SUPPORTING PEDESTRIAN WAYFINDING BY ANALYSING MOVEMENT PATTERNS

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Abstract

In the field of cartography, recent years are believed to have brought revolutions as profound as any in the past. Especially in the field of mobile navigation tools, digital maps, mobile devices with increasingly large displays, and ubiquitously accessible, location-based information continuously advance and push the development of efficient wayfinding services. Furthermore, recent advances in collecting and including volunteered, user-generated content in web services rapidly increase the amount of potentially available geographical information. This offers new opportunities for emerging mobile pedestrian navigation services: in contrast to common navigation tools used for vehicles, navigation services for pedestrians must fulfil more complex requirements in order to be accepted. For pedestrians, the shortest path does not always represent the optimal route for an individual's purposes. Studies have revealed that people often forgo to take the shortest path and prefer the "most beautiful", "most convenient", or "safest path". People exploring a new environment on foot would therefore especially benefit from systems providing information concerning route qualities, interesting facilities in the vicinity, and other useful location-related suggestions.

The vast and increasing amount of potentially useful information, however, also involves some negative effects. Overabundance of information may easily hinder effective information extraction. Hence successful wayfinding and information services have to take all the above factors into account in order to efficiently support pedestrian wayfinding and to avoid potential information overload. However, the goal of

developing efficient, customised navigation services can only be achieved by comprehensively investigating human spatio-temporal behaviour and related influence factors.

As part of the scientific project UCPNavi we investigate group-specific spatio-temporal behaviour in order to set the basis for developing customised mobile information services. The study aims at the development of a typology of pedestrian mobility styles based on the observation and analysis of pedestrian walking patterns, route-choice determinants and additional relevant influence factors (e.g. lifestyle-related attributes such as general habits, attitudes, and preferences). In order to thoroughly comprehend pedestrian spatio-temporal behaviour, an eclectic approach to investigate walking behaviour is necessary. Therefore, we use an “across-method” triangulation approach combining various complementary empirical methods of data collection and analysis to explore the subject from different perspectives. Within this two-stage approach, we have collected more than 100 datasets by shadowing and 130 questionnaires during the first empirical phase, and more than 100 trajectories using GPS or Bluetooth and more than 250 interview datasets during the second phase of the study.

In this contribution we present results of motion and interview data analysis based on data collected in a shopping mall and a shopping street. We also introduce an initial pedestrian typology based on qualitative-interpretative and quantitative-statistical data. Types are described according to characteristic attributes identified by route choice behaviour, walking patterns and interest foci. The relevant factors include velocities, stopping behaviour, categories of visited facilities, and individual preferences (general interests, preferences concerning qualities of routes or environments, orientation strategies, etc.). Furthermore, we highlight differences in the outcomes resulting from data collected by different empirical methods and in different investigation areas (indoor and outdoor).

The resulting typology of lifestyle-based pedestrian mobility styles and the identified characteristic attributes can serve as a basis to create pedestrian interest profiles in ubiquitous environments and to customise navigational and environmental information for mobile applications in order to fulfil individual needs. Moreover, a profound understanding of walking patterns and related influence factors is also beneficial for other research fields. Group-related behaviour patterns are crucial for the development of efficient geoinformation products, for the design of attractive urban environments, and for the determination of specific group-related parameters in agent-based simulation models.

Introduction

Mobile navigation services are becoming increasingly popular these days, as they disburden users from putting efforts into wayfinding and provide useful additional information. Meanwhile, it is common to use car navigation services. Mobile navigation tools for pedestrians, however, still seem to be at an early stage, and although there have been many developments in this field, commercial navigation services for pedestrians are still rare and commonly not much recognised.

Beside unsolved problems such as insufficient accuracy (requirements for pedestrians are higher than for car drivers), insufficient size of displays, and inadequate presentation forms (Millonig and Schechtner, 2006), especially comprehensive knowledge concerning route decision preferences and information requirements is still lacking. Choosing a specific route and actual walking behaviour depends on various influencing factors, e.g. the task a user wants to perform, the present environment, and the individual preferences associated with personal attitudes and lifestyles.

