Real-Time Anomaly Detection for Traveling Individuals with Cognitive Impairments

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ABSTRACT
We study real-time anomaly detection in a context that considers user trajectories as input and tries to identify anomaly for users following normal routes such as taking public transportation from the workplace to home or vice versa. Trajectories are modeled as a discrete-time series of axis-parallel constraints ("boxes") in the 2D space. The incremental comparison between two trajectories where one trajectory has the current movement pattern and the other is a norm can be calculated according to similarity between two boxes. The proposed system was implemented and evaluated with eight individuals with cognitive impairments. The experimental results showed that recall was 95.0% and precision was 90.9% on average without false alarm suppression. False alarms and false negatives dropped when axis rotation was applied. The precision with axis rotation was 97.6% and the recall was 98.8%. The average time used for sending locations, running anomaly detection, and issuing warnings was in the range of 15.1 to 22.7 seconds.

Author Keywords
Ubiquitous computing, deviation detection, emergency notification, location awareness, assistive technology.

ACM Classification Keywords
I.5.2 [Pattern Recognition]: Design Methodology - Classifier design and evaluation.

INTRODUCTION
Persons with mental impairments tend to be viewed as unemployable and systematically excluded from labor markets. However, this assumption has been challenged recently after the development of community rehabilitation, and supported employment services in particular. With sufficient and appropriate support on the job, many people with mental illness are capable of participating in the world of work to various levels, which not only provides them with financial support but also opportunity for social integration. However, employment opportunities for persons with mental disabilities are still very limited. Through employment, individuals with moderate and severe disabilities increasingly become integrated into community settings; on the other hand, less support and supervision are provided. Community integration includes community-based living and employment, recreation and leisure pursuits, use of community services, and independent movement in and around the community through the use of public transportation. Coupled with this increased independence and integration is risk.

With repeated training continued with daily practice, the individuals usually have no problems of getting lost or disoriented. However, there are occasions that trainees do forget how to travel to and from work. For examples, part-timers with fewer shifts have more chances of running into transportation problems because they forget the routes. For places with many distractions, few landmarks that help remain oriented, or surroundings that look similar, the situations can become worse. To decrease the risk for victimization of individuals with disabilities as they increasingly participate in their communities and seek social inclusion, mobile technology has been used in our solution with a focus on community integration and increased autonomous functioning.

Because individuals with disabilities are frequently dependent on others for support across environments, strategies and skills must be introduced that directly lead to access of those supports. To relieve their job coaches from labor-intensive aids with traveling to work, a PDA is carried by the individual who has cognitive impairments. The PDA enables individuals to respond to unexpected situations such as being lost by effectively using the handheld device to alert themselves or call for assistance in the support system. In this paper, we build a real-time anomaly detection system and conduct field experiments in community-based settings for individuals with cognitive impairments.

The PDA used in our study is location aware. The PDA carried by the individual with mental impairments sends the location back to the server sampled at fixed intervals. The trajectories are compared in real-time against norms which are previously constructed user transportation routines.

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Anomalies are detected in case deviation from the norms is determined by the proposed matching algorithm. Our study is aimed at two contributions: (1) develop a non-visual approach to anomaly detection, and (2) propose a low computational complexity algorithm for anomaly detection by comparing incremental trajectories against normal routes.

The rest of the paper is organized as follows. In the following section, we review existing research. Then we describe the main components of the proposed solution and the interactions among its modules. Experimental results in the context of supported employment are presented next. Conclusions are presented in the last section.

RELATED WORK

Deviation detection considers trajectories as input and tries to identify anomaly in following normal routes such as taking public transportation from the workplace to home or vice versa. Trajectory clustering is one of the methods of identifying normal routes from abnormal ones. There exist several recent publications on clustering moving objects and trajectories. The problem of clustering moving objects is studied by Li et al. [2] who use moving micro-clusters (MMC) for handling very large datasets of mobile objects. The problem of trajectory clustering is considered by Nanni et al [3]. They propose clustering trajectory data using density-based clustering, based on the distance between trajectories. The SCUBA algorithm of Nehme and Rundensteiner [4] is proposed for efficient cluster-based processing of large numbers of spatio-temporal queries on moving objects. However, trajectory clustering is performed only when trajectories of trips are completed. This makes the clustering algorithms less useful in identifying anomaly and discovering route deviation in the real time.

