts can't agree on the most representative example. Another related difficulty is that Goerlitz does provide a lot of sights, but most of them are only of architectural relevance. The distribution of the sights over the ontology is thus not balanced. A better way would be to ask the tourist after a sightseeing tour which sights he/she liked best and worst. Then this ranking could be compared to that one of the semantic matching algorithm. However this isn't possible as the tourists won't be willing to return to the test location after their tour. And waiting for feedback by email or mail might be in vain in most cases. However during the execution of the tour the DTG can observe the duration of staying at each sight and compare it to the average duration. A longer stay than average would indicate a bigger interest. Learning based on observations to improve the interest profile is an area for future research. In general it has to be hinted that, as the average age of the tourists already showed, the group of tourists coming to Goerlitz is a special selection. So the results are not necessarily representative for other destinations, but under the given circumstances they give an adequate impression of the current situation.

E. Entropy calculation

Given the values of the rank order correlation coefficient it can now be assumed that the semantic matching algorithm is able to rank the attractions based on the gathered generic interest profiles according to the desires of the tourist. Nonetheless an ambient intelligence device computing individualized tours might not be necessary, since the interests of the tourist are pretty much the same or fall into a couple of well-defined prototypical interest profiles. In such a case the tourists are best served by 2-3 standard tours and the DTG doesn't need to elicit the individual preferences but rather assign a tourist to one of the interest prototypes. Therefore the second crucial question was how diverse interest profiles are. In case there is a significant diversity of interests it makes sense to capture the individual profiles and compute personalized tours. A first way to make a statement about the diversity is to measure the

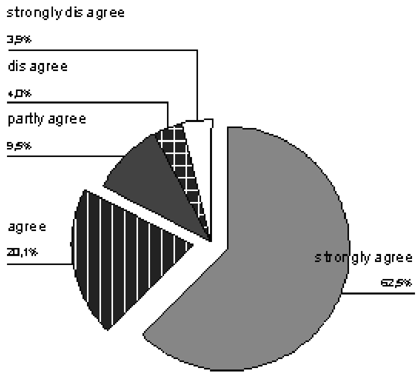


Fig. 11. Usability questionnaire results

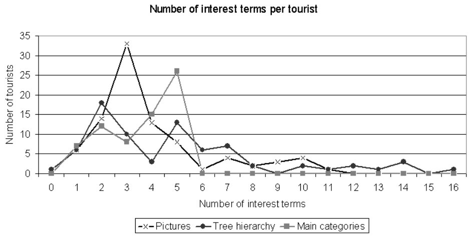


Fig. 12. Complexity of interest profiles

TABLE VI

COMPARISON OF ENTROPY AND OVERLAP

Method	**Relative entropy**	**Overlap**		
		Median	Mean	Min-Max
Images	0.85	40%	24%	1-40%
Tree	0.92	53%	36%	3-53%
Categories	0.98	27%	26%	17-34%

entropy [16]. Therefore each profile is seen as a combination of interests. Each combination has a certain probability of occurrence, which can be determined by dividing the frequency of each profile by the number of profiles in total. As some combinations appear several times, the associated profiles are only considered once so that the probabilities of the profiles add up to one in the end. The single probabilities are then used to compute the entropy:

$$H = -\sum_{k=0}^{L} p_k * log_2 p_k \tag{2}$$

where L is the number of profiles and p its probability. The entropy values describe the information content per profile in bits. If all profiles would have the same content, the entropy would be zero meaning that they don't contain any new information. The relative entropies displayed in TABLE VI indicate the deviation from the maximal entropy that is possible. As the values reach about 90%, each single profile does contain lots of additional information compared with the others. In other words the interest profiles are very different from each other and it might be difficult to split them into distinctive groups. The entropy differences among the methods are surprisingly small, but the main category profiles have the highest value indicating that the profiles have the highest diversity. Despite the fact that the main category offers only five possible interest fields each of them can be ranked in four steps. In contrast the image method produces least diverse profiles maybe because mainly main categories where chosen without differing percentages.

F. Interest profile analysis

A second way to analyze the degree of differences among the interest profiles is to compare their content. Fig. 12 shows the distribution of the number of different interest terms the tourists specified. This reflects an overview on the complexity of interest profiles, but doesn't give any hints on similar values or combinations. For the main category method only 5 indications were possible. But for both other methods most tourists also specified 2 to 5 interests, saying that an average interest profile consists of up to 5 interest terms.

In order to be able to make qualitative statements about the content the profiles have to be compared regarding the amount of different or equal elements. Therefore each profile was compared against the other profiles, determining how many elements are identical. The average amount of identical elements is expressed as a percentage of overlap, also to be seen in TABLE VI.