As findings reveal that there is a great diversity of different navigation strategies (e.g. Golledge, 1995; Millonig and Schechtner, 2006), conventional navigation systems fail to respond to individual preferences and requirements concerning spatial information. Future ubiquitous navigation systems and Location Based Services (LBS) will have to take into account individual preferences and wayfinding styles in order to provide efficient, personalised services to fulfil an individual's requirements.

Research on Pedestrian Spatio-Temporal Behaviour Patterns

Pedestrians usually do not always act in the same way when walking to a specific desired destination. Several studies have shown that there are significant differences among walking patterns, which are determined by various influence factors. Daamen and Hoogendoorn (2003) distinguish factors affecting the walking speed of pedestrians according to personal characteristics, characteristics of the trip, properties of the infrastructure, and environmental characteristics; Hartmann (1976) discovered significant variances in the spatial behaviour of observed tourists, and Koike et al. (2003) revealed differences by age groups in walking behaviour and length of stay in shopping malls. Studies on environmental preferences and route choice behaviour confirm that pedestrians prefer certain routes according to their environmental qualities, such as relative quietness, greenery, attractiveness, convenience, or safety (Blivice, 1974; Thomas, 2003).

A large variety of empirical methods has been used for investigating pedestrian behaviour patterns, where the most appropriate method for a study will depend on it's focus. A large number of research projects use traditional methods such as interviews or observations. Recent emerging localisation technologies are increasingly applied for measuring motion patterns of pedestrians. An overview about most commonly used methods in research on spatio-temporal behaviour of pedestrians and their specific advantages and drawbacks and appropriate application fields can be found in Millonig et al. (2009).

In general, it is assumed that behavioural strategies show certain regularities (Helbing et al., 2001). Investigating such regularities in observable motion patterns and internal preferences is useful to develop a typology of mobility styles. To achieve this goal, suitable methods for considering all relevant influence factors must be carefully selected. Given the variety and complexity of the factors influencing human behaviour, it is useful to benefit from combining the strengths that different methods offer. Therefore, a *triangulation* approach combining complementing methods can be expected to lead to the most comprehensive results (Denzin, 1977; Jakob, 2001).

Case Study on Group-specific Behaviour in Shopping Environments

In the currently ongoing project UCPNavi we examine the spatio-temporal behaviour of pedestrians in shopping environments. The shopping context was chosen in order to unveil different behaviour patterns which are not determined by differences of purposes people are following. In this way we expect to identify patterns based on internal influence factors like personal walking preferences and individual interests.

Methodology

The study comprises a multi-stage approach combining qualitative-interpretative and quantitative-statistical methods. Figure 1 outlines the empirical set-up of the study. The selection of appropriate methods had to fulfil several requirements: Firstly, we aimed at collecting data of sufficient quality and accuracy in larger environments (indoor and outdoor). Secondly, as it is assumed that people might change their behaviour when knowing that they are being observed, an unobtrusive form of monitoring was to be included. Thirdly, measurable behaviour patterns had to be combined with interview data in order to allow identifying relevant underlying intentions, preferences, and lifestyle-related factors. During two phases of empirical data collection, we have applied the following methods:

- Unobtrusive observation (shadowing)
- Non-disguised observation (tracking with localisation technologies)
- Interviews