Predicting personal destinations is the main principle behind much previous work in pervasive computing on modeling and predicting transportation routines. Most of this work shares the trait that candidate destinations are extracted from GPS histories, i.e. places that subjects have actually visited. Murmasse and Schmandt [6] used the loss of a GPS signal to indicate that a user had entered a building which is marked as candidate destination for future prediction. Ashbrook and Starner [7] cluster GPS-measured locations where a user spent a certain amount of time to extract possible destinations. In their work on learning and inferring transportation routines, Liao et al. [9] extracted destinations by statistical methods based on particle filters. Krumm and Horvitz [8] designed Predestination to predict the destination, not necessarily the route. In contrast, our previous work in anomaly detection [10] is more focused on extracting anomaly at times users are trying to follow transportation routines, not necessarily inferring personal destinations [8, 9].

The growing recognition that assistive technology can be developed for cognitive as well as physical impairments has led several research groups to prototype wayfinding systems [1, 5, 9, 16, 17, 18, 19]. Researchers at the University of Colorado have designed a solution for delivering just-in-time transit directions to a PDA carried by bus users, using GPS and wireless technology installed on the buses [5]. The Assisted Cognition Project at the University of Washington has developed artificial intelligence models that learn a user behavior to assist the user who needs help [9]. Later a feasibility study [1] of user interface was carried by the same team, who found photos are a preferred medium type for giving directions to cognitively impaired persons in comparison with speech and text. However, none of the navigation research for special needs has considered anomaly detection.

SYSTEM DESIGN

The Real-Time Anomaly Detection for Traveling Individuals (RADTI) system consists of four main components: the Client Devices; the Wireless Access Network; the Internet; and the Server Side that accommodates norms storage and anomaly detection.

There is a location module at the client devices. The module handles the end-system device hardware and returns the requested user-location data to the application, regardless of the type of technology or method of implementation that actually calculates the user's location. The Wireless Access Network serves as TCP/IP pipes over their underlying infrastructure. For example, a carrier network can use High Speed Downlink Packet Access (HSPDA) or General Packet Radio Service (GPRS) to facilitate data traffic.

In support of anomaly detection services, there are three modules at the Server Side: Web Server, Norms Repository, and Real-Time Anomaly Detection (RAD). Web Server that runs the http protocol is the data bearer that handles requests from the user and provides responses to it. Norms Repository is responsible for storing user norms of transportation routines. RAD includes box modeling of user trajectories and a box-based anomaly detection algorithm. Details of RAD will be provided later in this section.