As TABLE VI shows, the profiles aren't very similar towards each other; main categories even create interest profiles with the least amount of overlap concerning the median value. An average profile is only up to one third similar towards another. In general, if a profile contains 3 to 4 elements (which most profiles do according to Fig. 12), the profiles have a common element while the rest differs. All in all the overlap values emphasize the expression of the entropy values and are another quantitative indication that individual profiles are required when computing personalized tours for tourists. The data also suggests that the main category method produces most diverse profiles with few overlap and the highest entropy. As this method also possessed the highest correlation value it seems to be the best solution. In section V-H it is examined if profiles gathered by one of these three methods also create more diverse tours and thus have an impact on the behavior of tourists.

G. Clustering

A third way to analyze the similarity among the profiles is to try to constitute groups of tourists with similar interests, so called clusters. Clusters have a high intra-class similarity but a low inter-class similarity. The basic step is to determine the degree of similarity between two profiles. A common method is to determine distances. The distance between two profiles depends on the distance of their elements which makes some definitions necessary:

1) $Dist1(e1, e2) \rightarrow$ The distance between 2 interest elements (of one profile). Returns the number of branches between both interest elements within the ontology.
2) $Dist2(e, p) = Min(\forall_{ie \ni p} : Dist1(e, ie)) \rightarrow$ The distance between an interest element and a profile. Returns the minimal value of distances between the single interest element and each interest element in the profile.
3) $Dist3(p1, p2) = Max(\frac{1}{p1.elements} \sum_{1}^{p1.elements} Dist2(element_i, p2), \frac{1}{p2.elements} \sum_{1}^{p2.elements} Dist2(element_i, p1)) \rightarrow$ The distance between two profiles. Returns the maximal value of comparing profile 1 with profile 2 and profile 2 with profile 1

Finally this results in a matrix displaying the distances for each profile to any other profiles. Based on these distances the clustering was done by an algorithm based on AGNES (Agglomerative Nesting), described in [13].

```
Foreach profile p1
```

TABLE VII
CLUSTER RESULTS

Method	# of clusters	average # of elements
Tree	30	2.5
Images	40	2.3
Categories	31	2.2

```
Determine p2 with min distance to p1
If p2 belongs to a cluster
  Add p1 to that cluster
Else
  Create new cluster(p1, p2)
```

The algorithm creates clusters which are pairs or groups of profiles, putting the closest related profiles together. The average number of profiles in such a cluster is small. The clusters are mostly pairs as to be seen in TABLE VII.

For obtaining fewer and bigger groups the profiles would need to be more categorical. But a number of 30 groups and higher with less than three typical profiles in it can't be considered as clusters, because it's not possible to prepare standard tours for 30 clusters in advance. As there are very few profiles being closely related two each other an individual interest elicitation is compulsory. All in all these three ways of analysis show that meaningful clustering of interests is hard and might disappoint certain tourists having individual interests but being put into a general group nonetheless. For the DTG this result will be taken as a motivation for further improving the elicitation process of individual interests rather than searching for general clusters.

H. Simulated spatial behaviour

As described in the introduction the observed spatial behaviour of a tourist in Goerlitz is concentrated around the medieval town centre along an old trading route (Via Regia) (see Fig. 1). There are many sights which are only visited by few tourists most likely due to a lack of information. The spatial distribution shown in the introduction is a result of a parallel experiment conducted in Goerlitz in June/July 2005. The tourists have received a GPS logger and their tours were tracked and saved. The map with the spatial distribution shows a grid with the color of each cell indicating the number of visitors. It is assumed that the tourists will spread wider in the destination if they receive better information (contextual and personalized ones). Since this is one of the objectives of the DTG a simulation should give a first estimate of the impact the DTG might have on the spatial distribution of tourists in a destination. Therefore the interest profiles and the distribution of durations which were gathered during the field study were used to calculate individual tours for the tourists. To estimate the course of such a tour the single milestones were interpolated to receive the steps in between. Since pedestrians are not prevented from one-way streets or parks their tour is quite often like a bee line. The method works as follows:

1) For every gathered interest profile
   a) Rank the TBBs available in the TBB DB
   b) Compute a tour for [1/2, 1, 2] hours
      i) Interpolate the tour
      ii) Simulate the tour
      iii) Collect traces
2) Analyse the traces using the grid

