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Towards Falls Prevention: A Wearable Wireless and Battery-less Sensing and Automatic Identification Tag for Real Time Monitoring of Human Movements

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Abstract— **Falls related injuries among elderly patients in hospitals or residents in residential care facilities is a significant problem that causes emotional and physical trauma to those involved while presenting a rising healthcare expense in countries such as Australia where the population is ageing. Novel approaches using low cost and privacy preserving sensor enabled Radio Frequency Identification (RFID) technology may have the potential to provide a low cost and effective technological intervention to prevent falls in hospitals. We outline the details of a wearable sensor enabled RFID tag that is battery free, low cost, lightweight, maintenance free and can be worn continuously for automatic and unsupervised remote monitoring of activities of frail patients at acute hospitals or residents in residential care. The technological developments outlined in the paper forms part of an overall technological intervention developed to reduce falls at acute hospitals or in residential care facilities. This paper outlines the details of the technology, underlying algorithms and the results (where an accuracy of 94-100% was achieved) of a successful pilot trial.**

I. Introduction

Falls in hospitals are common and costly. It has previously been reported that fallers with dementia and delirium have significantly longer average length of stays (ALOS) and costs than age, gender and Diagnostic Related Groups (DRG) matched non fallers [1]. A UK report examining 200,000 incident reports over 12 months indicated that inpatient falls were the most common (40%) type of safety incident [2]. Falls were said to be directly responsible for 26 patient deaths, 530 hip fractures and about 1000 fractures. The psychological sequelae of falls to the individual include anxiety, depression, loss of confidence and fear of falling and ultimately a downward spiral of decline in health [3]. The occurrence of a fall also impacts negatively on staff and family resulting in feelings of fear, guilt, anxiety, defensive actions and at times these contribute to conflict and result in complaints, coroner's inquests and litigation [3].

There is a definite need for effective, evidence based interventions in acute hospitals, especially for older patients and those with cognitive impairment as highlighted in a recent systematic review and meta-analysis and technological solutions may be a way forward [3]. While many studies have investigated the use of body worn sensors in laboratory settings [4-6] and free-living environments [6-8] to detect falls or assess falls risk, very few have investigated *falls prevention in acute hospital or residential care environments*. Furthermore, the sensors employed have been battery powered, expensive, large and relatively heavy units requiring the wearer to recharge the unit during sleep or change batteries regularly. Nurse or carer staffing levels are lowest at night when patient confusion is increased and falls rates high [9] and therefore, a method that requires removal of the device at night is not practical. Moreover, cumbersome sensors need constant maintenance (e.g., battery replacement) and users' cooperation. Therefore such an approach is not effective in hospital or residential care environments, especially where many patients or residents have cognitive impairments.

In contrast, our approach relies on using a small, battery-less, low cost, ultra-lightweight, continuously wearable sensor enabled RFID tag that only requires a single attachment site over clothing. The device is capable of monitoring patients in real-time, at any location while preserving the privacy of the individual often violated by approaches that relies on cameras [10]. More significantly our approach does not require user cooperation and maintenance to ensure its success. Unlike other approaches, the task of activity classification is moved to powerful systems such as the backend devices and therefore the power consumption and implementation of the sensor is minimal. In this paper we present the results of the initial trial conducted to evaluate the ability of the device to remotely and unobtrusively monitor the activities of healthy subjects and to classify identified high risk activities.

II. RFID Primer

RFID is a wireless technology capable of unique and automatic identification of objects or people. In contrast to traditional identification technologies such as bar codes, RFID is a contactless technology that operates without line-of-sight restrictions [11]. All modern RFID systems infrastructure can be categorized into three primary components, namely tags, readers, and backend systems.

- **Tags**: Also called labels, contains a microchip that stores unique identifying information of the object/person to which the tag is attached and an antenna for communicating the information via radio waves. When a tag passes through a radio frequency (RF) field generated by an RFID reader, the tag reflects (or transmits) back to the reader the identifying information. Passive tags do not

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have their own power source and obtain power from the electromagnetic (EM) radiation emitted by readers and therefore have an indefinite operational life.

- **RFID Reader**: They are responsible for powering and communicating with tags [11]. RFID readers are generally placed at fixed locations with their antennae strategically placed to read tags passing through their EM field. RFID readers can read multiple co-located tags simultaneously (e.g., up to several hundred tags per seconds can be read by a modern RFID reader). The reading distance ranges from a few centimetres to more than 10 meters, depending on the types of tags, the power transmitted from the readers, and so on [11].
- **Backend Systems**: The readers are connected to a computer network in which the data are collected, processed, stored and shared (nursing staff, doctors, etc.)

III. METHODS

A. *Technology*

There are three key elements to the proposed novel falls prevention system: i) Wireless Identification and Sensing Platforms (WISPs) for activity monitoring and identification, ii) RFID readers and antennae infrastructure (reading WISPs), and iii) Patient Monitoring Software.

WISP: The Wireless Identification and Sensing Platform is a *wearable device* [12] that has the capabilities of RFID tags, but also support a tri-axial accelerometer sensor (ADXL330) with a minimum full scale range of +/- 3g. Like any passive RFID tag, WISP is powered and read by a standard off-the-shelf Ultra High Frequency (UHF) RFID reader. To an RFID reader, a WISP is an RFID tag; but inside the WISP, the harvested energy operates a 16-bit low power microcontroller (MSP430F2132). WISPs can be read at moderate range (about 3 m) and are estimated at around \$1 when mass manufactured [13]. The WISP devices weigh approximately 2 grams.