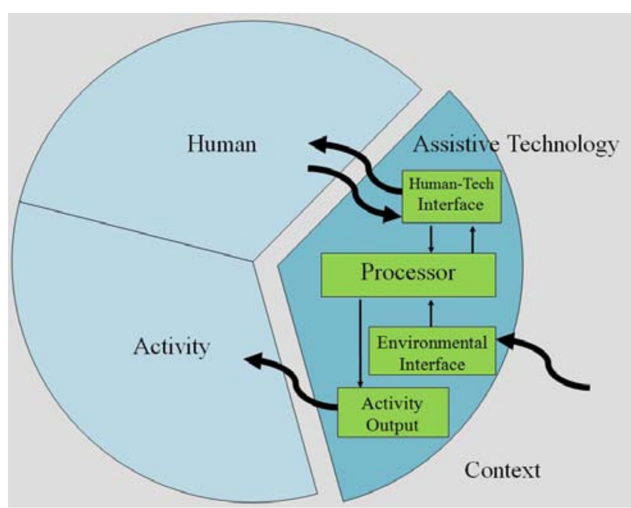

Figure 1. The HAAT model

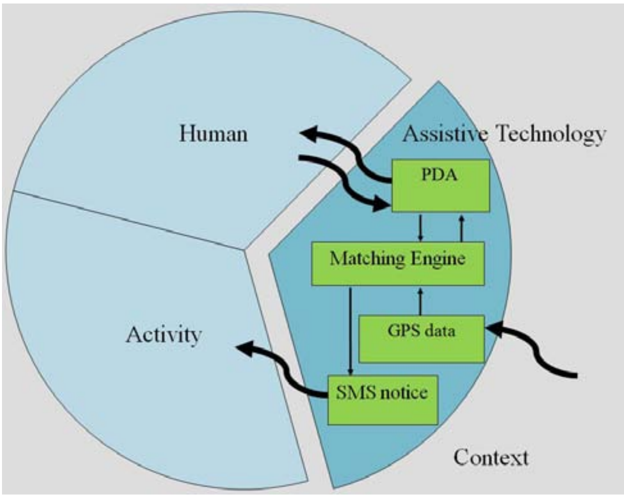

Figure 2. Model of the RADTI system

As informed by the human activity assistive technology (HAAT) model [14], an assistive solution such as RADTI should include have four components: the human, the activity, the assistive technology, and the context in which the first three integrated factors exist, as shown in Figure 1. Our RADTI prototype, aimed to assist with navigation safety for individuals with cognitive disabilities, is validated against the HAAT model for completeness. As shown in Figure 2, it consists of PDAs as user interfaces, GPS modules to connect with context, and a matching engine to process context.

Figure 3. A trajectory represented by a series of boxes

Box Modeling of Trajectories

Trajectories are modeled as a discrete-time series of axis-parallel constraints ("boxes") in the 2D space—each dimension is constrained between a minimum and a maximum value. We first discuss how such a model is generated for one time series based on the previous work of [11, 12, 13]. As shown in Figure 3, a trajectory is represented by a series of boxes, each with six attributes: the maximum value of longitude, the minimum value of longitude, the maximum value of latitude, and the minimum value of latitude, namely, $B_k.lon_{max}$, $B_k.lon_{min}$, $B_k.lat_{max}$, and $B_k.lat_{min}$ for a box with time index k. By using this structure we can summarize close data-points into one box, such that instead of recording the original data-points, we only need to record the four elements. Summarizing a spatio-temporal dataset that records locations of multiple objects at fixed intervals (e.g., every ten seconds) can significantly reduce running times of anomaly detection.

A box is started with a data-point. Incoming data-points update the box-based representations in the order of their arrival times. Therefore, the bound of a box is extended until the maximal bounds of that box reach some pre-defined segmentation thresholds. When a threshold is exceeded in at least one of the dimensions, a new box is created. The process is depicted in Figure 4. The larger the threshold is, the more summarized the trajectories are, meaning that we increase the efficiency of the anomaly detection (shorter running times) while potentially decreasing their accuracy.

