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A Mobile-Health Application to Detect Wandering Patterns of Elderly People in Home Environment

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Abstract—**Wandering is a common and risky behavior in people with dementia (PWD). In this paper, we present a mobile healthcare application to detect wandering patterns in indoor settings. The application harnesses consumer electronics devices including WiFi access points and mobile phones and has been tested successfully in a home environment. Experimental results show that the mobile-health application is able to detect wandering patterns including lapping, pacing and random in real-time. Once wandering is detected, an alert message is sent using SMS (Short Message Service) to attending caregivers or physicians for further examination and timely interventions.**

I. INTRODUCTION

The number of PWD worldwide is projected to quadruple to 115 million by 2050 and accounts for USD 640 billion in the annual cost of both informal and direct care [1]. Wandering is a frequently occurring and potentially risky behavior of PWD. The prevalence of wandering in PWD in community settings could be as high as 60% [2]. In long-term care, wandering appears more often in those diagnosed with Alzheimer's disease than vascular dementia. PWD who wander are found to have more severe cognitive impairment, greater spatial deficits, and socially disruptive behavior. The outcomes of wandering are also detrimental to PWD, e.g. falls, getting lost, and excursions to hazardous or off-limit areas that can result in death [3]. Wandering poses significant problems to both PWD and their caregivers. It increases the probability that an elderly person will be prescribed a psychotropic medication which leads to undesirable side effects such as dystonia [4]. Caregivers have to bear extra burden to surveillance wandering behavior. The burden on staff becomes even greater when there are liability concerns for redirecting and retrieving lost wanderers. 10% of all lawsuits filed against nursing homes are for liability issues related to the mismanagement of wandering [5]. Evidence maintains that if the wandering patient is managed appropriately, staff will experience lower frustration and more tolerant attitudes toward the patient [6].

Early diagnosis of dementia substantially helps treat the illness, reduce care costs, and delay premature institutionalization. Once transferred into formal care, the annual cost of care for a patient exceeds USD 32,000 in high income countries like the USA [1]. A review of the literature suggests that wandering can potentially be used as a diagnostic sign for preclinical dementia [7-8]. A study of 5 years of clinical records in patients with preclinical dementia [8] found that wandering is the earliest symptom followed by cognitive complaints. There is evidence to show that changes in gait and locomotion patterns begin many years prior to the onset of dementia [9]. Therefore, it is essential and beneficial to detect wandering behavior in elderly people as soon as it occurs.

Technologically speaking, there are applications to recognize wandering behavior of elderly people and PWD in both outdoor and indoor environments. In outdoor settings, Opportunity Knocks [10], iWander [11] and LaCaSa [12] use GPS-enabled phones to learn travel history of elderly people. Their systems aim to discover potentially erroneous behavior such as taking an incorrect bus, the subject's probability of wandering, or getting lost from disorientation. Their products are of limited capabilities (i.e. only able to track or locate wanderers). In other words, these systems mainly prevent outcomes of wandering (i.e. elopement or getting lost) and do not study dementia-related characteristics of wandering [13-14]. In contrast, a number of studies in nursing homes have applied a wide range of ambient devices (e.g. infrared sensors, RFID tags, and UWB technology) to measure dementia-related features of indoor wandering locomotion in PWD including temporal variability [15], spatial disorientation [16], walking speed variations [17], and tortuosity of travel paths [13]. However, they have not been able to automatically measure travel patterns (i.e. direct, pacing, lapping, or random) of PWD. These travel patterns have been used to characterize wandering by geriatricians and clinical researchers. In fact, wandering is clinically defined as a syndrome of dementia-related locomotion behavior and characterized by five aspects: frequency, repetitiveness, temporal distribution, spatial disorientation and inefficient travel patterns including random, lapping, and/or pacing [18].

Previously, we proposed a rule-based algorithm to classify travel patterns of PWD including direct, pacing, lapping and random [19]. The algorithm worked well on the locomotion dataset of an elderly with dementia. That dataset was pre-collected independently using a RFID system. In the current work, we have deployed the classification algorithm on a mobile phone and integrated it with a WiFi-based localization system. We successfully demonstrate that our new mobile application can detect wandering patterns of a person in real-time as he walks around his home environment. The application is also able to send an SMS alert to the attending caregiver once wandering is detected.

II. ARCHITECTURE OF THE MOBILE-HEALTH APPLICATION

Fig. 1 shows the architecture of our WiFi-based mobile-health application to detect wandering patterns.

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The hardware components include 4 WiFi access points (Range-Pro), a smartphone (Samsung Galaxy 3 using Android 4.1.1 “Jellybean” Operating System), and the embedded phone sensors (accelerometer and compass).The smart phone can be placed in the elderly subject’s shirt pocket when he/she moves around.

