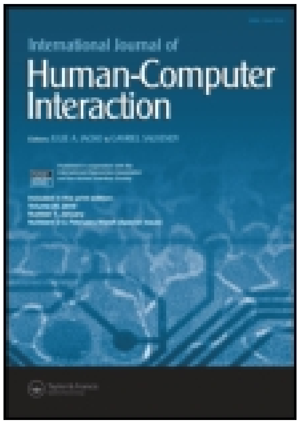

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iReminder: An Intuitive Location-Based Reminder That Knows Where You Are Going

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This article presents the design of iReminder, an intuitive location-based reminder that delivers reminding messages based on users' future routes. iReminder is implemented on mobile phones, and it can predict users' future routes by collecting their daily trajectory data. Then it delivers a reminding message via the mobile phone when it senses that the user is going to the task location. A field study was conducted on how iReminder extends its potential to help users perform everyday tasks and compared the method adopted by iReminder with the method used by traditional location-based reminders. The experimental results show that iReminder outperforms traditional location-based reminder because it delivers reminding messages more appropriately. A detailed discussion is also given to investigate the ideal message delivery point, and the discussion results show that a location-based reminding message is more useful and more likely to be accepted by the user if it is triggered by considering his or her future route.

1. INTRODUCTION

People are swamped with everyday tasks these days and often get annoyed when they forget the things they should have done. An effective, intuitive, and convenient way to remind people of these daily items without unnecessary interruptions is needed.

To put it in Norman's (1998) words, there are two types of aspects to reminders: the signal (there is something to remember) and the message (this is what to remember). A capable reminder should not only alert you that there is something you should do but also make you be aware of what the particular thing is. According to the statement, a mobile phone could be an ideal reminder, because it can offer both the signal and the message easily. To be more specific, signal can be the vibration or ring from the phone, and the message can be displayed on the phone screen. In addition, many researchers have conducted experiments to relate that the mobile phone is an ideal tool to help people to remember things, mainly because people always carry a mobile phone anyway, so they have access to it very easily and naturally (Ludford, Frankowski, Reily, Wilms, & Terveen, 2006). In their research, Kessell and Chan (2006) stated that "all participants carried their mobile phone with them at least 95% of the time" (p. 945).

Although some routines are based on the time of day, it is not always useful to deliver reminding messages based only on time. Dey and Abowd (2000) pointed out that current, traditional time-based reminder systems are not sufficient because they are not proactive and do not make use of rich contextual information to trigger reminders at appropriate times in appropriate locations. In daily life, many tasks cannot simply be associated with the time, such as picking up clothes from the dry cleaners on the way home and buying a newspaper at a newsstand. That is because people cannot always determine the specific time when they will complete these mundane tasks. In these situations, the appropriate timing for reminder delivery is associated with the locations rather than the time. Therefore, delivering location-based reminders could be useful for people as they tackle daily tasks. The study by Sohn et al. (2005) revealed that location-based reminders are useful, in large part because people use location in nuanced ways. Meanwhile, the availability of mobile phones equipped with global positioning system (GPS) makes it possible and easy to obtain people's real-time location. This also promotes the growth of location-based services (Amini, Brush, Krumm, Teevan, & Karlson, 2012; Ferrari, Rosi, Mamei, & Zambonelli, 2011; Ludford, Priedhorsky, Reily, & Terveen, 2007; Tang, Keyani, Fogarty, & Hong, 2006; Zhou, Ludford, Frankowski, & Terveen, 2005). In addition, many researchers have developed location-based reminder systems running on mobile phones, which deliver reminding messages on the basis of people's location. A new feature in iOS 5 (Viticci, 2011) is the built-in reminder application, which can deliver reminding messages based on one's arrival to or departure from a location. Yepa ("Yepa," 2012)

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is a location-based reminder for Android that allows people to create location-based to-dos and get notifications.

Many researchers have conducted field studies on location-based reminders, which deliver reminding messages for task locations within a fixed Euclidean distance. Generally, the task reminder will be triggered if the straight line distance between the user's current location and the task location is below the predefined threshold. However, Ludford et al. (2006) found that this simple delivery approach proves insufficient. That is partly because that a simple Euclidean distance or simply predicted reach time could not reflect the real contexts where users are situated. In this approach, the geographic layout of the space is largely overlooked, because it only uses the Euclidean distance as an indicator of the context, which neglects the real geographic context where users are situated. In addition, users' route patterns are not considered at all, which can suggest users' intents to a large extent. For example, a traditional location-based reminder will trigger the notification of a task to the user when the fixed Euclidean distance of the user and the task location is below the predefined threshold. However, in the real world, there might be no direct route for the user to reach the task location, and the user would need to take a long way to the task location. Therefore, it would not be appropriate timing to deliver that reminder. The user would choose not to fulfill that task at that time, as the user could find another, more convenient time (e.g., the user will pass by the task location in the near future) to fulfill the task.

A key issue in location-based reminders is whether the timing with which it delivers reminding message is appropriate. To offer better reminding experiences, the reminder should be able to determine the optimal timing to alert the user. From the mental models perspective, if the reminder delivers a notification when the user can get the task done only at a great cost (e.g., spending a long time), the reminding message is likely to be ignored by the user. Because a large number of location-based tasks are insensitive to timing, the user may choose to complete the task another time. A location-based reminder should deliver a reminding message to the user when she or he can complete the task as conveniently as possible. However, the Euclidean distance is not accurate enough to infer locations at which people can get the task done with the least cost, as the Euclidean distance cannot accurately represent the effort that a user should make to complete the task in a road network environment. Therefore, traditional location-based reminders cannot deliver reminders at appropriate times.

The limitations of the approach that these location-based reminders adopted in delivering location-based reminders motivate our work. To make more effective and appropriate message delivery, richer contextual information should be taken into account. On the other hand, many researchers have developed systems on obtaining a user's future route by collecting his or her trajectory data. Therefore, we came up with the idea of delivering reminding messages on the basis of the routes that users might take rather than the Euclidean distance. iReminder, a location-based reminder that adopts this approach, has been designed for this study. It delivers location-based reminders when it predicts that the user is going to the task location. We also conducted a field study to investigate its performance compared with traditional location-based reminders that deliver reminding messages based on Euclidean distance.

To the best of our knowledge, iReminder is the first location-based reminder that considers people's route patterns in delivering reminding messages. We imported a new feature, the user's daily routes, into location-based reminders. By obtaining users' future routes based on their route patterns and the recent trajectory data, iReminder offers a promising method to deliver location-based reminders more intuitively and more appropriately so that users get their tasks done. But how well it will improve users' location-based reminding experiences needs to be investigated. The purposes of the study presented in this article is to investigate whether our novel approach works in a real setting and whether iReminder could deliver more appropriate reminding messages than can the traditional location-based reminders. This article also attempts to discuss the better design of location-based reminders.