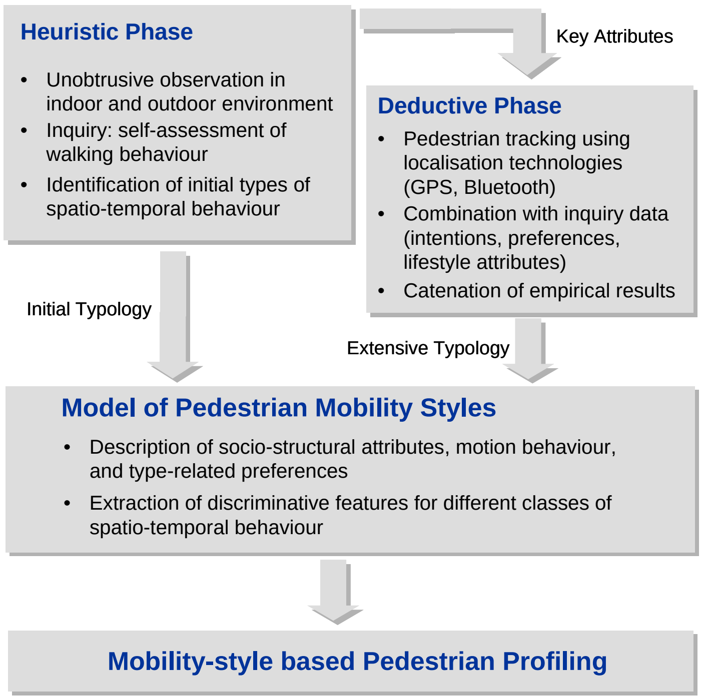

Figure 1. Study design

Initial results based on shadowing datasets

The results of the heuristic phase indicate that shoppers can be grouped into clusters with similar behaviour patterns within one group, and dissimilar behaviour patterns between members of different groups. 111 trajectories of individuals with a balanced gender and age ratio have been collected by using an unobtrusive shadowing approach (Millonig and Gartner, 2007). The analysis resulted in three behaviour clusters for the shopping mall and three similar clusters plus one additional behaviour cluster for the shopping street. Table 1 illustrates the four resulting clusters.

Cluster	**"Passionate Shoppers"**	**"Convenient Shoppers"**	**"Discerning Shoppers"** (only outdoors)	**"Swift Shoppers"**
Gender	mainly female	balanced	mainly female	mainly male
Av. age	balanced (outdoor lower average age)	low/balanced	middle	low/balanced (indoor lower average age)
Av. velocity	low	low/middle	middle	high
Frequency of stops	high	Middle	middle	low
Main interests	fashion, cosmetics, books, specialities	no main focus	specialities, exclusive products	food, daily needs

Table 1. Shadowing results (heuristic phase)

Clustering of motion-related features based on interview datasets

During the second phase of empirical data collection volunteers have been equipped with localisation devices (outdoor: GPS; indoor: Bluetooth). Additionally, detailed interviews concerning walking related preferences and general interests and attitudes have been conducted with all volunteers. In total, 103 persons have been tracked and interviewed: 51 on the shopping street and 52 in the shopping mall.

In a first step, interviews conducted in the outdoor shopping area have been analysed to build clusters of motion behaviour patterns. When dealing with clustering, it is important to 1) define what a cluster constitutes, 2) define a suitable similarity measure to compare datasets, 3) choose a clustering algorithm, 4) define a suitable number of clusters and 5) validate the clusters. In the following, the above issues are addressed.

We denote as a cluster a group of individuals showing similar motion features. For this purpose, we use 15 features from the interview data set: The number of long stops per hour, number of short stops per hour and the 13 binary variables (can only have value 0 and 1) describing the motion behaviour type based on walking preferences reported by the participants (e.g. rather slow or fast, preferring short or long paths). Defining a distance or similarity between features is the most crucial part of clustering – more important than the clustering algorithm itself. We use the Manhattan distance, also known as city-block distance, which is especially relevant for discrete data sets such as the 13 binary features describing an individual's walking type. While the commonly used Euclidean distance corresponds to the length of the shortest path between two samples, the city-block distance refers to the sum of distances along each dimension (i.e. "walking around the block"). For our dataset, the city-block distance between two binary interview features can also be interpreted as the total number of mismatching (yes/no) answers. As for the number of long and short stops per hour, we first normalise the values to lie in between 0 and 1, to avoid their dominance computation of the city-block distance. Figure 2 (a) visualises the 15 motion features of the 51 individuals. The first two columns are the normalised stops per hour, and remaining columns are the binary variables describing motion type.

As for the clustering algorithm, we use a variant of the family of spectral clustering published in Zelnik-Manor and Perona (2004). In contrast to the classical *k*-means algorithm, spectral clustering does not require an explicit model, but analyses an affinity matrix of pairwise non-negative similarities. We transform the pairwise city-block distances with an exponential function, such that smaller values correspond to smaller similarities. Figure 2 (b) shows the affinity matrix for our clustering problem, where higher values indicate higher similarities.