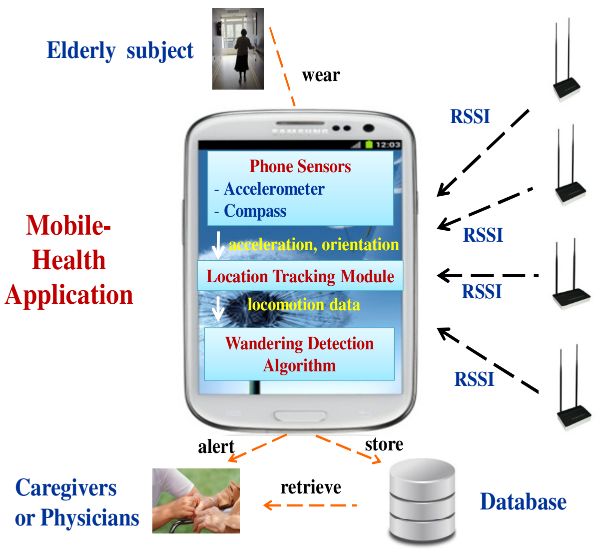

Figure 1.Overall Architecture of the Mobile-Health Application

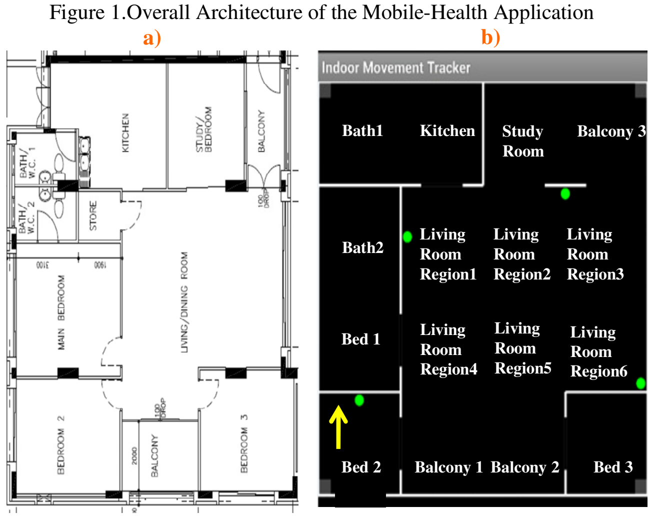

Figure 2.Actual Layout of the Home Residence (Fig. 2a) and its Sketch on the Mobile Phone (Fig. 2b)

The software components include the location tracking module and the wandering detection algorithm (shown in red in Fig. 1). The phone scans for and obtains the RSSI (Received Signal Strength Indicator) values from the 4 access points. The RSSI values together with the acceleration and orientation signals from the phone sensors are used by the location tracking module to determine the subject’s location. The wandering detection algorithm analyzes the locomotion data to detect and classify wandering patterns in real-time.

Once wandering is detected, an alert message stating the location, time and pattern of the wandering episode will be sent to the caregivers or attending physicians via SMS. These details on the wandering behavior will enable caregivers or physicians to provide appropriate and timely interventions. The locomotion data and detected wandering patterns can also be stored in a database (e.g. the phone memory or a local computer server placed at home). The attending physicians can access the database to examine the wandering behavior and its progress over time, from which any changes in the subject’s health and mental status can be recognized early.

The 4 WiFi access points are placed in the subject’s home environment. Layout of the home residence where we have deployed the integrated system is shown in Fig. 2. Fig. 2a is the actual layout of the house (12.6m x 12.75m). Fig. 2b is the layout reproduced on the mobile phone for easy visualization. The 4 green circles show where the 4 access points are located in the house. All the physical locations (e.g. bathrooms, living room, etc.) are also labeled accordingly in the figure.

III. Algorithms

In this section, we describe the algorithms we have developed to localize the subject and classify the wandering patterns as the subject moves around in the home residence.

A. *Location Tracking Module*

Our method relies on RSSI fingerprints to perform localization. We develop an Android application that scans for WiFi access points and obtain the RSSI values from each access point. The WiFi access points are placed at fixed known locations within the house and carefully spaced out (at least 3m apart). The RSSI map is established by collecting the RSSI values for 4 different directions (North, South, East, West) at every location. For reference, the arrow in Fig. 2b points to the North.