In section 2, we overview related work conducted by other researchers. The approach and architecture of iReminder are illustrated in detail in section 3. The process of conducting the field study is introduced in section 4. Then we list the experimental results in section 5, and an in-depth discussion is extended in section 6. Section 7 provides the conclusions of the field study we implemented and proposes the future work.

2. RELATED WORK

2.1. Location-Based Reminders

Michael (2000) put forward, a decade ago, that in many cases space rather than time may be appropriate to trigger reminders. He realized a location-based remembrance appliance that reminds users when they are entering the selected location. Marmasse and Schmandt (2000) developed comMotion, which was a location-aware computing environment that allows users to associate to-dos with physical locations in their daily lives by taking the advantage of satellite-based GPS position-sensing technology. comMotion learns about the locations in its user's daily life based on knowledge of the user's travel patterns. It allows users to set reminders associated with those locations and get reminders when they are near those locations. Afterward, with the worldwide popularity of GPS-enabled mobile phones, the perception of people's location was more convenient. Consequently, more studies about location-based reminders were coming out. Sohn et al. (2005) designed Place-Its, a location-based reminder that runs on a mobile phone, and they found that location-based reminders were helpful in reminding people of daily tasks through a 2-week exploratory user study. Liu, Li, Guo, and Lim (2011) proposed a location-based reminder system on mobile phones using image recognition technology. After users capture the images of their favorite products to the server, they will get notification when they are close to the place where the product is being sold. Google Now (Ha, 2012) can remind people about appointments by considering their travel patterns and the real-time traffic data, and then it can tell them the time they need to leave so that they will arrive on time. Studies conducted by previous researchers (Davidoff, Ziebart, Zimmerman, & Dey, 2011; Y. Q. Li, Guo, Liu, Gao, & Zheng, 2010) illustrated that location-based reminders are helpful and can play an important role in people's daily lives.

PlaceMail (Ludford et al., 2006) is a typical location-based reminder that uses the traditional reminding strategy to deliver location-based messages. Compared with other location-based reminders, PlaceMail introduced many new features, such as a Web-based interface and a voice input function to create a task, which is aimed at simplifying users' interactions with the system. However, the approach it uses for triggering reminding messages is almost the same as other traditional location-based reminders—delivering reminding messages based on the Euclidean distance of the task location and the user's position. They have conducted a thorough field study on PlaceMail. Specifically, when the user is stationary, the task reminder would be triggered if the straight line distance between the user's current position and the corresponding task location is below the predefined threshold; when the user is moving, it would deliver reminding messages when it senses that the user would reach the task location in a certain time given his or her current speed. Through a month-long field study, Ludford et al. (2006) concluded that this simple delivery procedure proves insufficient. That is partly because a simple Euclidean distance or simply predicted reach time cannot reflect the real contexts where users are situated. For example, a reminding message would be triggered when the reminder senses the Euclidean distance between the user and the task location is below a certain distance. However, in the real setting, the geographic distance between the user and the task location is not short enough for the user to go to the location. Thus, the reminding message is delivered so early that the user will forget to complete the task. iReminder surpassed those traditional location-based reminders by delivering reminding messages based on user's future route.

2.2. Movement Route Prediction

Currently, there are various approaches to route prediction. Froehlich and Krumm (2008) proposed an algorithm for predicting the end-to-end route of a vehicle based on the vehicle's past trips. The accuracy of their algorithm was evaluated through the experiment of observing 250 drivers' real-world GPS driving data. Giannotti, Nanni, and Pedreschi (2006) presented the MiSTA algorithm, which was based on the PrefixSpan algorithm (Pei et al., 2001) and obtained patterns from temporally annotated sequences. Gidófalvi and Pedersen (2009) presented a projection-based algorithm to find long, sharable route patterns. Similar research concerned with route prediction was conducted in Karbassl and Barth (2003); Karimi and Liu (2003); Simmons, Browning, Zhang, and Sadekar (2006); and X. Li, Zhang, and Lin (2012). However, most of these current methods were applied to vehicles, which would not be appropriate for personal walking movements, mainly because the trajectory data of personal movements were more diverse than that of a vehicle. A novel algorithm proposed by Chen, Lv, Ye, Chen, and Woodward (2011), called Continuous Route Pattern Mining (CRPM), was proposed to address this issue. CRPM can tolerate different kinds of disturbance in trajectory data. In addition, through the experiments they conducted, it was demonstrated that CRPM could extract longer route patterns than current methods. Therefore, we employed this approach to predict a future route in iReminder.

2.3. Route-Based Interaction Design

Previous researchers have conducted research about route-based interaction. Backseat Playground (Bichard, Brunnberg, Combetto, Gustafsson, & Juhlin, 2006) is a location-aware pervasive game that utilizes the routes of players. The game intends to provide rich and vivid narratives in vast geographic areas, and it generates journey events for the game by adopting a road-network-based method to predict the players' future routes. Chen, Chen, and Benford (2013) designed a location-aware pervasive game, YMYM (Your Way Your Mission), to exploit the routes of players. It provides a Google Maps–based tool for players to predefine the routes they are going to take in the experiment, and it utilizes self-reporting method to obtain the planned routes of players. The experimental results indicate that route predefining and self-reporting methods are an effective approach to obtain the planned routes of players. However, predefining the planned routes and self-reporting methods would take users' extra efforts. Therefore, we used the route prediction algorithm to obtain people's future routes by collecting people's daily trajectory data.

3. iREMINDER

On one hand, the design of iReminder originates from the situation of most existing location-based reminders, which does not take advantage of the user's richer contextual information. On the other hand, more and more trajectory-data-mining technologies, which can be used to obtain richer user contexts, are proposed. We then raised the idea of triggering reminding messages on the basis of users' future routes. iReminder was designed via a process of participatory design in which designers and potential users were all involved. We invited six participants into the design process of iReminder. Then we illustrated the basic idea of iReminder to them and let them talk about their opinions about iReminder. One of them raised privacy issues. To address this issue, the client of iReminder was designed to preprocess the raw trajectory data and then upload it to the server. Some participants reported to us that it is not very convenient to manipulate the map on the phone in order to set the task location. Hence, we offered a web interface to let users set tasks, and the client is designed to automatically synchronize the tasks. iReminder was designed with their advice in mind.

