

Field Study on Methods for Elicitation of Preferences using a Mobile Digital Assistant for a Dynamic tour Guide

Klaus ten Hagen
University of Applied Sciences
Brückenstr. 1
02826 Görlitz
++49 (03851) 4828265
K.tenHagen@HS-ZiGr.de

Ronny Kramer
University of Applied Sciences
Obermarkt 17
02826 Görlitz
++49 (03581) 476413
RKramer@HS-ZiGr.de

Marko Modsching
University of Applied Sciences
Obermarkt 17
02826 Görlitz
++49 (03581) 476413
MModsching@HS-ZiGr.de

ABSTRACT

Knowing tourists' individual preferences provides the possibility to offer personalized tours. The challenge is to capture these preferences using a mobile device. During a field study in Görlitz three methods for elicitation were evaluated by computing the correlation between the tourists' and the algorithms' rankings. The results served to clarify fundamental questions en route to develop a personal tour guide. 1) Is it possible to seed interest profiles in the mobile context with all its distractions that allow the accurate prediction of actual rankings of sights? 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 tourists, do they really visit different attractions than before? Analyzing the interest profiles gives an insight into their actual diversity, discusses their necessity and helps simulating an improved distribution of tourists at a destination.

Categories and Subject Descriptors

H.5.2 [Information Systems]: Information Interfaces and Presentation – *user interfaces*.

General Terms

Algorithms, Design, Experimentation, Human Factors.

Keywords

Dynamic Tour Guide, Personalized Tour, Mobile Recommender, Preference Elicitation.

1. INTRODUCTION

The behavior of tourists strongly depends on the availability and quality of information. A lack as well as a flood of information can be disorientating and forces many tourists to join the majority visiting major sights and often missing interesting ones close by. This also causes a few crowded places in contrast to many empty. One target of the Dynamic Tour Guide (DTG) – a mobile application enabling a spontaneous and guided tour – is to support tourists discovering a destination individually. Therefore it provides personalized tours and information to tourists by means of pervasive computing based on the actual context which is

defined by personal interests, location and schedule of a tourist. (See ten Hagen et al. for further details.)

The challenges are to elicit the preferences of a tourist in mobile context to seed an interest profile, to rank the available sights by these interests (semantic matching), to compute an individual tour based on these data and to adapt the tour to spontaneous choices made by the tourist when executing the tour. The specification of interests in mobile context is difficult as a mobile device provides less than 4% of the pixels of a PC. Furthermore, many distractions, e.g. traffic noise, make tourists less patient in interacting with an application. Thus time and information bandwidth is severely limited compared to a standard PC environment. This paper suggests three different GUIs and models considering these constraints. The gathered interest profiles are subsequently benchmarked in order to determine the accuracy of the elicitation process. The diversity of the tourists' interests is analyzed in order to study the necessity to gather individual profiles. A simulation of tours based on the gathered profiles indicates that an improvement of the tourists' distribution can actually be achieved.

2. RELATED WORK

In a survey of tourists in Heidelberg by Freytag (2003) around 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. 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.

In chapter 9 of Kempermann et al (2004) an examination of the different behavior of first-time and repeat tourists at theme park destinations is presented. 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. One can predict that the DTG may help tourists in both cases to pick out and discover the sights they are really interested in by providing all information that are invisible or inaccessible for tourists.

¹ Published in 21st Annual ACM Symposium on Applied Computing, Dijon, France, December, 2006,

The precondition is to get to know their interests in order to make recommendations. Gretzel and Fesenmaier (2005) not only mention the recommendation aspect, but also the persuasive component of a recommendation system. The primary goal is to get to know the preferences of users, but as this is a complex task it is better to get some clues and then to suggest things what can influence the choice of users by the way of representation.

Eliciting ones preferences is not a trivial task and there is no general solution to do so, at least not in mobile context. But solving this problem may lead to fundamental improvements in eTourism, e.g. more personalized information provision to enable the tourists to enjoy a destination to its full potential, which is one of the main problems as the above mentioned research activities pointed out.