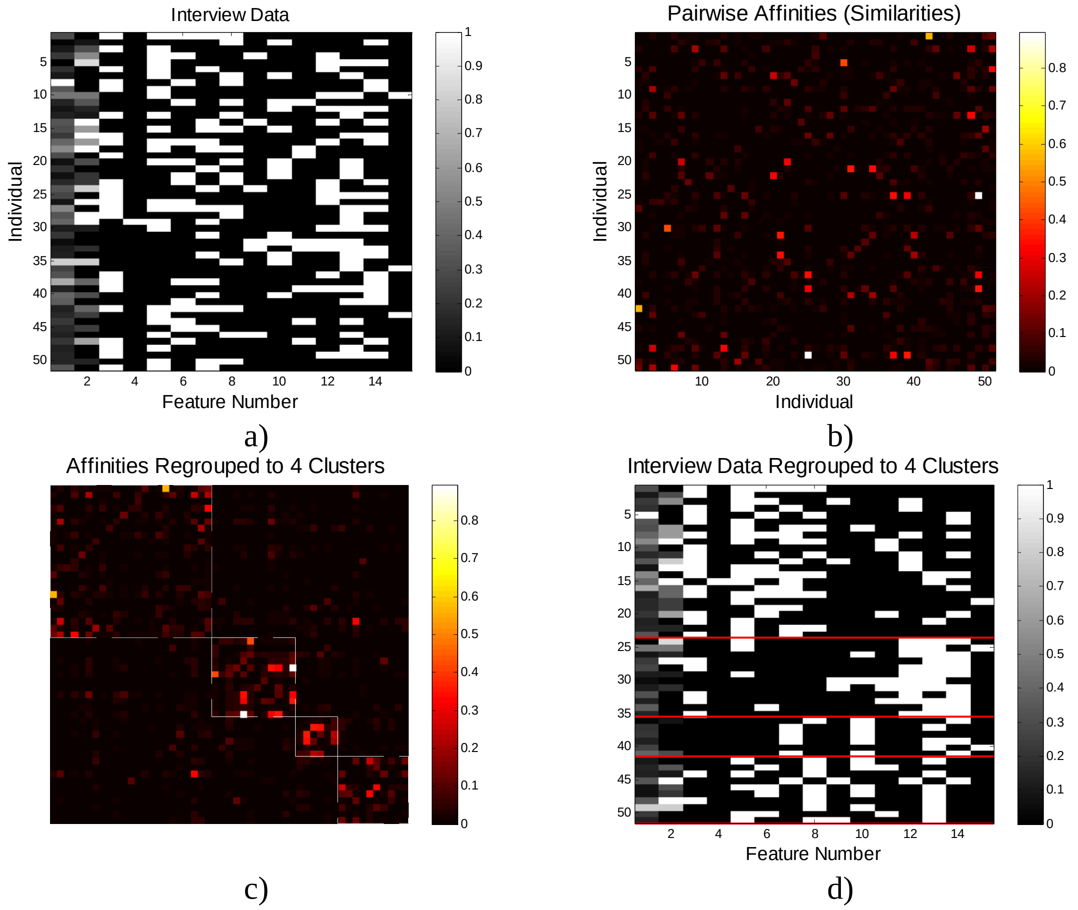

Figure 2. Spectral Clustering of 15 features describing walking type

The clustering approach of Zelnik-Manor and Perona (2004) also provides a technique for automatically selecting a suitable number of clusters for a given dataset. From the set of possible cluster numbers {2, 3, 4, 5}, the algorithm suggests 4 as the optimal number of groups. Figure 2 (c) shows the pairwise affinities regrouped into four clusters. Ideally, the pairwise similarities of samples within a cluster (dashed line) are high, and the similarities of samples of different clusters are low. Figure 2 (d) shows the 15 features of the interview data grouped into the four clusters.

Initial results based on interview datasets

The clusters comprise four groups of motion behaviour patterns, which we have further analysed according to specific characteristics: gender, age, duration of stay and available amount of time at the time of data collection, as well as the categories of shops the participants have visited during observation (according to the statements in the interview forms).