The design of iReminder is to deliver reminding messages based on the routes users are about to take instead of the "geofence" radius around a place. The geofence radius is the radius around a point location, indicating a virtual perimeter for a real-world geographic area. Because it senses where the users are going, it knows when and where to deliver convenient messages. The details of this novel way are illustrated as follows. To predict a user's future route, the user's past trajectory data should be collected in advance. In addition, to get a high accuracy of future route prediction, adequate trajectory data are demanding. iReminder can predict a user's future route based on his or her route patterns and recent trajectory data by adopting the CPRM algorithm (Chen et al., 2011), which is detailed in section 2. Then the reminder will be triggered when iReminder predicts that the user is about to go to the task location. As shown in Figure 1(a), a user receives a reminding message when the task location (the yellow star) is on his or her future route (the arrows). The traditional location-based reminders deliver reminding messages when the Euclidean distance between the user and the task location is below the predefined threshold, as shown in Figure 1(b). The design principles of iReminder are as follows:

- Deliver reminders based on the user's future route.
- Record the user's trajectory data and extract the route patterns of the user.
- Allow the user to easily associate the task with any location.
- Avoid revealing the user's private information.

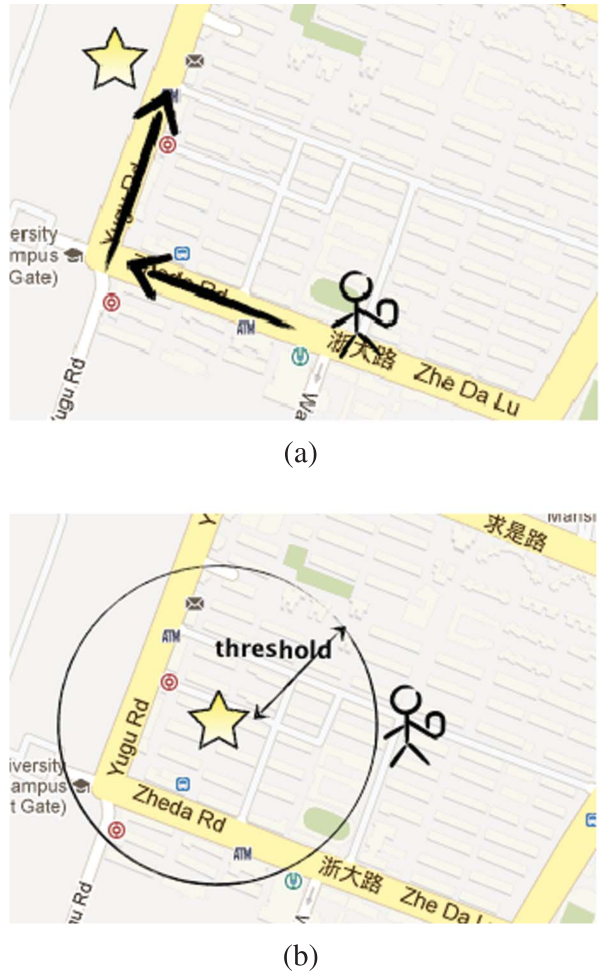


FIG. 1. The design of iReminder (a) and traditional location-based reminders (b) (color figure available online).

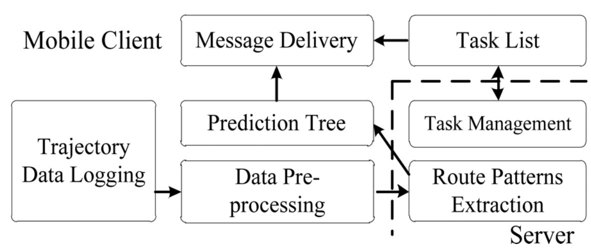


FIG. 2. The architecture of iReminder.

3.1. Architecture

iReminder uses a client-server architecture. The client is implemented on the mobile phone equipped with GPS and is developed on Java ME platform. The client is mainly responsible for collecting users' trajectory data and delivering reminding messages based on their future routes. A browser-based client for users to manage their tasks is also implemented. The web server is designed for managing users' personal tasks and extracting their route patterns. The architecture of iReminder is shown in Figure 2, and the detailed functions of iReminder are presented as follows.

3.2. Task Management

iReminder offers a web interface to let users create, edit, and delete tasks, as shown in Figure 3. As for creating tasks, users can easily associate their tasks with any physical locations by using a web application, which is implemented based on Google Maps API.[1] Specifically, users can drag the map on the web and then mark the location on the map with a click, as shown in Figure 4. The method we adopted in place acquisition is more convenient as compared with the method used in PlaceMail (Ludford et al., 2006), which required researchers to consult participants about the places they frequented previously, and then imported the locations of these places from Google

[1] Available at: http://code.google.com/apis/maps/documentation/javascript/v2/reference.html

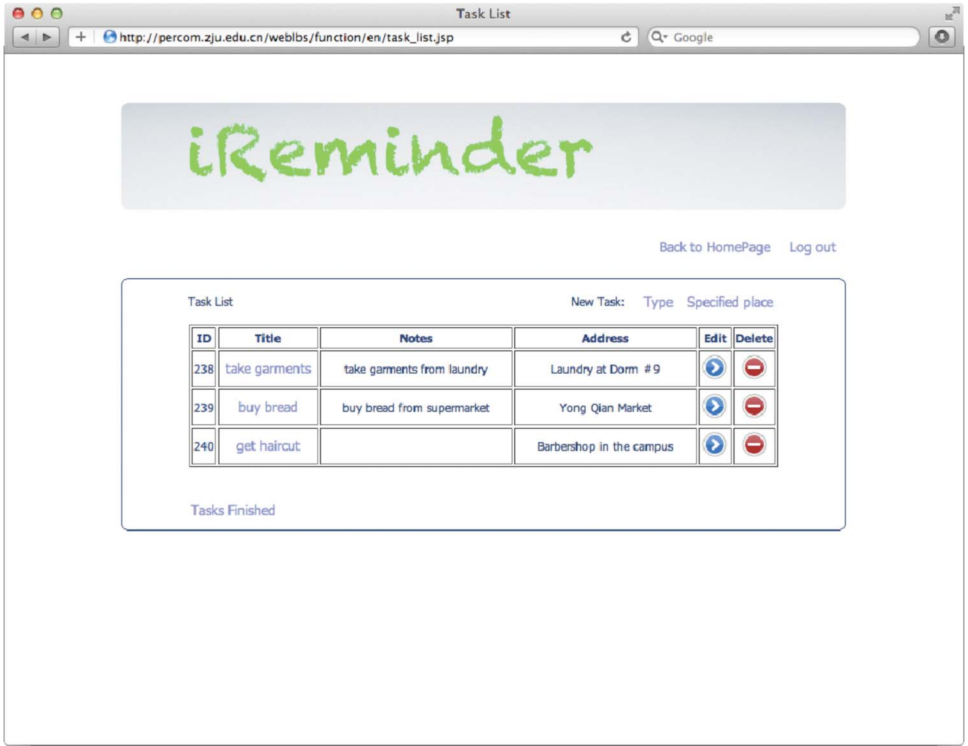


FIG. 3. The iReminder and Euclidean distance based reminder web design (Task List) (color figure available online).