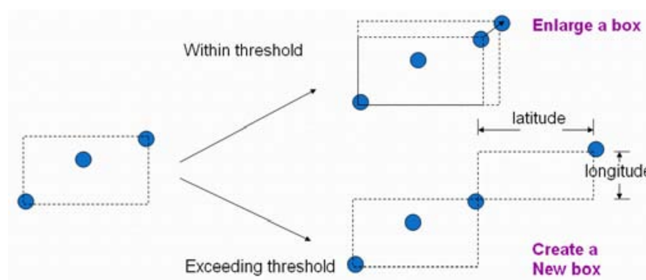

Figure 4. A box is enlarged or a new box is created

A **T.UpdateBOX()** function updates an existing box with the minimal and maximal bounds according to the inserted data-point in the trajectory **T** . The **T.CreatNewBOX()** function initializes a new box in the trajectory **T** with bounds and properties updated by the first incoming data-point (on the first arrival, the minimum and the maximum are equal to the data-point values). When summarizing the dataset, we read the data describing each user separately in the order of its sampling times. We summarize the location records into a single box as long as they are close enough to each other (do not exceed some pre-determined distance threshold from the current bounds). When a record is far enough from its earlier records, we start summarizing it into a new created box. Algorithms of **T.UpdateBOX()** and **T.CreatNewBOX()** are provided in Figure 5.

```
T.UpdateBOX():
    if ( position.lon > T.B.lon_max )
        T.B_i.lon_max = position.lon
    if ( position.lon < T.B.lon_min )
        T.B_i.lon_min = position.lon
    if ( position.lon > T.B.lat_max )
        T.B_i.lat_max = position.lat
    if ( position.lon < T.B.lat_min )
        T.B_i.lat_min = position.lat
```

```
T. CreatNewBOX():
    T.B_i.lon_max = position.lon
    T.B_i.lon_min = position.lon
    T.B_i.lat_max = position.lat
    T.B_i.lat_min = position.lat
```

Figure 5. Algorithms for box update or new box creation

A user trajectory is transformed into a series of boxes with discrete-time index. The algorithm can be described in Figure 6, where t_lon is the threshold for longitude and t_lat is the threshold for latitude.

```
While (server receives user's position){
        if ( is the first BOX )
                T. CreatNewBOX()
        else if ( |position.lon − B.lon_max| < t_lon
        && |position.lon − B.lon_min| < t_lon
        && |position.lat − B.lat_max| < t_lat
        && |position.lat − B.lat_max| < t_lat
        )
                T.UpdateBOX()
        else
                T.UpdateBOX()
                T.CreatNewBOX()
}
```

Figure 6. Algorithm for constructing a box series from a user trajectory

Box Similarity

Using the box-based representation of trajectories we can define the similarity measure between two boxes as follows. Similarities are values between 0 and 1. When two boxes overlap with each other, their similarity equals to 1. The farther two boxes are, the smaller their similarity is. For 2D trajectories, similarities can be decomposed into longitude similarity and latitude similarity, namely SimLon, SimLat, which can be computed according to the algorithm in Figure 7.

```
Input: two BOXes T_d.B_j · T.B_i
Output: similarity measures SimLon, SimLat

Sim( T.B_i , T_d.B_j ):
        SimLon = 1 - max( 0 , ( max(T.B_i.lon_min , T_d.B_j.lon_min ) − min(T.B_i.lon_max , T_d.B_j.lon_max )) / ( min(T.B_i.lon_max , T_d.B_j.lon_max ) − max(T.B_i.lon_min , T_d.B_j.lon_min )))
        SimLat = 1 - max( 0 , ( max(T.B_i.lat_min , T_d.B_j.lat_min ) − min(T.B_i.lat_max , T_d.B_j.lat_max )) / ( max(T.B_i.lat_max , T_d.B_j.lat_max ) − min(T.B_i.lat_min , T_d.B_j.lat_min )))
```

Figure 7. Box similarity

The algorithm for measuring the similarity between two boxes has time complexity of $O(1)$.

Real-Time Anomaly Detection (RAD)

The comparison between two trajectories where one trajectory has the current movement pattern **T** and the other is a norm $\mathbf{T_d}$ can be calculated according to **Sim(** $\mathbf{T.B_i}$ **,** $\mathbf{T_d.B_j}$**)** that computes similarity between the two boxes $\mathbf{T.B_i}$ **and** $\mathbf{T_d.B_j}$**.**

```
T.CompareBOX():
while(!EOF){
        if(Sim( T.B_i , T_d.B_j)>SimThreshold ){
                j++
                levelDanger = 0
        }
        else{
                levelDanger++
                if (levelDanger>dangerThreshold){
                        alert.send();
        }
}
```