3. METHODOLOGY

The field study, conducted in Görlitz in June/July 2005, was designed to answer the following questions in particular: (1) The DTG computes an optimal tour according to the interest profile of a tourist. Therefore the most fundamental question is: Is it possible to build a mobile system that collects information from the tourist, which is sufficient to select attractions? (2) In case an effective mobile “interest gathering” capability can be built, the next question is: How diverse are the interests of tourists? Are the interest profiles so similar anyhow that the optimal tours hardly differ and thus the tourists are best served by following the beaten tracks? In case only 2-3 prototypical interest profiles exist, then the corresponding number of standard tours would be 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?

3.1 Experimental setup

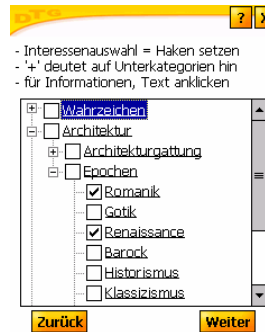
Before the experiment could start, about 80 sights of the city Görlitz were modeled semantically, which means that they had to be assigned to classes of an ontology. The ontology is a classification of all tourist attractions and of all fields of interests as well. Additionally pictures and describing text were collected for each sight in order to provide fair means for the tourist to rank the concrete sights appropriately.

For a timeframe of about 4 weeks, 234 tourists were given a MDA, which is a PDA type mobile device with an integrated mobile phone. Their first task was to complete a questionnaire asking for age, gender and previous experience with certain computing and communication technologies. The second task was to use one of three applications to express their interests:

- Hierarchical browser:

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

SAC'06, April, 23-27, 2006, Dijon, France.
Copyright 2006 ACM 1-59593-108-2/06/0004...\$5.00.



- Inspirational images:



- Main categories



The hierarchical structure of the ontology is visualized by a tree view element. The user can select any category he/she 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.

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. However these images make a lot of screens necessary and therewith lead to a difficult orientation between the levels.

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.

After the participants had expressed their interests using one of the three methods the semantic matching algorithm ranked all available sights appropriately. The two best ranked, the two worst ranked and the two middle ranked sights were picked out and displayed on the screen of a PC. The tourist was then asked to rank the six concrete attractions using descriptions and pictures provided for each. The purpose was to find out the method that was able to predict the behavior of the tourist in ranking the concrete sights. In other words it was searched for the preference elicitation method, which produced the highest correlation between predicted ranking and the ranking created by the tourist. If a tourist brings the sights into the same ranking as the algorithm, then the highest possible correlation has been achieved.

3.2 Current state analysis

Using GPS receivers is a good method to track the changes of the tourists' positions together with a timestamp. Analyses of the track logs then identify the most and longest visited places as well as the tourist distribution in general. This distribution can be

visualized in a map by dividing it into a grid and coloring each cell according to the number of visits of that cell proportional on the total number of visits. Such a map is shown in Figure 1.

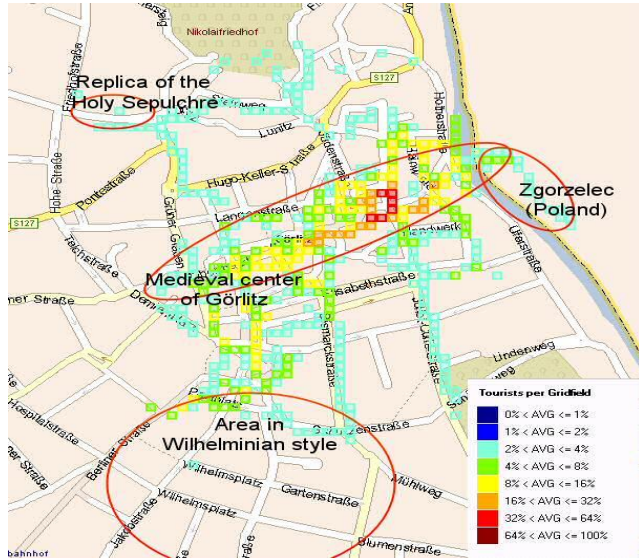


Figure 1: Distribution of tourists

As to be seen, most tourists move within a limited area in the medieval center of Görlitz. Many attractive sights apart from that area hardly receive any attention. Two circles mark two important architectural attractions: One of the most consistent and largest ensembles of buildings in Wilhelminian style in Europe and a replica of the Holy Sepulchre. Both are architecturally important, but nonetheless rarely visited even by visitors with a strong interest in architecture. This situation might easily be improved by providing better contextual information.

