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Collaborative Filtering Based Route Recommendation for Assisting Pedestrian Wayfinding

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Abstract

Mobile pedestrian wayfinding service is one of the most popular Location Based Services. In the era of Web 2.0, current mobile wayfinding services usually suffer from the following problems: the lack of social navigation support (utilizing other people's experiences), and the challenge of making user-generated content useful. This paper designs a collaborative filtering based route recommendation method to address these problems. With the proposed method, smart services like "in similar situation, other people similar to you always choose this route" can be provided in mobile wayfinding systems. These kinds of smart services will significantly improve the quality of the chosen route, thereby effectively supporting users' wayfinding tasks.

Keywords: mobile pedestrian wayfinding services, route calculation, user-generated content, social navigation, collaborative filtering

1. Introduction

Recent years have seen raising interest in Location Based Services (LBS) with the continual evolution of mobile devices and communication technology. Mobile pedestrian wayfinding service is one of the most popular LBS applications. It aims at effectively assisting pedestrian's wayfinding tasks in an unfamiliar environment. Recently, mobile pedestrian wayfinding service is becoming more and more accessible not only in city wide outdoor environments but also in many indoor environments, such as shopping malls, complex buildings, and train stations.

Mobile pedestrian wayfinding services are designed to facilitate pedestrian's wayfinding. In our daily life, we often ask other more experienced people in the surrounding area for orientation and route advices (social strategy of wayfinding).

These techniques utilizing “experiences of other people” are also known as social navigation (Dourish and Chalmers 1994). Research has shown that experiences/information from similar users in similar context can help current problem-solvers to gain more efficient and more satisfying answers to their problems (Wexelblat 1999). However, this aspect has widely been ignored in current mobile wayfinding services.

What’s more, in recent years, we have seen a trend toward incorporating Web 2.0’s “participation” notion into LBS applications. These LBS applications employing the “participation” notion enable users to annotate their personal experiences and feelings to physical places during using the systems. The user-annotated information (known as user-generated content, UGC) reflects the perspectives and experiences of other users who solved their similar spatial tasks in this situation. It can be very useful for current users (e.g., wayfinders). However, little work has been done on investigating how UGCs can be used to generate value/benefits for mobile wayfinding services.

Recommendation methods, especially collaborative filtering (CF) may be a promising solution for the two problems mentioned above. CF recommends items that people with similar tastes and preferences liked in the past. By incorporating CF into wayfinding systems, smart services can be provided for users, which use other people’s wayfinding experiences (i.e., UGCs) to provide social navigation support. This paper focuses on introducing CF into mobile wayfinding services to address the two problems mentioned above.

The rest of this paper is structured as follows. In section 2, we outline related work. Section 3 proposes a collaborative filtering based route recommendation method for mobile wayfinding services. In section 4, we discuss some related issues and implications. Finally, section 5 draws conclusions and presents future work.

2. Related Work

Our research concerns how social navigation can be introduced into mobile wayfinding services in the era of Web 2.0. This issue mixes several mainstream trends and concepts, such as mobile wayfinding services, social navigation, Web 2.0, and recommendation systems. From these aspects, we summarize the related work.

2.1 Mobile Wayfinding Services

Mobile wayfinding service is one of the most important LBS applications. Research on mobile wayfinding services can be divided into three parts (Huang and Gartner 2010a): positioning, route calculation (selection), and route communication (presentation). Positioning determines the position of the user. For outdoor navigation, GPS is often employed. For indoor navigation, additional installations (e.g., WiFi, Bluetooth, and RFID) are required. Route calculation focuses on computing

the “best” route from origin to destination. How to communicate route information efficiently and enable wayfinders to easily find their way with little cognitive load is the key question of route communication. This paper mainly focuses on route calculation.

Findings in pedestrian behavior research have shown that pedestrian – especially when having enough time – favors different route qualities than simple shortness, e.g., simplicity, safety, attractiveness, and convenience (Golledge 1995). There is some research focusing on calculating different “best” routes for users. For example, the route with minimal number of turns and the route with minimal angle by Winter (2002), the route with least instruction complexity by Duckham and Kulik (2003), and the reliable route which minimizes the number of complex intersections with turn ambiguities by Haque et al. (2007). However, all of the above routes are mainly based on the geometrical characteristics of the road network, which may not accurately reflect the quality (e.g., simplicity, safety, attractiveness, convenience) of the route.