Figure 8. Comparing a box in the current trajectory with a box in the normal trajectory

levelDanger is a parameter used to indicate how many times the similarities are determined lower than threshold values in consecutive box comparisons. If it is equal to 0, there is no risk of being lost. The higher the value of levelDanger, the greater the risk is. We use dangerThreshold to determine whether a alarm should be made. In practice, dangerThreshold is set to very small values, such as 1 or 2. The real-time anomaly detection algorithm can be summarized in Figure 9. Figure 10 shows RAD processes incoming data-points of a current trajectory.

```
While (server receives user's position){
    if ( is the first BOX )
            T. CreatNewBOX()
    else if ( | position.lon − B.lon_max | < t_lon
        && | position.lon − B.lon_min | < t_lon
        && | position.lat − B.lat_max | < t_lat
        && | position.lat − B.lat_max | < t_lat
        )
            T.UpdateBOX()
    else
            T.UpdateBOX()
            T.CompareBOX()
            T.CreatNewBOX()}
```

Figure 9. Real-time anomaly detection algorithm (RAD)

Figure 10. RAD algorithm monitoring incoming data-points against norms (in blue boxes) using box modeling

Complexity of RAD

The algorithm for detecting anomaly by incrementally measuring the similarity between two trajectory segmentations has O(m) time complexity in the worst case and O (1) space complexity, where m is the maximal amount of boxes in each of the two compared trajectories. Given l norms for simultaneous comparison, the complexity of the RAD algorithm is O(lm).

EXPERIMENTS

Subject Recruitment

Finding and recruiting appropriate participants is significantly more difficult than in mainstream HCI research and conducting human subjects studies with vulnerable populations remains a challenge to us. Individuals of disabilities and ages in various ranges were recommended by the participating rehabilitation institutes that we have been partnering with and screened according to degrees of cognitive impairments, the ability to achieve daily living tasks, and severity of loss in short-term memory. Priorities were given to medium and low functioning patients as opposed to high functioning and very low functioning ones. Moreover, assessment on individual capabilities also took into account the ability to operate the PDA and understand its feedback. Table 1 lists the basic profiles of eight volunteers with sensitive and irrelevant data omitted. The participants, except Fiona, were receiving pre-training programs in community-based employment projects sponsored by Affirmative Actions Initiatives, Labor Affaires Bureau, Taipei. Our proposed system was developed to help them become more qualified for job positions such as mail courier and parking patrollers.

ID	Gender	Age	Education	Syndromes
Al	M	28	High School	Traumatic Brain Injury (TBI), Physical impairments
Ben	M	27	High School	Intellectual and Developmental Disabilities (IDD)
Craig	M	46	High School	Schizophrenia
Doug	M	38	High School	Traumatic Brain Injury, Dementia
Ed	M	30	High School	Schizophrenia
Fiona	F	48	Elementary School	organic brain syndrome, Epilepsy, IDD
Gordon	M	27	College	Traumatic Brain Injury (TBI)
Helen	F	20	High School	Intellectual and Developmental Disabilities, Schizophrenia

Table 1: Profiles of 8 volunteers

Al has TBI after a car accident. He has received very good rehabilitation and has been able to remain employed on a paid job as a janitor. For more demanding jobs with higher pay such as kitchen assistance and gas station management, Al has been always looking but not yet succeeded yet. Ben has IDD and he has mild difficulties in memorizing routine procedures in his workplace. He occasionally gets lost and has to call for help by cellular phones. Craig has schizophrenia and currently he is unemployed although he really wants a job. Doug has dementia and is forgetful about the routes or work procedures. He has been under unemployment since a car accident happened to him some years ago. However, he works very hard in the occupational rehabilitation center in order to get employed in the future. Ed has schizophrenia. Fiona has organic brain syndromes and exhibits exercise fatigue. Her family hires a caregiver to accompany her all day long. However, she was found to become playful with the PDA in hand and enthusiastic in the experiment. Helen has both IDD and schizophrenia, which makes her unable to distinguish ambient sounds from those imagined from within. Gordon had a car accident two years ago and remained hospitalized in an ICU for 11 months until earlier this year. Now he is receiving occupational therapy. Getting a paid job is one of his wishes. Helen has both IDD and schizophrenia.