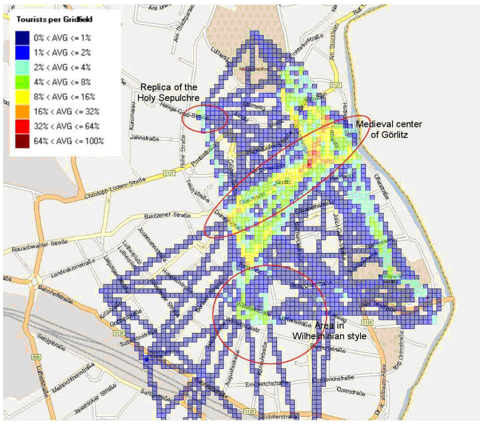


Fig. 13. Simulated distribution of tourists

Fig. 13 presents the same fragment of the map as shown in Fig. 1, again with the colored amount of visitors inside the grid cells, but now based on a simulated distribution. The map looks a bit more crowded as it contains more tours, actually one tour for each interest profile. The position of some grid cells may be a result of the interpolation as the tourists aren't usually able to walk in-between streets. Furthermore many tourists have used the GPS logger in the field study for only a short time. Since the same distribution of durations was used for the simulation, there are still many tours with a duration less than 60 minutes. In that short amount of time only sights in a limited area can be reached. That's the reason for the ongoing concentration at the medieval center. But for the tourists who spent more time with sightseeing the tours are spread much wider throughout the city. Especially there are a lot more tourists coming to the area which is built in Wilhelminian style. Even some sights behind the railway station are visited now.

VI. CONCLUSION

The DTG is a mobile agent capturing a generic interest profile. This profile is used to rank and select concrete attractions in a destination to compute a personalized tour. This tour is being adapted to actual behaviour of the tourist, e.g. longer staying time at sights or spontaneous decisions to e.g. visit a souvenir shop. Three different methods to elicit generic preferences were compared in a field trial in Goerlitz. Semantic matching based on profiles gathered by the best methods was able to predict the ranking of concrete sights by 50% of the tourists with a rank order correlation of better than 0.6. An in-depth analysis of the gathered generic interest profiles indicated that they are surprisingly diverse. Finally an experiment having compared the current spatial distribution of tourist in Goerlitz with one based on simulated tours using the gathered interests and tour durations indicated that context-aware information will help to enjoy a destination at its full potential.

ACKNOWLEDGMENT

This project is part of VESUV in cooperation with Siemens AG, Microsoft's European Innovation Center (EMIC) and Fraunhofer Institute IGD. VESUV is supported by the Federal Ministry for Economics and Labour (BMWA).

REFERENCES

[1] Abowd, Gregory D.; Atkeson Christopher G.; Hong, Jason; Long, Sue; Kooper, Rob; Pinkerton, Mike. Cyberguide a mobile context-aware tour guide. *Baltzer/ACM Wireless Networks*, 1997.

[2] Bussler, Christoph; Cardoso, Jorge; Fensel, Dieter; Sheth, Amit. Semantic web services and processes. *Semantic composition and quality of service*, Irvine CA, 2002.

[3] Cheverst, Keith; Davies, Nigel; Mitchell, Keith; Friday, Adrian; Efstratiou, Christos. Developing a Context-aware Electronic Tourist Guide: Some Issues and Experiences. *Distributed Multimedia Research Group*, Lancaster University, UK, 2002.