In daily life’s wayfinding, we often employ some social strategies, such as asking other more experienced people in the surrounding area for orientation and route advices. This technique is also known as social navigation which is based on the observations that may seem really obvious and simple: much of the information seeking in everyday life (e.g., choosing where to visit next or which route to take) is performed through watching, following and talking to other people (Höök 2003). Social navigation is always used to help users effectively finding relevant information on the Web, such as the Footprints system (Wexelblat 1999) and the Kalas system (Svensson et al. 2005). It is important to note that very few studies on introducing social navigation technique into mobile wayfinding services have been done so far. An exception is Gam et al. (2007) which proposed to use other people’s trails (i.e., wayfinding experiences) for wayfinding assistance and mainly focused on trail modeling. However, a comprehensive investigation of how social navigation can be used to assist users’ wayfinding is missing.

2.2 LBS in the Era of Web 2.0

The Web is gradually evolving from 1.0 to 2.0. Web 2.0 allows users to do more than just retrieve information. Users are also encouraged to contribute their data.

Recent years have seen a trend towards incorporating Web 2.0’s “participation” notion into LBS. These applications, such as Geonotes (Espinpza et al. 2001), E-Graffiti (Burrell et al. 2002), CityFlock (Bilandzic and Foth 2008) and Hycon (Hansen et al. 2004), enabled users to annotate their personal experiences and feelings (i.e., UGCs) to physical places or objects during using the systems (“situated authoring”). Users can also access other users’ UGCs. However, these systems can only be viewed as a new form of computer-mediated communication (information exchange) which is location-based.

Little work has been done on investigating how UGCs can be used to generate value/benefits for LBS. In fact, UGCs in LBS reflect the perspective and experiences of other people who solve their spatial tasks in this situation. It seems obvious in our daily life that experiences/information from past users (especially similar users) in similar context can help current users to effectively solve their problems (Wexelblat 1999). This is also true for mobile wayfinding services. However, little research has been done on this aspect.

2.3 Collaborative Filtering in LBS

Collaborative filtering (CF) is the most popular recommendation approach. It is well-known through its Amazon-like recommendation: “users who bought ... [i.e., like you] also bought ...”. CF aggregates opinions of similar users in similar context to help current user effectively identify information of interest from a potentially overwhelming set of choices (Resnick and Varian 1997). User-based CF is the most well-known CF. It measures similarities between the current user and other users, and then aggregates the opinions of the N most similar users for recommendation.

CF has been proven to be an effective tool for providing relevant information/items for users in e-commerce or Web-based applications. In recent years, more and more research started to apply CF into LBS applications, such as shop recommendation (Takeuchi and Sugimoto 2006), event recommendation (de Spindler et al. 2006), and POI recommendation (Chen 2005). However, to the best of our knowledge, none of the research incorporates CF into mobile wayfinding services.

2.4 The UCPNavi Project

In Huang and Gartner (2010b), the UCPNavi (Ubiquitous Cartography for Pedestrian Navigation) project which aims at investigating how mobile wayfinding services can benefit from introducing smart environment and Web 2.0 was proposed. In order to illustrate the potential benefits, a smart environment with an indoor positioning module and a wireless communication module was set up to support users' wayfinding, and facilitate users' interaction and annotation with the smart environment. The smart environment helps to collect UGCs explicitly and implicitly during users' wayfinding, such as ratings, comments, feedbacks, and moving trajectories. Based on the collected UGCs, especially explicit ratings and moving trajectories, several collective intelligence based route calculation algorithms were developed to provide smart wayfinding supports to users, i.e., “the nicest route”, “the least complex route”, “the most popular route”, and “the optimal route”.

The proposed collective intelligence based mobile wayfinding is a good start for addressing the problems mentioned in Section 2.1 and 2.2. However, it makes community-at-large recommendation (route suggestions) to individual users. It is

not especially made for any particular user but all get the same recommendation. This paper aims at extending the collective intelligence based mobile wayfinding solution and providing contextual and personalized route recommendation: “in similar context, other people similar to you always choose this route”.

3. Collaborative Filtering (CF) Based Route Recommendation

In this section, we analyze why CF-based route recommendation method can be used to solve the problems mentioned above. After that, the proposed CF-based route recommendation for wayfinding will be discussed in detail.

3.1 Why CF-Based Route Recommendation?

CF recommends items that like-minded users liked in the past. The main idea of CF is to automate the process of “word-of-mouth” (Heylighen 2001). “Word-of-mouth” is one of the most important social navigation techniques: in daily life, when people make decisions on different options that they have no prior experiences of, they always seek advices from others who have such experiences. From this aspect, CF can be viewed as an implement of social navigation (Shardanand and Maes 1995, Svensson 2003), and can help to provide social navigation support in mobile wayfinding services.