To improve the localization accuracy, we harness the phone’s embedded sensors (accelerometer and compass). The usage of accelerometer is two-fold. Firstly, the acceleration value collected will help to determine if the subject is walking. This information in turn helps to decide whether or not to update the current location of the subject. Secondly, the acceleration value will also help to determine if the subject stops walking or is resting. This will mark the end of the ambulation or wandering episode (if the subject has been wandering). To minimize false detection of walking or resting (e.g. when the phone is shifted but no movement has occurred or when the subject stands up and sits down at one place), we first use a low-pass filter to isolate the gravity component of the acceleration magnitude and later remove it using a high-pass filter. Our experiment results show that the magnitude fluctuates between 0.04 and 0.25 while the phone is stationary. Thus, the walking magnitude threshold is set at 0.3 and any value registered above this threshold for more than 2 seconds will deem the subject to be walking.

The orientation sensor (compass) helps to determine the direction of movement. One of the problems of using RSSI fingerprints for localization is the RSSI values are very similar to each other at nearby locations. Therefore, with information regarding the direction of movement, we can narrow down the possible locations and subsequently determine the most probable location.

Upon launching the application, the system determines the start location and subsequently updates the location as the subject moves. To achieve this, the phone scans for access points and obtains the RSSI values at the frequency of 0.4 Hz. The obtained RSSI values are compared with the pre-collected ones (from the RSSI map) using L^2-Norm measure to determine the possible locations. To increase the reliability, we reiterate the scanning and comparison steps for at least 3 times before establishing the start location. Subsequently, when the subject is deemed to be walking using values obtained from the accelerometer, the program retrieves the direction of movement from the orientation sensor to determine the next location (the one with least RSSI difference using L^2-Norm measure).

B. Wandering Patterns Detection Algorithm

The wandering detection algorithm classifies the movements into corresponding patterns: direct, random, pacing, lapping. Direct is a single straightforward path from one location to another. Random is a continuous path with multiple points in no particular order. Pacing is a repeating path back and forth between two points. And, lapping is a repeating circular path involving at least three points [18]. The wandering patterns detection algorithm was reported earlier in [19] and will not be presented here due to the limited space of this paper.

IV. Evaluation and Discussion

A. System Performance

The above algorithms are integrated and installed on a smart phone. To evaluate the performance, a study subject carries the phone (by either holding it in the palm or putting it in the pocket) and executes 40 pre-defined walking paths. As the subject walks, the mobile application detects wandering patterns in real time, displays the results on the phone screen, and logs all the details (time, locations and patterns detected). The detected patterns are compared with the ground truth (established by manually classifying the patterns based on the pre-defined walking paths) for evaluation.

Table 1. Performance Results of 40 Walking Exercises

Patterns	**Total Number of Patterns in Ground Truth**	**Patterns Detected by the Program**		
		Total Number	Correct Detection	Incorrect Detection
Direct	11	16	11	5
Random	13	8	8	0
Pacing	12	12	12	0
Lapping	11	11	11	0

Table 1 summarizes the performance results of 40 walking exercises. In Table 1, the patterns, correct and incorrect detection results are color coded for easy verification. The recall value ranges from 61% (8/13 for random) to 100% (12/12 for pacing and lapping). In all the misclassifications, random patterns are classified as direct (5 cases).We will discuss these cases using the examples in Fig. 3.

Fig. 3 shows examples of wandering and non-wandering patterns detected by our application. Blue lines represent forward movements (step forward) or right turns whereas red lines represent backward movements (turn back and step forward) or left turns. Yellow circle represents the start location and yellow arrow shows the current direction the subject is heading. The white color text displays the time and location captured by the tracking module and also the corresponding wandering pattern (capitalized text) classified by the wandering patterns detection algorithm. The locations displayed in Fig 3 are abbreviated by taking the first 3 characters of the labels in Fig. 2, except that living room regions 1-6 are displayed as LivR1-6 respectively.

In Fig. 3a, the subject wanders from the kitchen to the bedroom 3. He laps around in the living room, then paces around the balcony1 and lingers randomly around the house entrance in the living room before reaching the bedroom3. Fig 3b shows that the subject walks directly from bedroom 2 to the study room. This is not considered wandering; hence, the pattern (Direct) is not displayed with the text.