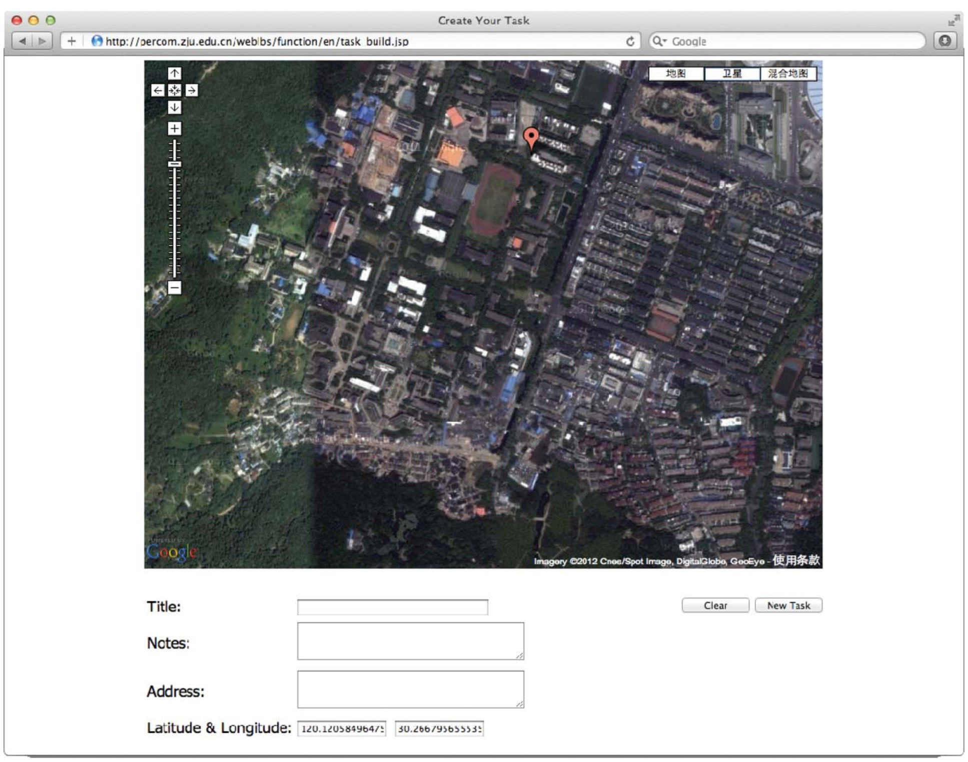


FIG. 4. The web design for iReminder and Euclidean distance based reminder (Create a task associated with a specified location) (color figure available online).

Map to its database. In addition, we collected the physical locations of some meaningful places within the area of interest, such as a supermarket, ATM, and so on. By doing this, if a user specifies a kind of place from the place list, such as a supermarket, she or he will attach the locations with all the surrounding supermarkets. Meanwhile, users can drag the marker on the map to change the location of the task and edit the task description on the web page. In addition, when deleting a task, a form window will pop up to let the user fill out the reasons why she or he wants to delete it. To simplify the user's operation, the mobile client is developed to download a user's tasks automatically once she or he logs in.

3.3. Trajectory Data Collecting

Users are required to use iReminder to record their daily trajectory data for a period of time before using it to perform everyday tasks. To alleviate the problem of the disclosure of a user's privacy, we remove the physical location information in a user's raw trajectory data by transforming it into sequences of cells, and then the file containing the sequences (i.e. regional sequence files) is uploaded to the server over an HTTP connection for route patterns extraction. On the basis of the experiences gained from Chen et al. (2011), the length of a cell is set to 50 m. By doing this, the server can perform trajectory data mining but it does not have sufficient information to reconstruct users' routes in a real setting.

3.4. Route Patterns Extraction

In our system, we employ the CRPM algorithm proposed by Chen et al. (2011) to perform route patterns extraction. Through trajectory data mining by using CRPM, a user's route patterns file, which contains the essential information to make route prediction, is generated and then it is transmitted to the mobile client over an HTTP connection.

3.5. Predicting Future Route and Message Delivery

Task reminding is implemented on the mobile client and works as follows. First, the mobile client builds a prediction tree according to the received route patterns. Second, a user's future route is predicted based on his or her recent route and the prediction tree. Third, the mobile client searches in his or her task list to find the tasks with a location on the predicted future route. If any qualified task is detected, a corresponding reminding message will be delivered. We define the future route as the next two regions, rather than all the future regions that users will pass by in order to avoid reminding users too early in case they may forget the task. Moreover, the location will be considered as being on the future route if the Euclidean distance between the task location and the center of either of the two future regions is below 50 m. The value of the Euclidean distance is set at 50 m because places of interest in the real-world environment (e.g., markets, gyms) are mostly on the sides of the street. All the computations for delivering reminding messages of iReminder are performed on a mobile phone other than sending GPS readings to the server to determine the point to deliver reminding messages, which is the process PlaceMail used. By doing this, iReminder largely reduces the requirements of HTTP connection. Every notification is delivered with vibration lasting 2 s, and the details of the task are displayed on the screen of the mobile phone.

4. FIELD STUDY

As we mentioned, PlaceMail (Ludford et al., 2006) is a typical location-based reminder that uses the traditional reminding strategy to deliver location-based messages. It delivers location-based messages when it senses that the user is entering the range of the predefined threshold of the task location. Specifically, PlaceMail delivers reminding messages by adopting two different approaches based on whether or not the user is moving. When the user is moving, it delivers reminding messages when the predicted reach time is below 2 min. When the user is stationary, it triggers reminders when the Euclidean distance between the task location and the user's current position is below a half mile. To study the performance of iReminder, we implemented a location-based reminder that used the reminding strategy adopted in PlaceMail (Ludford et al., 2006) when the user is stationary, called Euclidean distance based reminder (EDBR). Because iReminder considers people's future routes, we deem that it will offer more intuitive and personalized reminding services to users. Therefore, we hypothesize that iReminder could deliver reminding messages more appropriately than EDBR. In addition, a filed study was conducted to investigate the usage of iReminder and EDBR, as ubiquitous computing (Stanton, 2001) technologies are usually embedded in the environment, or carried by the user throughout everyday life (Consolvo et al., 2007).

4.1. Participants and Apparatus

We recruited 12 participants, who were all familiar with mobile phones, to be involved in the field study. There were eight male and four female participants, with ages ranging from 21 to 25 years ($M = 22.83$, $SD = 1.27$). They all had a mobile phone equipped with internal GPS sensor, allowing them to use iReminder and EDBR in the field study. They all had experience in using GPS on mobile phones.