Additionally, previous research has shown that CF can help to make UGCs useful. Some examples are “users who bought ... also bought ...” at Amazon, “the most viewed” at YouTube, “the most popular tags” at Flickr, and “the most popular bookmarks” at Del.icio.us. These kinds of recommendations have been proven to be very useful for users in e-commerce or Web-based applications. The same is true for mobile wayfinding services. CF can help to make UGCs useful, which will provide wayfinders with smart services, such as “in this situation, other people similar to you always choose this route” and “people who visit this place also visit that place”. The highly available UGCs will also be an abundant data source which makes CF ready for mobile wayfinding services.

To sum up, CF is a promising tool for the above problems in current mobile wayfinding services: the lack of social navigation, and the challenge of utilizing UGCs.

3.2 CF-Based Route Recommendation

Because of its intuitiveness, user-based CF is employed in this paper to provide smart route recommendation in mobile wayfinding services. The process of user-based CF includes three key stages: data collection for building user profiles (generally, in the form of ratings), computation of user similarities, and aggregation of

ratings from the N most similar users (or users with bigger similarity with the current user) for recommendation.

3.2.1 Building User Profiles

The first stage of a CF process is to build user profiles (generally in the form of ratings) from feedback on items made over time. In the UCPNavi project (Huang and Gartner 2010b), users are enabled to directly interact and annotate with the physical environment. This functionality provides a basis for collecting users' feedback during their wayfinding.

For wayfinding, the route (from origin to destination) users need to follow can be viewed as route segments connecting by different decision points (areas). In Huang and Gartner (2010b), we encouraged users to explicitly give ratings for these two kinds of elements. Rating for a decision point is designed to reflect the level of complexity (cost of effort) of making right decision (choosing the right road to follow) at this point. It is represented as $R_{DP}(user, previous, current, next)$. For example, $R_{DP}(user, A, B, C) = 4$ is the rating for the decision point B , and can be viewed as the complexity of navigating from point A to node C through B . Rating for a route segment is designed to reflect user's level of interest (attractiveness) for the route segment. For example, $R_{RS}(user, A, B) = 1$ means that the user likes route segment AB very much. In Huang and Gartner (2010b), users' moving trajectories are also employed to unobtrusively infer the current user's implicit ratings for decision points and route segments.

In order to provide route with optimal trade-off between complexity and attractiveness, we define a popularity rating for each decision point, which depends on both the ratings for route segments (attractiveness), and ratings for decision points (complexity). The popularity rating is computed as:

$$R_{pop}(user, pre, cur, next) = \lambda_d * R_{DP}(user, pre, cur, next) + (1 - \lambda_d) * R_{RS}(user, cur, next) \quad (1)$$

Where $R_{DP}(user, pre, cur, next)$ and $R_{RS}(user, cur, next)$ are rating for decision point and rating for route segment respectively. λ_d determines the weight of the impact for the complexity. Similar to Huang and Gartner (2010b), λ_d is set as 0.25. It is important to note that, other factors like road length can be also included. However, we do not consider road length in this paper.

Before using the wayfinding system, user (wayfinder) is requested to provide some demographic information, i.e., *gender* ('male', 'female'), *age group* ('<15', '15-35', '36-55', '>55'), *education* ('university', 'other'), *profession* ('student', 'staff', 'other') and *type* ('tourist', 'other'). Also some contextual information is obtained and recorded, i.e., *time of the day* ('daytime', 'night'), *day of the week* ('weekday', 'weekend'), *season of the year* ('spring', 'summer', 'autumn', 'win-

ter'), *weather* ('rainy', 'sunny', 'snowy', 'windy') and *temperature* ('<0', '0-5', '5-15', '>15'). Additionally, user's wayfinding information (i.e., *origin* and *destination*) is also stored.

Fig. 1 depicts the data model of user profile. A user profile includes one set of demographic information, and has at least one set of wayfinding history. A wayfinding history is associated with one set of contextual information, and has many popularity ratings. The demographic information is given by user via a questionnaire before wayfinding. User also has to specify the origin and destination of her/his wayfinding task. The system will obtain contextual information from mobile devices or Web automatically.