Table 2 describes the main characteristics of each cluster. Although the characteristics of the resulting clusters show strong similarities with the previously identified types of behaviour, there are some significant differences

Cluster	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Preferred walking style	fast, goal-oriented, rather short paths	long paths, rests, flexible routes	short paths, convenient, rather flexible	pre-defined stops, long paths
Gender	65.2 % female 34.8 % male	33.3% female 66.7% male	50 % female 50 % male	60 % female 40 % male
Av. age	balanced (range: 14-58)	low (range: 22-36)	high (on av.) (range: 25-62)	balanced (range: 25-56)
Frequency of Stops	high (long st) rel. high (short st.)	low (long st.) rel. low (short st.)	av. (long stops) low (short st.)	av./high (long st.) rel. high (short st.)
Categories of visited shops/ facilities	food, fashion, jewellery, books, department stores	lowest interest in fashion shops, electronics, drug store, books	restaurants, exclusive/ specialised shops, books	highest interest in fashion shops, interior decorations
Duration of stay	comparatively short	rather high	low on average, wide range	comparatively long
Available time (on average)	sufficient	sufficient/plenty	plenty	sufficient/plenty

Table 2. Preliminary results interview data analysis

The “Passionate Shoppers” identified during the analysis of shadowing datasets seems to be represented both in Cluster 1 and in Cluster 4. Both clusters mainly consist of female participants, show a comparatively high amount of long and short stops, and high interest rates in fashion and accessories. However, the two clusters differ in speed and available amount of time; participants belonging to Cluster 1 seem to be more stressed (they report to walk fast and goal-oriented and stay for a comparatively short time), whereas participants belonging to Cluster 4 take more time for shopping.

Individuals who have been allocated to Cluster 3 seem to represent “Discerning Shoppers”. They take enough time to perform their shopping tasks, but do not stop as frequently and above-average at shops offering exclusive or specialised goods. Their average age is higher than in the other clusters, which might explain their distinctive preferences.

Cluster 2 finally resembles “Convenient Shoppers”. They prefer flexible routes, long paths and like to take a rest from time to time. The relatively high amount of male participants is also reflected in the categories of visited shops or facilities: individuals belonging to this cluster show little interest in fashion shops and highest interest rates in electronics shops. This cluster also represents the youngest group; no member is older than 36.

“Swift Shoppers” do not seem to be part of the sample observed on the shopping street. This may be caused by the fact that people had to actively participate in this part of data collection (as opposed to data collection during the heuristic phase, where people have been followed unobtrusively). It can be assumed that individuals belonging to this group of shoppers were not willing to participate when being addressed by the observers. Hence, this result confirms a major drawback of interview surveys: specific groups can not be reached by the use of this instrument.

The behaviour of shoppers has already been investigated previously when analysing the wayfinding behaviour of pedestrians in shopping environments. Babin et al. (1994), and Titus and Everett (1995) state that the behaviour of shoppers is determined by "shopping values": "utilitarian" shoppers are expected to strive to complete shopping tasks in an efficient way, whereas "hedonist" shoppers are expected to enjoy the activity and take more time for shopping. According to their results, women seem to be more hedonist than male shoppers, who rather show utilitarian behaviour. Albeit the results of the analysis based on shadowing datasets confirm this assumption, the initial results of the analysis of interviews in our study show a different picture. The largest group among the identified clusters (almost half of the sample) consists of persons (mainly females) who predominantly seem to act under time pressure and do not have much time to enjoy their shopping activities. The only group largely consisting of male participants, however, seem to have more time and pleasure when shopping, although they stop less frequently than members of other clusters.

Conclusion and Outlook

The initial results of the analysis of data collected during the deductive phase of the study partly confirm the results from the previous (heuristic) phase. One behavioural type could not be identified, which may be caused by the methodology (people had to be motivated to participate); one other type could be subdivided into two types of behaviour. In a next step, features concerning general attitudes and preferences collected in the interviews will be analysed in order to refine and interpret the behaviour types based on actual activities. Attributes like education, profession, family background (number of children, size of household), general interests and attitudes will disclose further details and potential determinants for specific behaviour patterns. Additionally, we will also include trajectories collected by GPS in the analysis in order to compare reported behaviour and motion patterns recorded by GPS localisation.

Subsequently, the datasets collected in the indoor investigation will be analysed in a similar manner to examine potential differences between indoor and outdoor behaviour. Finally, we plan to validate the outcomes in at least one other context situation to explore the stability of behaviour patterns in different situations. In the end, the results can form the basis for mobility-based pedestrian profiling in mobile wayfinding services. Furthermore, the outcomes can also be beneficial for other research fields, such as for calibrating pedestrian simulation models. Based on the results of this project, also further questions, like potential differences in behaviour patterns in different cultures, can be considered.

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