4.2. Design and Measures

A comparative within-groups experiment was designed to study the performance of iReminder and EDBR. Each participant was required to use iReminder and EDBR with the order counterbalanced, to eliminate the habituation in using the reminders, which may probably affect the results of the experiment. As for the geofence threshold in EDBR, we set it as 200 m rather than the half mile used in Ludford et al. (2006), because the participants used EDBR mainly on campus. The basic interactions with iReminder and EDBR were implemented in the same way. Therefore, the only difference of these two systems is the methods they use to trigger reminding messages.

To record the real contexts users situate when receiving reminding messages. We designed two option buttons (i.e., Accept and Ignore), which show up on the screen when a reminding message is delivered on the phone. Each participant was informed that she or he should choose Accept if she or he would be going to fulfill the task when receiving the reminding message. Otherwise, the participant was required to choose Ignore. The response would be sent immediately to the server. When a user selects Accept, the task is ticked off from his or her task list, and the user will not be reminded again. However, there may be two scenarios when a user selects Ignore: the user would not like to do it right now but she still wants to get reminders later, or the user would not like to complete it and does not want to get reminders again. The first scenario is mainly because the delivery point is not appropriate, and if the user would like to be reminded next time, then the task would still be in his or her task list by default. For the second scenario, the user may have already completed the task or the user may have cancelled the task and not deleted it previously. When this situation occurs, the user has to delete this task manually to avoid getting the corresponding reminder again. Therefore, if Accept, we deem the corresponding message delivery a successful reminder; if Ignore, it is deemed a failed reminder.

Instant feedback was designed to investigate the performance of iReminder and EDBR. This shows up on the screen when a user selects Accept/Ignore for each message delivery, which includes five statements:

S1. I am near the task location now.
S2. I am going to visit the task location right now.
S3. I definitely remembered this task before I received this message.
S4. I feel free to fulfill the task right away.
S5. This reminding message is very useful.

S1 is used for letting participants report their positions. S2 is proposed to observe how often the messages are delivered when participants are going to visit the task location, and this is used for investigating whether the message delivered when users are going to the task location will affect the usefulness of the reminder. S3 is proposed to find out how often participants are likely to forget the task they set previously. S4 is used for investigating how convenient the user can get the task done when receiving its corresponding reminding message. The overall evaluation of a reminding message can be represented by the response to S5. Each statement can be reported on 5-point Likert scales from 1 (*strongly disagree*) to 5 (*strongly agree*), and participants were required to score these five statements when the survey was shown on the phone. Then the user's current GPS position was delivered to the server along with the responses to these five statements.

Therefore, we quantified the performance of EDBR and iReminder using Acceptance Rate, which is the value of accepted reminder deliveries divided by the number of reminder deliveries. We also use the instant feedback that participants submit when receiving reminding messages to analyze the usages of these two location-based reminders.

4.3. Procedure

Before the field study, we had a face-to-face semistructured interview with each participant. In the interview, we detailed the concepts and the main functions of iReminder and EDBR to them, respectively, and they were instructed to use iReminder and EDBR to perform everyday tasks step by step.

First, iReminder has to collect participants' trajectory data before it could perform task reminding. It took them 2 weeks to collect trajectory data. When they finished trajectory data collection, they were required to upload the regional sequence files processed from the trajectory data to the server for route patterns extraction, and they would get route prediction tree on the mobile phone. Then they began to set tasks to use it to perform task reminding, and they were required to use it just as they wanted. On the other hand, EDBR does not need to take participants' extra efforts before using it to get reminders, therefore participants could use it to perform task reminding directly. In addition, all the participants were informed that iReminder and EDBR would gain access to their positions and were told that their private trajectory data would not be revealed. The field study was conducted with their permission. Figure 5(a) shows a participant receives a reminding message on the road, and Figure 5(b) shows he is going to complete the task. Figure 5(c) is the interface of the reminding message delivered on the phone. The whole field study lasted for 2 months. In addition, we had a poststudy interview with each participant when he or she finished the field study. During the interview, we asked them about their experiences when using EDBR and iReminder, and they were encouraged to report to us anything they encountered during daily use. Meanwhile, a poststudy questionnaire was administered to them, shown in Table 2. Ignore table callout here The questionnaire was designed to be answered with 5-point Likert scales ranging from 1 (*strongly disagree*) to 5 (*strongly agree*), which aims to collect participants' overall evaluations on the performance of iReminder and EDBR. The results of these questionnaires are related in section 5.

5. RESULTS

5.1. Basic Usage

There were 335 tasks created by all participants using iReminder and EDBR. However, 29 of those tasks were deleted by participants manually before the corresponding reminding messages were delivered by reminders. The reasons that such tasks were deleted by users manually attributed to various possibilities, such as the task had been completed by the user

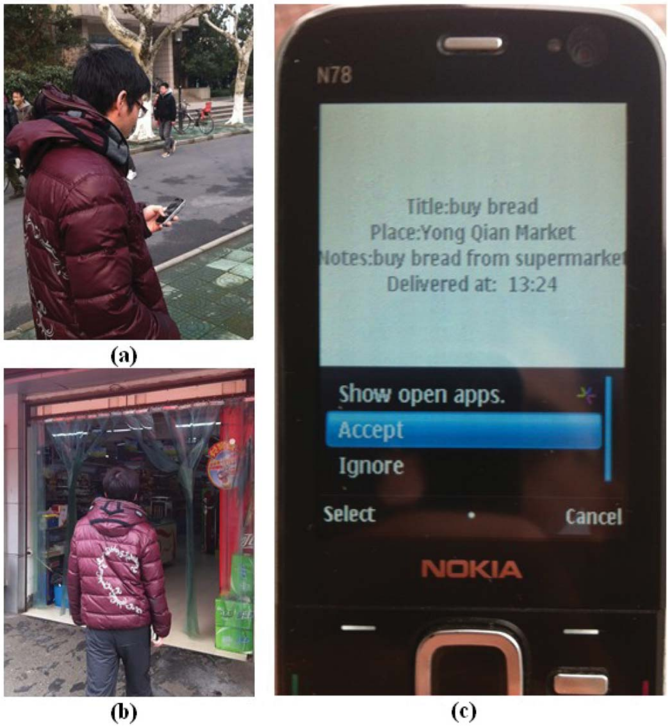


FIG. 5. A participant interacts with iReminder (color figure available online).

before the reminder delivered its corresponding reminding message, or the task was no longer scheduled in the user's task list. Therefore, we discarded those data and ended up with 146 tasks set by using iReminder and 160 tasks set by using EDBR. In iReminder, the average number of tasks created by each participant was 12.16 ($SD = 3.95$) and for EDBR was 13.33 ($SD = 6.67$). In addition, 170 responses to the survey of iReminder and 198 of EDBR were collected. The results show that the tasks set by EDBR were more than the tasks set by iReminder.

5.2. Comparison of EDBR and iReminder

Because the performance of a reminder system is mainly determined by the appropriateness of the delivery points, we quantified the various aspects about the delivery point to compare these two systems. The results are listed as follows.