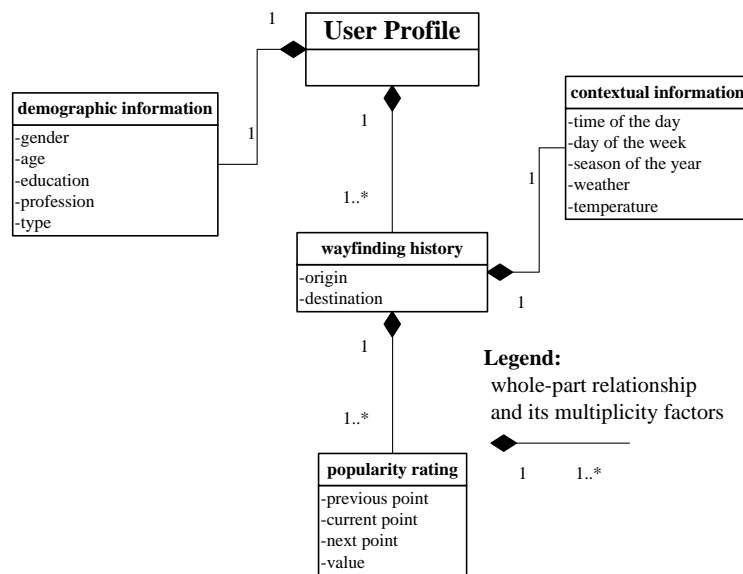


Fig.1. Data model of user profile

3.2.2 Measuring User Similarity

The key in CF is to locate other users whose opinions can be used for generating recommendation (i.e., suitable route) for the current user. In this paper, we identify these users (i.e., other wayfinders) in terms of their similarities with the current user, and similar users are defined as users with similar demographic information, similar contextual information, and similar wayfinding information in their user profiles.

Similarity between two sets of demographic information is computed as the ratio of the number of corresponding dimensions (i.e., gender, age, education, profession, or type) whose values are the same and the number of dimensions. For example, the similarity between demographic information <male, 15-35, university, student, other> and <female, 15-35, university, staff, other> is 3/5. The same meth-

od is also applied for measuring similarity between contextual information, and similarity between wayfinding information.

User similarity is then measured as the sum of the product of each similarity (i.e., similarity between demographic information, similarity between contextual information, and similarity between wayfinding information) and its importance weight:

$$Sim(u1, u2) = \lambda_{demo} * Sim_{demo}(u1, u2) + \lambda_{cont} * Sim_{cont}(u1, u2) + \lambda_{way} * Sim_{way}(u1, u2) \quad (2)$$

Where $\lambda_{demo} + \lambda_{cont} + \lambda_{way} = 1$.

The importance weights (i.e., λ_{demo} , λ_{cont} , λ_{way}) can be estimated and learned from data collected in the smart environment. In recognizing the importance of task information (i.e., wayfinding information), we assign a bigger weight for the similarity between wayfinding information. For our smart environment, we set $\lambda_{demo} = 0.2$, $\lambda_{cont} = 0.3$, and $\lambda_{way} = 0.5$.

3.2.3 Making Recommendation

With the user similarity measure, users whose similarity value with the current user is bigger than a threshold ϵ can be identified, and are considered as neighbors. These neighbors' popularity ratings are combined into a prediction by computing a weighted average of them, using user similarities as the weights (Adomavicius and Tuzhilin 2005). The predicted rating (for the current wayfinding task) of the current user u on decision point cur can hence be formulated as:

$$R_pop_p(u, pre, cur, next) = \frac{\sum_{c' \in \bar{c}} R_pop(c', pre, cur, next) * Sim(u, c')}{\sum_{c' \in \bar{c}} Sim(u, c')} \quad (3)$$

Where \bar{c} denotes the set of users whose similarity value with the current user u exceeds the threshold ϵ and who have rated the decision point cur . ϵ is set as 0.3 in the proposed mobile wayfinding system. If no neighbor has been found, a default rating will be assigned.

By using the same method, the predicted ratings for other decision points will be computed. It is important to note that for different decision points, the set of neighbors may be not identical.

The route other people similar to the current user always choose (like) can be viewed as route with the minimal predicted ratings (overall) for decision points. Similar to Huang and Gartner (2010b), we represent these predicted ratings in a *restricted pseudo-dual graph* (see (Winter 2002)) and use classical Dijkstra's al-

gorithm to do the route calculation on this pseudo-dual graph. As a result, smart services like “in similar situation, other people similar to you always choose this route” can be provided.

4. Discussion

In this section, we discuss some related issues and implications of the proposed CF-based route recommendation method.