4. RESULTS

The age of the 234 participants 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. The percentage of female and male was 40% and 60%. More than 2/3 of the participants stated a regular use of the PC. Still more than 1/3 often works with the internet and a handy, while almost nobody uses an MDA. 90% own a PC or a handy.

4.1 Interaction Duration

Table 1 shows statistics of the interest elicitation process in mobile context: the overall duration, the number of clicks needed and the interaction duration with single panels. Surprisingly for all three methods tourists spent about 2 minutes or less specifying their interests with about 9 seconds per screen using a total of 22 clicks.

Table 1: Preference elicitation: Duration, number of clicks and panel view

Method		Tree	Images	Categories
Duration of elicitation process	Mean	2.03	2.12	2.03
	Median	1.44	1.28	1.50

[min]				
Clicks	Mean	16	29	21
	Median	12	13.5	19
Duration of panel view [sec]	Median	5	9	8
	Min	2	3	4
	Max	10	20	13

4.2 Interest Selection

Evaluating the gathered interest profiles allowed an insight into the selection behavior. The most important question here is how detailed the interests of tourists are and how detailed they are willing to specify them. Five main categories are offered. Close to 40% of the tourist selected interest terms out of at least 2 different categories and about 4 different ones in general. The diagram in Figure 2 displays the deepest levels the tourists reached when specifying their interests for the tree and image version.

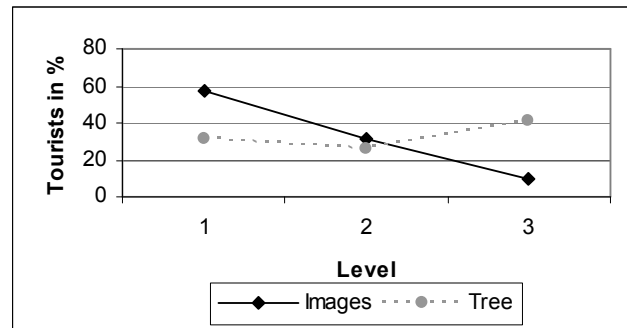


Figure 2: Distribution of the interest selections over the three levels

For both these methods (image and tree) a selection of interests of deeper levels was possible. And indeed further analysis indicated that about 70% of the tree explorer users and 40% of the image version users made use of this and specified more detailed interests than only top-level categories.

But this analysis also shows that more than half of all tourists using the inspirational image method didn't specify interests in any deeper level than the first. The usage pattern was thus very similar to the much simpler method using main categories as they mainly selected top-level categories. In contrast the third level was used most often from tourists working with the tree explorer.

4.3 Spearman Correlation Coefficient

A comparison of the 6 sights ranked by the tourist with the ranking of the semantic match algorithm 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 (=1), the worst one is an opposite list (= -1). If the value is zero then no correlation is recognizable. The correlation value is determined by the formula of Spearman which compares two ranked lists according to Lowry (1999-2005). The difference in the rank of each sight in both lists is determined and squared. The condition is that the elements must be ordered ordinal:

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

with $n = \text{number of elements}$, $d = \text{difference of the element positions}$, $i = \text{index}$.

The correlation results are listed in Table 2. From a correlation perspective the median correlation for the relatively simple method using five main categories and the imaginative method using images are equally effective in capturing the interests of the tourists. The last method is using a Windows Explorer style hierarchy browser.

Table 2: Preference elicitation: Correlation

Method		Tree	Images	Categories
r_s coefficient	Mean	0.47	0.48	0.52
	Median	0.54	0.6	0.6

Taking a look at the single correlation values shows, that more than half of all tourists have reached a correlation higher than 0.5 what means that for the majority of the tourists the recommendations are pretty good. Only very few caused a negative correlation as Figure 3 illustrates.