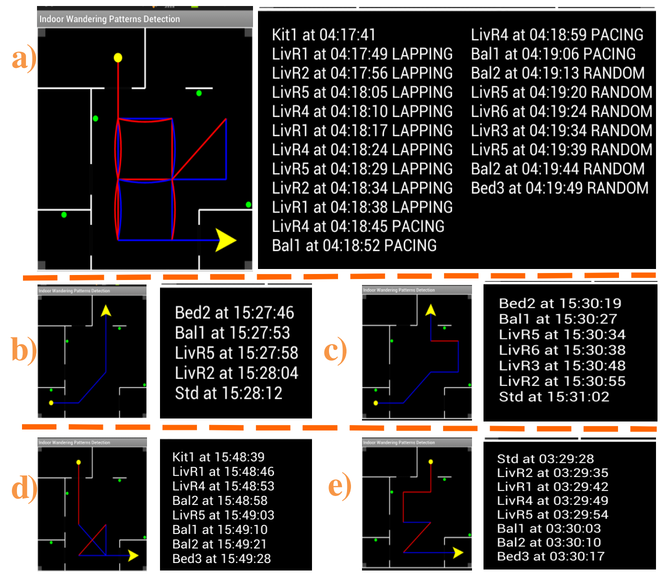

Figure 3. Screen Capture of Test Cases from the Phone

Fig 3c also showcases a walking path from bedroom 2 to the study room. However, the subject does not move efficiently in this case. He passes through living room regions 6 and 3 unnecessarily (without doing anything there). This is classified as a random movement in the ground truth but the application detects it as direct. Similarly, in Fig. 3d and 3e, the subject walks from the kitchen and the study room to bedroom 3 respectively. He wanders in the living room and the balcony 1 and 2 before reaching the destination. Our application does not recognize these as wandering patterns (random) because there is no repetitive path in his travels. Therefore, it considers these cases as efficient travel patterns (direct). To rectify these misclassifications, we have to incorporate the layout of the monitoring area in our wandering detection algorithm. In fact, if the layout of the house is incorporated, the application can apply shortest path algorithm to reason that the most efficient path from bedroom2 to the study room should be the one shown in Fig. 3b. Hence, by comparing the most efficient path and the actual travel path (e.g. Fig. 3c), the application can detect whether or not the subject is wandering. Similarly, the application will also be able to detect the sub-paths from living room region 5 to balcony1 and then to balcony2 (in Fig. 4d and 4e) are inefficient travels (or wandering).

B. Discussion

1) Limitations

There are several limitations in our current work.

Firstly, the sampling rate of the RSSI values is low (0.4Hz). The application may not update the locomotion data promptly if the subject moves from one location to another too quickly. Secondly, the localization accuracy of our application is around 2.5m. Therefore, the application will not be able to recognize wandering patterns in finer (less than 2.5m diameter) location resolution. Thirdly, the phone is placed horizontally on the palm (screen facing up) or vertically in the pocket (screen facing in) in our experiments. Other placements of the phone, e.g. in the pants pocket, may pose new challenges for tracking the direction of movement correctly.

2) Systems' Comparison

Table 2 compares our system (WiFi+ Phone) with other 2 commercial systems that have been used to detect indoor wandering locomotion for PWD. The first is a UWB cum WiFi based system (Ubisense [14]) and the second is an RFID based system [15-16].

TABLE 2. SYSTEMS' COMPARISON

Performance Criteria	Ubisense	RFID (POWERTAG)	WiFi + Phone
Localization Accuracy	15 cm	2-3m (Physical Rooms)	2.5m (Physical Rooms)
Cost	14800 USD	11600 USD	800 USD
Scalability	Yes but costly	Yes	Yes
Non-Intrusiveness	Yes (using wearable tags)	Yes (using wearable tags)	Limited (using mobile phones)
Ability to Detect Wandering Patterns	Not integrated	Not integrated	Integrated

Compared to the other 2 systems, our solution is not only more cost-effective, it is also integrated with the ability of detecting wandering patterns. Our system cost is mainly for the 4 access points and the mobile device. The other two systems have been used to collect locomotion data of PWD in nursing homes; however, they still heavily rely on human coders to recognize wandering patterns. Ubisense is a commercial system that provides very accurate location data (15cm-30cm) but it is very costly to scale up. The reasons are because Ubisense is a wired (not wireless) and line-of-sight system. Hence, to surveillance two separate bedrooms, the number of sensors required and the costs will be doubled. Both Ubisense and RFID attach wearable tags of small dimensions (83mm x 42mm x 11mm for Ubisense tag and 28mm x 42mm x 6.8mm for RFID tag) to the subjects for monitoring purposes. Our application assumes the subject to be carrying a mobile phone when he/she moves around. In reality, it may be difficult for PWD to comply with this requirement due to their illness. To enhance the practical feasibility of our proposed solution, the mobile phone can be replaced by a compact wearable circuit tag that only incorporates accelerometer, orientation sensor and WiFi.

V. CONCLUSION

We have developed a mobile-health application to detect indoor wandering patterns in real-time. In the future, we will improvise the wandering detection algorithm by incorporating the layout of monitoring areas and rectify the limitations of our current work. Additionally, we will improve the location tracking module so that it can tolerate different phone orientations and enhance the localization accuracy by adapting results from latest localization algorithms [20].

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