4.1 Do Users Really Want to Contribute?

An important issue relates to users’ interaction and annotation is what motivates users to contribute. Nov (2007) made a survey on people who contribute to Wikipedia, and identified some main factors which motivate people to contribute, such as fun, ideology, values, understanding, enhancements, protective, career, and social. Burrell et al. (2002) noted that users “seemed to have benefited from feelings of altruism and expertise resulting from contributing notes to help out others”, and users are also motivated to contribute “when they thought themselves experts, when there is a pay off or when it is very easy to do”.

In recognizing these aspects, we make the way of contributing as simple as possible. Also user’s implicit feedback (i.e., moving trajectories) is employed to unobtrusively infer the current user’s implicit ratings. As a result, abundant data (explicit ratings and implicit ratings) can be collected to empower the CF-based route recommendation.

4.2 A Pure CF Method?

Traditionally, CF measures user similarity between two users by comparing their ratings given to the same items. Pearson correlation coefficient and cosine similarity are often employed to do this comparison. In order to get accurate recommendation, user has to rate lots of items before asking for recommendation. As a result, pure CF methods often suffer from the “new user”, “new item” and “sparsity” problems (Adomavicius and Tuzhilin 2005).

In the proposed method, user similarity is computed as a combination of similarity between demographic information, similarity between contextual information, and similarity between wayfinding information. Before asking for route recommendation, user only needs to provide some demographic information, and specify the origin and destination of her/his wayfinding task. The system will obtain contextual information from mobile devices or Web automatically. As a result, the proposed method does not have the shortcomings that pure CF methods have. However, the proposed method doesn’t consider the wayfinding history of the cur-

rent users. In order to provide more accurate recommendation, methods in pure CF will be evaluated and combined with the proposed method in the future.

4.3 A Better Route Calculation Approach?

Currently, shortest or fastest route is often employed in mobile wayfinding services. However, as pointed out in the section 2.1, pedestrian may prefer different route qualities than simple shortness, e.g., simplicity, safety, attractiveness, and convenience (Golledge 1995).

In recognizing that, some researchers proposed to use geometrical characteristics of road network to calculate different “best” routes (e.g., Winter 2002, Duckham and Kulik 2003, and Haque et al. 2007). However, the route qualities with respect to simplicity, safety, attractiveness or convenience are hard to measure and can’t be accurately reflected by the geometrical characteristics of road network (e.g., number of turn, and the degree of angle). What’s more, for different people, these qualities may be measured/perceived differently.

Our proposed method relies on other wayfinders’ feedback which reflects their navigation experiences in the environment. If similar users in similar context consider a specific route is attractive, this route can also be viewed as an attractive route for the current user in the current context. From this aspect, other users *help the current user to define/measure the route qualities*. As a result, compared to other route calculation algorithms, our approach will provide results which are more suitable to the users.

It is also important to note that although the proposed method is motivated by social navigation in our daily life, they have some differences. In daily life, people in the surrounding area may give route advices which are biased (only fit to herself/himself), and may be not suitable to you. However, it is also impractical to ask lots of people for advices. Instead of asking opinions from a lot of people, the proposed method aggregates/averages similar users’ opinions, and making suitable route recommendation.

5. Conclusions and Future Work

The ubiquity of mobile devices (such as cell phones and PDAs) has led to the introduction of Location Based Services (LBS). In this paper, we focused on one of the most important LBS applications - mobile pedestrian wayfinding service. Current mobile wayfinding services often ignore the social navigation aspect (i.e., using other people’s experiences) which however is always used in our daily life. Also, in the era of Web 2.0, more and more UGCs are created/generated in lots of LBS applications. How to make these UGCs useful has become very challenging.

In recognizing these challenges, we proposed a collaborative filtering based route recommendation method. After analyzing why CF-based route recommenda-

tion can be used to solve these problems, three key issues of the proposed method were discussed in detail: building user profiles, measuring user similarity, and making recommendation. With the proposed method, smart services like “in similar situation, other people similar to you always choose this route” can be provided. These kinds of smart services use other people’s wayfinding experiences (i.e., UGCs) to provide social navigation support in mobile wayfinding services, and can significantly improve the quality of the chosen route, thereby effectively supporting current users’ wayfinding tasks. The proposed approach can be applied to outdoor pedestrian wayfinding, indoor pedestrian wayfinding, and car navigation.

It is important to note that the user similarity measurement employed in the proposed method is still very simple, and needed to be improved. Also, although we have analyzed the proposed method’s potential in solving the problems of current mobile wayfinding services from a theoretical perspective, some user tests are still needed to evaluate the proposed method in an empirical manner. However, in consideration of the great popularity and usefulness of social navigation in our daily life (social strategy in daily wayfinding), we are very confident that the proposed method can effectively support users’ wayfinding tasks.

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