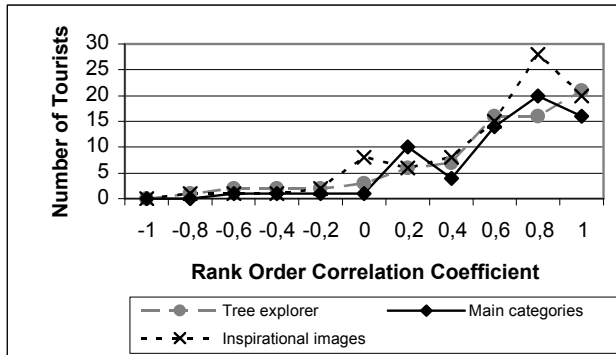


Figure 3: Preference elicitation: Correlation

4.4 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 interest profiles according to the desires of the tourist. Nonetheless an ambient intelligence device computing individual 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. Therefore the next crucial question is how diverse are the gathered interest profiles?

A way to assess the diversity independently of the actual distribution is to measure the entropy. Therefore each profile is interpreted 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. The single probabilities are then used to compute the entropy:

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

with $L = \text{number of profiles}$, $p = \text{probability of profile } k$.

The computed entropies are displayed in Table 3. If all profiles are different the entropy is the binary logarithm of the number of profiles. As the values are between 85% and 98% of the maximal entropy most profiles are unique.

Table 3: Diversity of interest profiles: Entropy

Method	Max Entropy	Actual Entropy
Tree	6.23	5.76
Images	6.49	5.56
Categories	6.09	5.97

Computing the entropy of the distribution of selected interests within the ontological hierarchy gives an impression if the tourists select the same nodes within the same branch or if the selections are spread evenly across the whole tree structure. The values indicate very individual interests as the entropies reach about 90% of best case evenly distributions for all methods.

4.5 Clustering

Another approach is to find out possible similarities between these profiles and 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. A basic value to express the degree of similarity between two elements is their distance. The aim is to determine the distances between the profiles to be able to make a statement about their similarity. The distance between two profiles depends on the distance of their elements which makes some definitions necessary:

1) The distance between 2 interest elements (of one profile) = $Dist1(e1, e2)$

2) The distance between an interest element and a profile:

$$Dist2(e, p) = MIN(\forall_{ie \in p} : (Dist1(e, ie)))$$

3) The distance between two profiles:

$$Dist3(p1, p2) = MAX\left(\frac{1}{p1.elements} \sum_1^{p1.elements} Dist2(element_i, p2), \frac{1}{p2.elements} \sum_1^{p2.elements} Dist2(element_i, p1)\right)$$

The distances for each profile to any other profiles are determined and result in a matrix. Based on these distances the clustering was done by the following algorithm:

```

Foreach profile p1
  Determine profile p2 with the lowest distance towards p1
  If profile p2 belongs to a group
    Add profile p1 to that group
  
```

Else

Create a new group with $p1$ and $p2$

The algorithm creates groups of profiles, putting the closest related profiles together. In this case the average number of profiles in such a cluster is small. The clusters are mostly pairs. 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 to each other an individual interest elicitation is compulsory.

4.6 Simulated Behavior

Sufficient to prove that the DTG provides information to the tourist instead of adding ambient noise, it needs to be shown that the tourists with access to the data change their behavior. The best possible method was to capture the spatial behaviour of different tourists with and without the DTG. Figure 4 presents the individually calculated tours as the same fragment of the map like shown in Figure 1 which displays the spatial distribution of the tourists determined during the field trial in the summer of 2005 - again the colors indicate the percentage of tourists.

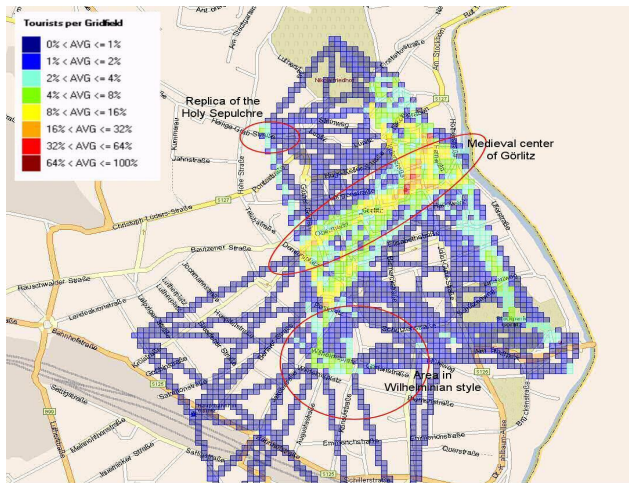


Figure 4: Simulated spatial behavior

The interest profiles collected during the field trial were used to calculate the individual tours. Since no quantitative data about the start and end points of tours is available for Görlitz, they were chosen randomly for the simulations. In the course of the simulation studies it became clear that in order to get tourists to an area the following conditions must be met: (1) the area needs to offer a certain density of attractions, (2) all need to be modeled appropriately and (3) a system like the DTG must make this information available to the tourists. All together a clear improvement is visible.