[4] Fink, Josef and Kobsa, Alfred. User Modeling for Personalized City Tours, in *Artificial Intelligence Review*, vol. 18, p.33-74, Kluwer Academics Publishers
[5] Nguyen Q.N., Cavada D., Ricci F. On-Tour Interactive Travel Recommendations. In *Information and Communication Technologies in Tourism 2004*, Proceedings of the International Conference, Cairo, Egypt, January 26 - 28, 2004. Pages 259-270. Springer
[6] Djikstra, Jan; Jessurun, Joran; Timmermans, Harry. A Multi-Agent Cellular Automata Model of Pedestrian Movement. *Pedestrian and Evacuation Dynamics*, Schreckenberg and Sharma (eds.), Springer-Verlag, Berlin, 2001.
[7] Enarro. *http://www.eNarro.com*, 2004.
[8] Freytag, Tim. Stdtetourismus in Heidleberg Ergebnisbericht zur Gstebefragung 2003. *Geographisches Institut der Universitt Heidelberg*, Heidelberg, 2003.
[9] Godart, Jean-Marc. Beyond the Trip Planning Problem for Effective Computer-Assisted Customization. *Information and Communication Technologies in Tourism*, Andrew Frew et al. (eds.), Springer Computer Science, 2003.
[10] Goerlitz. emphhttp://www.goerlitz.de/, 2003.
[11] Gretzel, Ulrike; Fesenmaier, Daniel. Persuasiveness of Preference Elicitation Processes in Destination Recommendation Systems. *Information and Communication Technologies in Tourism*, Andrew Frew et al. (eds.), Springer Computer Science, 2005.
[12] Horrocks, Ian; Li, Lei. A software framework for matchmaking based on semantic web technology, 2003.
[13] Kaufman L.; P. J. Rousseeuw. *Finding Groups in Data: an Introduction to Cluster Analysis*, John Wiley & Sons, 1990.
[14] Kempermann, Astrid; Borgers, Aloys; Oppewal, Harmen; Timmermans, Harry. Predicting the Duration of Theme Park Visitors' Activities: An Ordered Logit Model Using Conjoint Choice Data. *Journal of Travel Research Vol.41*, Sage Publications, 2003.
[15] Kempermann, Astrid; Chang-Hyeon, Joh; Timmermans, Harry. Comparing First-time and Repeat Visitors' Activity Patterns in a Tourism Environment. *Consumer Psychology of Tourism, Hospitality and Leisure Vol.3*, CAB International, 2004.
[16] Sloane, N. J. A., Wyner, Aaron D.. *"Claude E. Shannon Collected Papers"*, IEEE Press, 1993, pp. 5-83.
[17] Lowry, Richard. Concepts and Applications of Inferential Statistics. chapter 3b: Rank-Order Correlation http://faculty.vassar.edu/lowry/webtext.html, 1999-2005.
[18] Maedche, Alexander; Staab, Steffen. Services on the Move: Towards a P2P-Enabled Semantic Web Services. *Information and Communication Technologies in Tourism*, Andrew Frew et al. (eds.), Springer Computer Science, 2003.
[19] Malaka, Rainer; Zipf, Alexander. DEEP MAP challenging IT research in the framework of a tourist information system *7th International Congress on Tourism and Communication, ENTER2000* Eds D. R. Fesenmeier, S. Klein adn D. Buhalis, Springer Computer Science, 2000. Deep Map The Multilingual Tourist Guide. *European Media Laboratory*, Heidelberg, Germany, 2001.
[20] Navigon. *http://www.navigon.de*, 2004.
[21] Poslad, Stefan; Laamanen, Heimo; Malaka, Rainer; Nick, Achim; Buckle, Phil; Zipf, Alexander. *CRUMPET: Creation of user-friendly mobile services personalised for tourism*, 2001.
[22] Ricci, Francesco; Woeber, Karl; Zins, Andreas. Recommendations by Collaborative Browsing. *Information and Communication Technologies in Tourism*, Andrew Frew et al. (eds.), Springer Computer Science, 2005.
[23] Schmidt-Belz, Barbara; Posland, Stefan. User Validation of a mobile Tourism Service. *HCI mobile Guides Workshop*, Udine (Italy), 2003.
[24] Schmidt-Belz, Barbara; Laamanen, Heimo; Poslad, Stefan; Zipf, Alexander. Location-based Mobile Tourist Services First User experiences. *Information and Communication Technologies in Tourism*, Andrew Frew et al. (eds.), Springer Computer Science, 2003.
[25] Shoval, Noam; Isaacson, Michal. The Application of Tracking Technologies to the Study of Pedestrian Spatial Behaviour. *The Professional Geographer*, 2005.
[26] ten Hagen, Klaus; Kramer, Ronny; Mueller, Patrick; Schumann, Bjoern; Hermkes, Marcel. Semantic Matching and Heuristic Search for a Dynamic Tour Guide. *Information and Communication Technologies in Tourism*, Andrew Frew et al. (eds.), Springer Computer Science, 2004.
[27] Modsching, Marko; Kramer, Ronny; Gretzel, Ulrike; ten Hagen, Klaus. Capturing the beaten paths: A novel method for analysing tourits' spatial behaviour at an urban destination *Information and Communication Technologies in Tourism*, Martin Hitz et al. (eds.), Springer Computer Science, 2006.
[28] ten Hagen, Klaus et al. Context driven adaptive tour computation and information presentation. *First International Workshop on Managing Context Information in Mobile and Pervasive Environments*, Ayia Napa, Cyprus, 2005.

Prof. Dr.-Ing. Klaus ten Hagen studied EE/CS from 1983-1987 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 codesign. One outcome of his work was the HW/SW cosimulation capability in the system simulator COSSAP. (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 2000-2001 he developed the patent eSilicon Access WIP tracking system and from 2001-2003 he was VP of Engineering at SigmaQuest. Since March 2003 he is a professor at the university of Zittau-Goerlitz. Prof. ten Hagen is the author of numerous publications and two US patents. More information about his research interests and academic functions can be found at www.ten-Hagen.org.

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-Goerlitz. As his diploma he researched the matchmaking of interests in eTourism applications, which also resulted in a publication. Since November of 2004 he is 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.

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-Grlitz. During his study he did some research together with Prof. Dr. Jrg 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/Grlitz. As his diploma he researched for an additional TaskTrainer-module called TaskExaminator to perform software-based exams. Since November of 2004 he is working as a research assistant at this iniversity for the projects IKAROS (http://www.ikaros-projekt.de) and VESUV (http://www.vesuv-projekt.de). The main focus of both projects is the development of context aware software agents and services for mobile collaborative networks.