All of the 8 participants experienced being lost before. For example, Helen two years ago disappeared from her workplace without particular reasons or telling anyone. Soon she was found again. However, her grandfather at home received a phone call misinterpreted as her granddaughter missing. There was a panic that lasted for hours before the situations were properly communicated later. Doug, a few months ago, wanted to take a bus home. Unfortunately he took a wrong one accidentally. What made things worse was that he got off the bus at the final station because he could not identify the usual stop. He used no cell phones so he could not contact anyone he was familiar with. The time was very late and there was no bus that departed any more. His family was very anxious and even called the police in the late night. He was only found the morning of the next day. Job coaches of the 8 subjects considered the device might empower their autonomous functioning, reduce risks while getting lost, and therefore improve their traveling experiences.

Experimental Design and Settings

Throughout the years of 2007-2008, each subject participated in 20 independent sessions, resulting in a total of 160 sessions as a whole. Each session was a trip with an individual returning home from community-based training in the afternoon. The travel time ranged from 0.5 ~1.5 hours or so, including transits for some. For each user, the first 10 trips followed norms built earlier while in the latter 10 we arranged deviations in the middle of the trips. Public transportation was used in all of the 8 routes. In each session, a shadow team of three always followed the subject during the trip for the purpose of maintaining security, observing, and recording. We tested the functions of the RADTI system and evaluated its performance with regard to its ability to identify the anomaly in real time. In order to receive quality satellite signals for positioning, subjects were reminded to sit on the window seat of the vehicles while on board. Figure 11 shows Doug in the field trial.

Figure 11. Doug holding the PDA (left) and the shadow team

Results

Performance was measured in terms of the extent of exactness and completeness. A measure of exactness or fidelity is precision, whereas a measure of completeness is recall. In our scenario, what matters is whether a subject deviates from a normal routine path. Therefore, precision is defined as the number of true anomalies identified divided by the total number of anomalies returned by the match (which may include certain false alarms). Recall is defined as the number of true anomalies identified by a match divided by the total number of true anomalies (which should have been identified). F-measure is defined as (2 * precision * recall) / (precision + recall) in information retrieval terminology.

The PDA with GPS turned on runs out of battery very quickly. For the Asus 500 series PDA that we used, the battery lasts for about 3.5 hours when GPS is in use. To make things worse, GPRS and HSDPA also consume significant amounts of battery power, depending on how often the packets are sent over the air. Therefore, we had to conduct a pilot run to decide the frequency of GPS data update to the server before our participants joined the experiments. To do so, we did a pilot run that set the intervals of GPS data update to be 1s, 2s, 4s, 8s, 16s, 32s, and 64s, respectively. The value of levelDanger was set to 2 and SimThreshold was set to 0.6. We measured the battery life and the F-measure in outdoor environments. The results were depicted in Figure 12. The results indicated a trade-off between the F-measure and battery life. Finally, we decided to set the update interval to be 8 seconds. Under such a condition, the F-measure was 0.91 and the battery would hold 1.7 hours which was good enough for tracing an individual going back home on public transportation.