5. CONCLUSION

In order to enjoy a destination to its full potential a tourists needs information and an intelligent agent providing a higher level service. An experiment having compared the current tourist distribution in Görlitz with the proposed one by the DTG based on the measured interests and tour durations has proven that these kinds of tours make sense as there is the chance to serve

individual preferences. They help to spread the tourists more evenly across the destination and give exposure to a much wider set of services. As the field study has also proven the most effective way of getting to know the tourist's interests is the easy and intuitive method only offering a couple of main categories. Too complex structures are hard to display on mobile devices and lead to confusion. For further improvement of the interest profile the complex hierarchy in the background can be considered to be suitable nevertheless.

6. ACKNOWLEDGMENTS

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).

7. REFERENCES

- [1] Abowd, Gregory D.; Atkeson Christopher G.; Hong, Jason; Long, Sue; Kooper, Rob; Pinkerton, Mike (1997): *Cyberguide – a mobile context-aware tour guide*, Baltzer/ACM Wireless Networks.
- [2] Cheverst, Keith; Davies, Nigel; Mitchell, Keith; Friday, Adrian; Efstratiou, Christos (2000): *Developing a Context-aware Electronic Tourist Guide: Some Issues and Experiences*, Distributed Multimedia Research Group, Lancaster University, UK.
- [3] Dijkstra, Jan; Jessurun, Joran; Timmermans, Harry (2001): *"A Multi-Agent Cellular Automata Model of Pedestrian Movement, Pedestrian and Evacuation Dynamics"*, Schreckenberg and Sharma (eds.), Springer-Verlag, Berlin.
- [4] Freytag, Tim (2003): *„Städtetourismus in Heidelberg – Ergebnisbericht zur Gästebefragung 2003“*, Geographisches Institut der Universität Heidelberg.
- [5] Gretzel, Ulrike; Fesenmeier, Daniel (2005): *"Persuasiveness of Preference Elicitation Processes in Destination Recommendation Systems"*, Information and Communication Technologies in Tourism 2005, Andrew Frew et al. (eds.), Springer Computer Science.
- [6] Kaufman L.; P. J. Rousseeuw (1987): *"Finding Groups in Data: an Introduction to Cluster Analysis"*, John Wiley & Sons, 1990.
- [7] Kempermann, Astrid; Chang-Hyeon, Joh; Timmermans, Harry (2004): *"Comparing First-time and Repeat Visitors' Activity Patterns in a Tourism Environment"*, Consumer Psychology of Tourism, Hospitality and Leisure Vol.3, CAB International.
- [8] Lowry, Richard (1999-2005): *"Concepts and Applications of Inferential Statistics"*, Subchapter 3b: Rank-Order Correlation. <http://faculty.vassar.edu/lowry/webtext.html>
- [9] Ricci, Francesco; Woeber, Karl; Zins, Andreas (2005): *"Recommendations by Collaborative Browsing"*, Information and Communication Technologies in Tourism 2005 (eds.), Andrew Frew, Springer Computer Science (ENTER 2005).

- [10] Schmidt-Belz, Barbara; Posland, Stefan (2003a): *“User Validation of a mobile Tourism Service”*, Workshop “HCI mobile Guides”, Udine (Italy).
- [11] Shoval, Noam; Isaacson, Michal (2005): *“The Application of Tracking Technologies to the Study of Pedestrian Spatial Behaviour”*, The Professional Geographer.
- [12] Ten Hagen, Klaus; Kramer, Ronny; Müller, Patrick; Schumann, Bjoern; Hermkes, Marcel (2005): *Semantic Matching and Heuristic Search for a Dynamic Tour Guide*, Information and Communication Technologies in Tourism 2005, Andrew Frew et al. (eds.), Springer Computer Science.