Acceptance rate. An important criterion of users' satisfaction of reminders is the frequency of successful reminding notifications, which can be indicated by the acceptance rate. We calculated the acceptance rate of the 12 participants, and pairwise comparison shows that the mean acceptance rate of iReminder ($M = 0.85$, $SD = 0.06$) was significantly higher ($t = 2.57$, $p < .05$) than that of EDBR ($M = 0.78$, $SD = 0.10$). It suggests that the reminding messages iReminder delivered were more likely to be accepted by participants than the EDBR messages. In addition, from the statistical point of view, the prediction accuracy of the algorithm in iReminder is 86.5% on average by the tenfold cross evaluation.

Instant feedback. The instant feedback that participants submitted is to help us to measure the usefulness of each reminding message to participants, which indicates the whole performance of the reminder system. We calculated the mean scores for every participant in terms of each statement accepted or ignored. The mean scores of all participants obtained for illustrating the specific aspects of reminding message delivery are presented in Table 1.

S1. I am near the task location now.

Table 1 shows that the scores of S1 in both iReminder and EDBR were above 3.5, which suggests that most of the notifications were delivered at the location where users considered to be near the task location. It is predictable that the score of S1 in iReminder is relatively higher, because EDBR is mainly based on the Euclidean distance between the task location and user's current position. As for iReminder, which delivers reminding messages based on people's future routes, it suggests that the point where participants would like to pass by the task location was always thought to be near it. On the other hand, with respect to the actual distance of the delivery point and the task location, it shows that the thresholds we set on iReminder and EDBR were both appropriate.

S2. I am going to visit the task location right now.

As shown in Table 1, the score of S2 in iReminder ($M = 3.97$, $SD = 0.29$) was significantly higher ($t = 6.31$, $p < .01$) than that in EDBR ($M = 3.14$, $SD = 0.32$), which is mainly because iReminder considers the preference of the user's future route, whereas EDBR delivers reminding messages just based on the straight-line distance between the task location and the user's current position. In total, approximately 80% of the reminding messages given by iReminder were at occasions when participants planned to visit the task location (score >3), whereas the corresponding figure was only near 55% in EDBR. The score of S2 shows that the accuracy of route prediction in iReminder was acceptable and it indeed delivered reminding messages at the moment when participants were likely to visit or pass by the task location. Furthermore, pairwise comparison shows that the mean score of S2 when accepted ($M = 3.94$, $SD = 0.24$) in iReminder was significantly higher ($t = 11.05$, $p < .01$) than that when ignored ($M = 2.02$, $SD = 0.62$). Also, in EDBR, the score of S2 when accepted ($M = 3.48$, $SD = 0.27$) were significantly higher ($t = 11.04$, $p < .01$) than that when ignored ($M = 1.76$, $SD = 0.42$), which suggests that the reminding messages will be more likely to be accepted if delivered when the participant is planning to visit the task location.

S3. I definitely remembered this task before I received this message.

The response to this statement can be used as an indicator of how often reminding messages matter to participants and change participants' behaviors. The mean score of S3 in iReminder was 2.76 ($SD = 0.29$), and in EDBR it was 2.67 ($SD =$

TABLE 1
The Mean Scores of Each Statement in iReminder and EDBR

Statement	The Scores When Accepted		The Scores When Ignored		Total	
	iReminder M (SD)	EDBR M (SD)	iReminder M (SD)	EDBR M (SD)	iReminder M (SD)	EDBR M (SD)
S1	4.12 (0.24)	3.95 (0.29)	2.89 (0.46)	1.97 (0.29)	3.95 (0.29)	3.65 (0.28)
S2	3.94 (0.24)	3.11 (0.25)	2.02 (0.62)	1.89 (0.17)	3.97 (0.30)	3.14 (0.32)
S3	2.63 (0.56)	2.61 (0.54)	2.68 (0.47)	2.45 (0.52)	2.76 (0.29)	2.67 (0.33)
S4	3.80 (0.33)	3.27 (0.39)	1.63 (0.40)	1.80 (0.21)	3.70 (0.23)	3.08 (0.27)
S5	3.83 (0.32)	3.24 (0.38)	1.72 (0.33)	1.71 (0.24)	3.87 (0.31)	2.96 (0.18)

Note. EDBR = Euclidean distance based reminder.

0.33). On one hand, that might suggest that participants indeed often forget to do trivial things in daily life and the reminders were useful to help participants cope with daily tasks. On the other hand, it shows that the score of S3 in iReminder was measurably higher than that in EDBR, which may suggest that iReminder delivers reminding messages when the user is planning to complete the task, and it is more likely to be accepted by the participant.

S4. I feel free to fulfill the task right away.

This statement is to determine whether the reminding message is delivered at the point when it is convenient for participants to implement the task. In other words, it serves as a metric to measure the appropriateness of this notification, because if a reminding message is delivered at an inappropriate time, whether too late or too early, it would not be helpful to users. An ideal task notification should let users feel free to implement it rather than deliver unnecessary interruptions to them. As for S4, the mean score in iReminder ($M = 3.70$, $SD = 0.23$) was significantly higher ($t = 7.79$, $p < .01$) than that of EDBR ($M = 3.08$, $SD = 0.27$), which suggests that messages delivered by iReminder make participants feel more comfortable compared with EDBR.

S5. This reminding message is very useful.

This statement serves as the overall evaluation of the reminding message deliveries. The mean score in iReminder ($M = 3.87$, $SD = 0.31$) was significantly higher ($t = 9.73$, $p < .05$) than that of EDBR ($M = 2.96$, $SD = 0.18$), which suggests that iReminder outperformed EDBR in delivering location-based reminding messages.

Questionnaire. A total of 24 questionnaires were collected (2 systems × 12 participants) and obtained with 0.85 measured by Cronbach alpha values. Table 2 shows the mean score of each question concerning with the overall performance of iReminder and EDBR. Q1 and Q2 were focused on the usability of system, and both the scores of iReminder and EDBR were higher than 3, which suggest that it is easy for users to use them. However, the scores of Q2 shows that iReminder ($M = 3.50$, $SD = 0.52$) was harder ($t = 2.16$, $p = .054$) to use compared with EDBR ($M = 3.92$, $SD = 0.67$). This may be due to the fact that iReminder needs participants to take extra efforts to collect their trajectory data for a period of time, which may increase the burden of using iReminder. Q3 to Q5 are mainly concerned with the specific performance of reminders. The scores of S3 in iReminder and EDBR were both higher than 3.5, which indicate that they can both remind participants to fulfill tasks in participants' daily lives. However, as for the appropriateness of reminding message delivery, the score of Q4 shows that the tasks iReminder ($M = 3.58$, $SD = 0.51$) reminds to do were more likely ($t = 1.82$, $p = .096$) to get done by participants than those delivered by EDBR ($M = 3.17$, $SD = 0.72$). The score of Q5 shows that iReminder ($M = 3.83$, $SD = 0.39$) delivered reminding messages more appropriately ($t = 2.16$, $p = .054$) than EDBR ($M = 3.42$, $SD = 0.51$) did. In addition, the score of Q6 shows that most participants were willing to use them in the future.