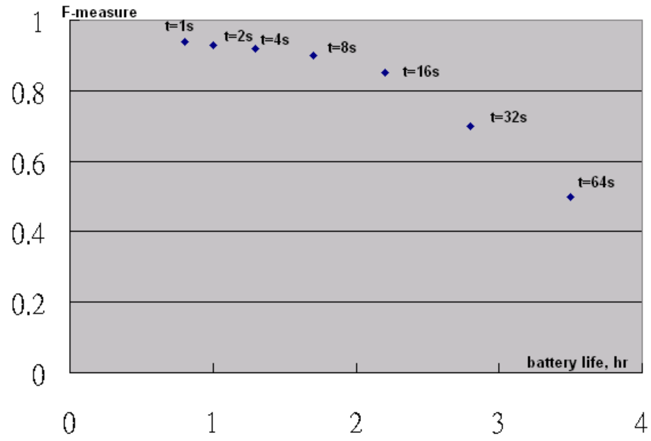

Figure 12. Trade-off between F-measure and battery life

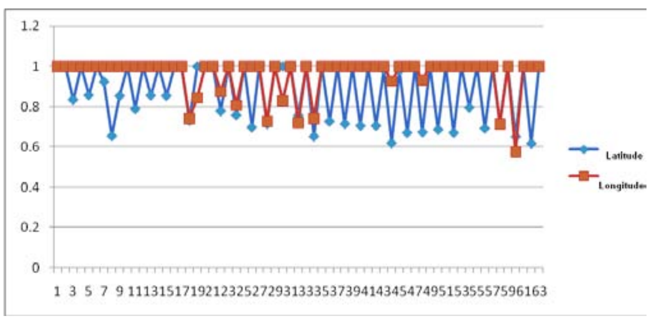

Figure 13. A similarity plot of a trajectory without anomalies

Typical trajectory similarity plots are depicted in Figures 13 and 14. Figure 13 indicates no anomalies in the whole trajectory where box similarities are always higher than the threshold, namely 0.6. Figure 14 depicts a trajectory which has anomalies after epoch 55.

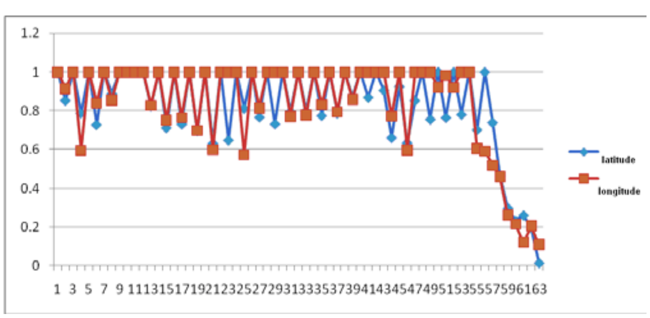

Figure 14. A similarity plot of a trajectory with anomalies after epoch 55

False alarms may happen when a trajectory is mostly horizontal or vertical due to the fact that the box is axis parallel and there is intrinsic inaccuracy in GPS. For a person who travels in a horizontal path, the two bounds of longitudes are very close to each other. The box will look like a horizontally stretched rectangle. In case the GPS is not accurate enough during the trip time, the box comparison will be negatively impacted. Figure 15 depicts a false alarm where no anomalies actually happen.

One way of fixing the problem is rotating the axes when users travel in a Manhattan style cities. With axis rotation, the box formed will have a aspect ratio closer to 1.0 even if they travel horizontally or vertically. For the same trajectory in Figure 15, the axis rotation eliminates the false alarms as shown in Figure 16.

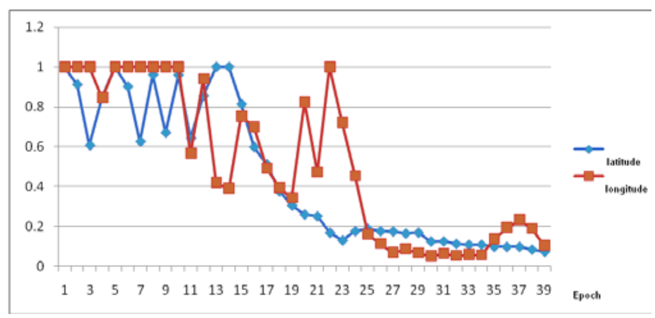

Figure 15. A similarity plot of a trajectory with false alarms

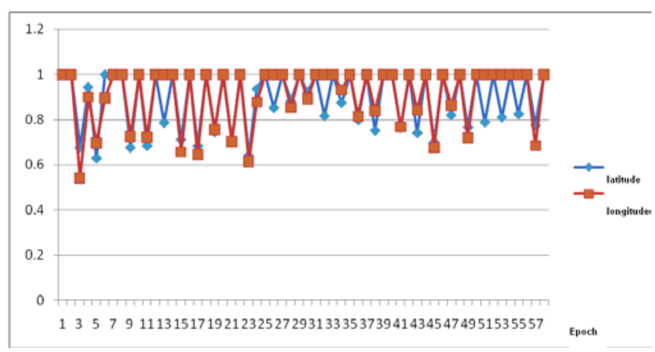

Figure 16. A similarity plot of a trajectory with false alarms eliminated by 45-degree axis rotation

In Table 2, we summarize the experimental outcomes based on the observations of the field trips. The results show that the number of false negatives was 4 and the number of false alarm was 6 without axis rotation. Therefore, recall was (80-4)/80=95.0 % and precision was 80/(80+8)=90.9% on average. However, both false negatives and false alarms dropped when the axis rotation was applied by 45 degrees. Recall and precision with axis rotation were (80-1)/80=98.8% and 80/(80+2)=97.6%, respectively. The average elapsed time used for the sending location data, running anomaly detection, and issuing warnings was in the range of 15.1 to 22.7 seconds. In case anomalies were detected, a SMS notice was issued to the shadow team and the PDA alerted its user by vibrating and sounding voice-over alarms.

Considering the reading and verbal limitations with our subjects, TLX assessment was conducted in the form of oral interview. In the meantime, 21 gradations were simplified

ID	Normal Trips	Deviated Trips	False positives	False negatives	False positives (axis rotation)	False negatives (axis rotation)	Elapsed Time (seconds)
Al	10	10	1	1	0	0	17.4 ± 3.8
Ben	10	10	1	0	0	0	19.2 ± 4.2
Craig	10	10	0	0	0	0	18.9 ± 3.3
Doug	10	10	3	1	1	1	19.1 ± 4.4
Ed	10	10	0	0	0	0	16.0 ± 5.4
Fiona	10	10	0	0	0	0	22.6 ± 7.0
Gordon	10	10	2	0	1	0	15.1 ± 5.9
Helen	10	10	1	2	0	0	22.7 ± 4.1

Table 2. Experimental outcome of 8 participants

Index	A	B	C	D	E	F	G	H
Mental demand	1	1	1	3	2	2	1	2
Physical demand	1	1	2	3	2	2	2	2
Temporal demand	2	2	1	2	2	2	1	2
Efforts	1	2	2	3	2	2	2	2
Frustration	2	1	2	2	2	2	2	2
Performance	5	5	5	4	4	4	5	4

A: Al, B: Ben, C: Craig, D: Doug, E: Ed, F: Fiona, G: Gordon, H: Helen

Table 3. Subjective assessment of task load on PDA users

Besides technical evaluation, subjective workload measurement is also important. To evaluate the task load subjects may have experienced during device use, we adopt Hart and Staveland's NASA Task Load Index (TLX) method [15] which assesses work load on 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales. NASA TLX includes 6 indices: mental demand, physical demand, temporal demand, performance, effort, and frustration.

and reduced to only 5, i.e. 1 to 5 representing very low, somewhat low, neutral, somewhat high, and very high, respectively. The survey results are summarized in Table 3.

In this study, the subjects unanimously found mental and physical demands and efforts to operate the device low or very low except that Doug considered them neutral. In addition, an individual did not feel rushed to accomplish the expected level of performance. The pace of the task was not hurried either. No significant frustration was experienced by the participating users. The performance of the proposed system was considered high or very high. During the interviews, all the participants felt comfortable recommending the system to their friends.

CONCLUSIONS

User-location information along with advances in information technology and ubiquitous communications are facilitating the development of mobile location-based networking that will add convenience and welfare to people's everyday lives. This paper has described a real-time anomaly detection system to support people with cognitive impairments when navigating their way. Although our sample size is small, our data provide preliminary evidence that the system is able to identify the anomalies in real time. The system has enhanced previous work on location-based services and added care providing interactions. The experimental results show that the precision is 97.6% (with axis adjustment) and the recall is 98.8% for the participants with cognitive impairments.

Therefore, the system may be helpful for reducing risk while increasing independence in the process of community integration. Our study suggests a promising avenue for further research in providing ambient intelligence to people with cognitive deficits. In addition, subjective assessment task load has been conducted for all the participants involved which provided proof of social validity.

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