To sum up, from the statistical point of view, iReminder outperforms EDBR in delivering reminding messages. The reminding messages delivered by iReminder are more likely to be accepted by participants, which leads to a better reminding experience to them. That supports the hypothesis that iReminder could deliver reminding message more appropriately than EDBR. In addition, it indicates that iReminder works in daily life, and the method we adopted can enhance the performance of location-based reminder.

6. DISCUSSION

To investigate the real uses of iReminder and EDBR, we analyzed the experimental results, which reflect the appropriateness of message delivery in detail. In addition, through the semistructured interview, the real usage scenarios are described to help us understand the performance of iReminder and EDBR better and to investigate what factors affect the ideal message delivery. Possible improvements of iReminder are given based on the analyses and discussions.

TABLE 2
The Mean Scores of Each Question in the Poststudy Questionnaire

Questions	iReminder M (SD)	EDBR M (SD)
1. I get accustomed to use it very quickly.	3.58 (0.67)	3.67 (0.65)
2. It is convenient to use the reminding system to perform task reminding.	3.50 (0.52)	3.92 (0.67)
3. It certainly helps me to remember trivial things in daily life.	3.92 (0.90)	3.17 (0.94)
4. I usually implement the task after receiving its corresponding reminding message.	3.58 (0.51)	3.17 (0.72)
5. The reminding message is usually delivered at an appropriate time.	3.83 (0.39)	3.42 (0.51)
6. I will definitely use it in the future.	3.67 (0.65)	3.33 (0.49)

Note. 1 (*strongly disagree*) to 5 (*strongly agree*). EDBR = Euclidean distance based reminder.

A key issue in a reminder system is to determine the appropriate point for delivering a reminding message. If a reminding message is delivered earlier than it could be implemented, the user will forget to do this task; if it is delivered too late, it will also fail. In addition, if a reminder is always unwanted, users will get easily annoyed.

Through the quantitative analysis, here are some interesting findings to illustrate the best delivery point. Among the 368 responses to survey from iReminder and EDBR, we found that the score of S2 was correlated with that of S4 ($r = .72$, $p < .01$) and S5 ($r = .73$, $p < .01$). This suggests that the usefulness of a reminding message was correlated with whether the message is delivered at the point when users are likely to visit the task location. In particular, if a message is delivered when the user is more likely to visit the task location, it usually leads to a better reminding experience.

These findings may explain why iReminder outperforms EDBR: iReminder delivers reminding messages when the user is going to visit the task location, whereas EDBR delivers reminding messages just based on the Euclidean distance. Therefore, iReminder delivers reminding messages when people are more likely to visit the task location. The score of S2 "I really plan to visit the task location right now" presented in section 5 indicates that the delivery made by iReminder is more likely to be at the point when users are going to the task location than EDBR.

To illustrate the scenario of message deliveries, we picked up some task records randomly from one participant, and drew them on Google Earth. We present the genuine picture captured from Google Earth marked by the actual GPS values, which aims to restore the real situation to the utmost.

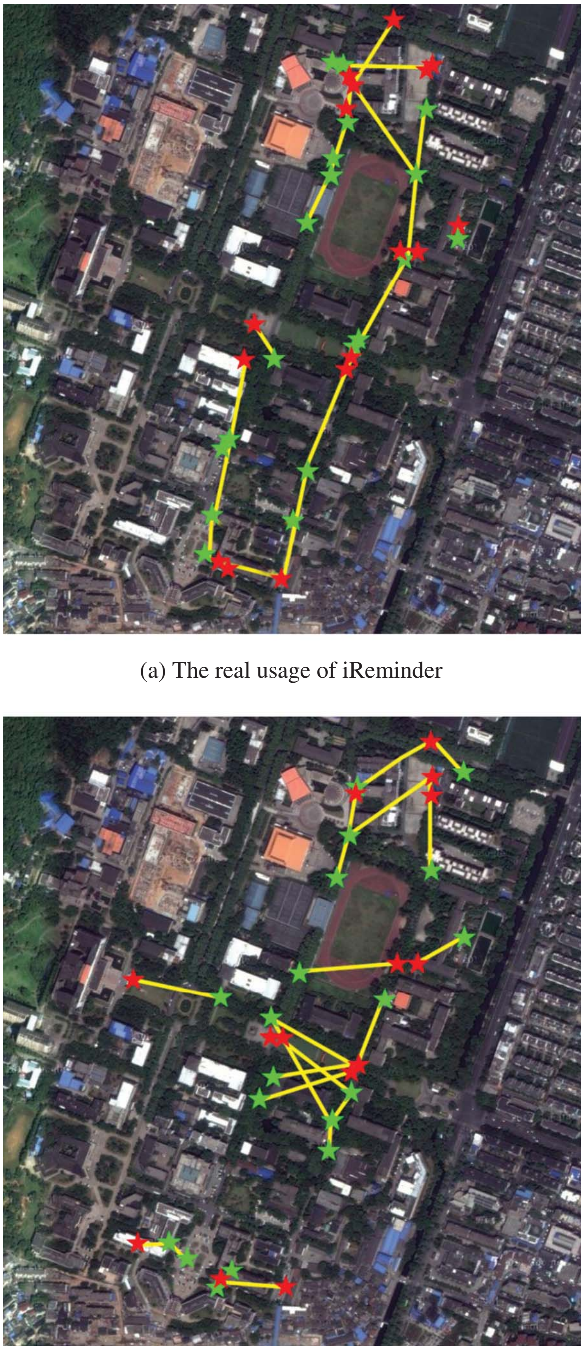
The two figures shown in Figure 6 are the real usages that occurred in iReminder and EDBR. A task location is presented as a red star, and a green star denotes a reminder delivery point. The yellow line connecting a red star and a green star stands for a pair of a task location and its corresponding delivery point.

Figure 6(a) is the actual situation conducted in iReminder, and Figure 6(b) is the situation when using EDBR. One can see that on Figure 6(b), the yellow lines, denoting the pairs of task location and reminder delivery point, appear more disordered than those on Figure 6(a). On the contrary, most of the yellow lines on Figure 6(b) cross over the buildings or some obstacles, whereas the lines are more "behaved" in Figure 6(a), stretching along the actual road. The line crossing over the buildings or some obstacles means there is usually no direct route to reach the location and the participant has to detour to visit it. That also suggests that EDBR may deliver reminding messages when it is inconvenient for participants to complete the task, whereas iReminder delivers reminding messages when participants are more likely to go complete it.

In addition, we interviewed participants to acquire more specific information about this phenomenon in the poststudy interview. Some participants' reports about iReminder are quoted as follows:

> It just happens. It reminds me to do the task naturally just when I am going to pass by the task location. For instance, it just reminds me to take milk when I'm going to dormitory; on the way to lab, it just reminds me to borrow books when I'm passing the library.

As for the reminding messages made by EDBR, with a value of S2 below 2, a participant pointed out, "It reminds me to do some tasks when I feel not comfortable to fulfill it right away, particularly, when I have already planned to go elsewhere." That suggests that if the message is delivered when one does not plan to go to the task location, the reminding message will not be helpful. In particular, one of the participants complained to us, "When using EDBR, I always receives the message notifications when I am engaged with other stuff at the day, and it annoys me." Based on the quantitative and qualitative results, we argue for the following.



(a) The real usage of iReminder

(b) The real usage of EDBR

FIG. 6. The real usage of iReminder (a) and Euclidean distance based reminder (b) (color figure available online).

Euclidean distance as the criterion to deliver location-based reminding message is too simple to make an appropriate delivery because the Euclidean distance is not able to accurately reflect the real distance of the user and the task location for the complexity of the road network in the city. This has been mentioned by Ludford et al. (2006), who also found that the traditional geofence radius around a place proves insufficient. They proposed that effective delivery depends on people's movement patterns through an area and the geographic layout of the space. Although the real geographical layout of the space can reflect the real distance between the current position of the user and the task location, the route to the task location may not be appropriate for the user to take. Therefore, the user's route patterns can be used to determine the ideal point for reminding the user to get the task done. This is in accordance with what Ludford et al. found. However, we consider the future route predicted based on user's route patterns and recent trajectory data as an ideal factor to delivery reminding messages. This is because people's intents can be obtained through the prediction of their future routes, and people are more likely to get the things done when it can be completed on their way. If the reminding messages are delivered on all the user's possible routes, the user will be extremely likely to get unwanted reminding messages. The method iReminder adopts can reflect the real geographical layout of the space and predict the future route through the data mining of user's historical trajectory data, in which way it delivers reminding messages when it senses the user is probably going to fulfill the task. Therefore, users are very likely to accept the messages delivered by iReminder.

In summary, the appropriateness of a location-based delivery can be largely determined by the factor of whether the reminding message is delivered when users have planned to visit the task location. The experimental results show that the geographical layout of the space seems too simple to offer ideal reminding messages in practical use, and delivering a reminding message when a user will pass by the task location will be more natural and useful.

Although the results just presented indicate that iReminder performs well in most situations, there are still some limitations that we want to point out as implications of our future work.

6.1. Collect data seamlessly

Many participants complained about iReminder, "Collecting data is really frustrating, because to collect data consumes my phone's battery and needs my extra operations, and it doesn't even allow me to get reminders." However, it is inevitable to collect one's trajectory data in order to predict one's future route. To put it into actual use, iReminder should develop a more convenient method to record users' trajectory data seamlessly and automatically.

6.2. Hybrid strategy to delivery message

One participant reported to us that she sometimes needs to think twice to set tasks when using iReminder, considering whether she has ever been to the task location. This is because iReminder barely could extract one's route patterns that contain the locations where one has never been to; therefore it would not be able to perform task reminding associated with such locations. This may explain why the tasks set by iReminder in the field study are fewer than the tasks set by EDBR. A possible way to address this issue is to adopt a hybrid strategy to trigger reminding messages. Specifically, the reminder can remind participants by adopting the method that traditional location-based reminders use if the task location is set at a place where one has never been to; otherwise, it uses iReminder's method.

6.3. Message delivery based on various contexts

It is common that people want to take newspapers from the mailbox when arriving home; people hope to remember to take an umbrella in case it rains. Those situations indicate that it is necessary to know whether participants are arriving on the task location or leaving from it. iReminder does not explicitly allow participants to set reminders on arrival or on departure of a location, although it senses users' future routes, which contain the information about the direction of user's route. A more ideal reminder would allow participants to define these occasions and deliver reminding messages based on such contexts. To make message delivery more appropriately, a reminder should sense people's current contexts as much as possible; to make message delivery more personal, a reminder should be able to find out people's habits and current specific situation by obtaining the current contexts of people. For instance, if it is raining, it would not be very appropriate to remind the user to pick up the dry cleaning.

7. CONCLUSIONS AND FUTURE WORK

In this article, we have presented the design of an intuitive location-based reminder, iReminder. It works well in participants' daily lives by using the method of future route prediction for reminding. Furthermore, it outperforms EDBR, which uses the method traditional location-based reminder to trigger reminding messages. The experimental results indicate that a location-based reminding message is very likely to be accepted when the user is about to go to the task location. Therefore, a reminder system can deliver more appropriate reminding messages on the basis of users' future routes.

In addition, iReminder outperforms EDBR in delivering appropriate location-based reminding messages by considering a user's future route, which makes location-based reminder go further. In terms of making more ideal message deliveries, a reminder should be able to learn people's habits by perceiving various contexts of people. Route prediction can be used well in a location-based reminder as users' complementary contextual information. Therefore, a reminder based on route prediction could deliver reminding messages at a more appropriate time. It also gives guidance to location-based services that not only knowing where people are but also sensing where they are going can make location-based services more intuitive, because knowing where people are going can predict what behavior they will take next, to a certain extent. The method iReminder adopts by taking the advantage of the ubiquitous computing capability of mobile devices suggests that ubiquitous computing is everywhere and it could be used to offer users more personalized and useful services. Moreover, users' past contextual information could be very useful, especially in ubiquitous computing. As for location-based reminders, there are various contexts that can be obtained due to the availability of smartphones equipped with various sensors, and we would like to see more novel reminders, which deliver appropriate reminding messages based on richer contextual information of people.

We readily acknowledge that our research is exploratory, and due to the time and other constraints, the field study we conducted has not covered all the aspects of iReminder in its everyday use. Many questions remain to be investigated. It is obvious that the algorithm we adopted in predicting users' future routes is of vital importance to delivering appropriate messages and further study needs to be focused on the relationship of the prediction accuracy of the algorithm and its usability in the practical use. Furthermore, the relationship between the amount of trajectory data and the prediction accuracy of the future route, and how the prediction accuracy of the future route would affect user's reminding experience, needs to be investigated. On the other hand, how often the tasks are eventually implemented needs to be recorded to help us evaluate the reminders more thoroughly. How these two different reminding strategies would influence the power usage is an interesting research area. We also like to combine richer contextual information with iReminder, such as the local weather and user's activities, to offer users more personalized and appropriate reminding experiences. On the other hand, other location-based services combined with route prediction could be proposed, such as a suggestion of restaurants on the way home.

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