RFID Readers and antennae infrastructure: Speedway ® Revolution Reader (190 × 175 × 30 mm, mass, 680 g), used in the design is produced by Impinj incorporation. Each reader multiplexes between 4 antennae (260 × 260 × 33 mm, mass 1 kg) to transmit and receive RF signals (920 MHz - 926 MHz in Australia) from tags.

Patient Monitoring Software: Data transmitted over the network by readers are received by the middleware in the Patient Monitoring Software for processing and persistent storage. The monitoring software will automatically identify high falls risk related activities in real-time. These high risk activities by patients will result in the Patient Monitoring Software generating an automated alert (*who*, *when*, *where*, and doing *what*) via a paging system to pagers carried by staff to seek attention from a clinician to mitigate the risk and automatically record the incident at the same time.

B. *Subjects*

The data was obtained using 10 healthy adult volunteers, aged from 23 to 30 years with a mean age of 26.4 years and standard deviation of 2.12 years. Each volunteer was given scripted routines of activities of daily living (ADLs) that incorporated high risk activities we have identified (see Section IV). Each volunteer was given three separate scripts with random ordering of the ADLs and high risk activities. The algorithms were not customized to each subject and relied on training data instead.

C. *Instrumentation*

The WISP tags attached over the sternum (where they were placed outside of their normal attire) and were used to collect sensor data during the trial. These devices are small and portable and pose no risk to subjects. The data were streamed with a sensitivity of ±1.5 g (where g = 9.81 ms^{-2}). However the samples of acceleration data received per unit time is limited by the read rate (reads/s) of the WISP. The read rate is a function of its distance from the RFID reader antenna. Therefore the acceleration data received were post processed to achieve a consistent sampling rate of 40 Hz per channel. The three axes of the WISP, when fastened onto the subject's chest, are aligned with the anteroposterior (*x*-axis), medio-lateral (*y*-axis) and longitudinal or dorsoventral (*z*-axis) axes of the subject's frame of reference.

IV. HIGH RISK ACTIVITY EXTRACTION

Falls commonly occur around patients' or residents' beds, bathrooms and/or toilets [14]. The majority of falls are not witnessed with patients not seeking assistance when transferring or toileting even when they are carefully instructed [3]. Consequently, we have identified the following high risk activities as eventually leading to falls: i) entering into a toilet or a bathroom facility without the aid of caregiver or leaving a patient's room without the aid of a caregiver; ii) getting up from a chair without the aid of a caregiver; iii) activity involving getting off a bed; and iv) mobilizing without a walking aid.

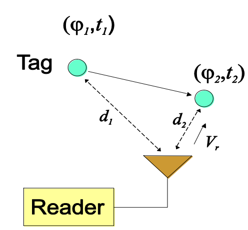
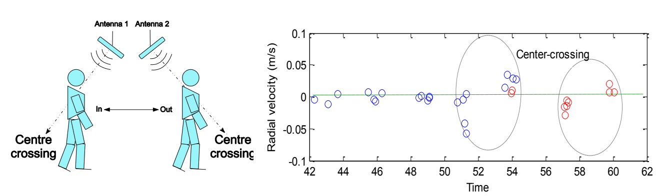


Figure 1. Illustration of TD-PDOA measurement

A. *Entering or Leaving a Patient Room or a Rest Room*

$$V_r = -\frac{\frac{1}{2}\left(\frac{\varphi_2-\varphi_1}{2\pi}\lambda\right)}{t_2-t_1} = -\frac{c}{4\pi f}\frac{\Delta\varphi}{\Delta t} \qquad (1)$$



(a) (b)

Figure 2. (a) The experiment setup, (b) illustrates the centre-crossing at the two antennae for a person going from In→Out. Here the crosses and circles represent estimations at Antenna 1 and Antenna 2, respectively. In →Out is indicated by a centre crossing at Antenna 1 followed by Antenna 2.

The projection of the tag velocity vector on to the line of sight between the tag and the reader can be estimated by Time Domain Phase Difference of Arrival (TD-PDOA) measuring the phase of a tag at different time moments at the same frequency [15] as illustrated in Fig. 1. We can measure the difference of phase (φ_2-φ_1) at different times and attribute it to the path difference d_2 - d_1. Then it can be shown that the radial velocity of the RFID tag is given by (1) where $\lambda=c/f$ (c is the speed of light and f is the frequency of the transmitted wave from the reader). The negative sign in (1) defines direction of the radial velocity in the derivation as being opposite to the change in distance of the tag at time t_1 and t_2.

Fig. 2 shows the time sequence of radial velocity evaluated at two overhead antennae where the direction of the radial velocity changes from negative to positive as the person moves across the centre crossings of Antenna 1 and Antenna 2. Therefore by using two overhead antennae as illustrated in Fig. 2(a), a person's traversing direction can be identified by analyzing and comparing the centre-crossing evaluated by both antennae. Here, the antennae are hung up over the head and lean in around 50 degrees. For this experimental setup, paths followed by volunteers were not specified and thus were random. We performed 80 translations to evaluate the effectiveness of our approach.

B. Getting Up or Sitting Down on a Chair

It is possible to identify two phases in standing-to-sitting (StSi) and sitting-to-standing (SiSt) transitions: i) an initial leaning forwards followed by; ii) a leaning backwards; (SiSt follows the opposite order). In both StSi and SiSt transitions, the displacement of θ (inclination angle between the trunk and vertical axis) approaches a maximum value and then recovers [9]. A similar trend in $sin\,\theta$ was also observed, as indicated in Figure 3 and provided a non-linear scale to increase the sensitivity of the results.

The candidate StSi and SiSt postural transition (PT) were detected in terms of the pattern of $\sin\theta$. As shown in Fig. 3, t_{PT} is the estimation of time at which PT of StSi or SiSt occurs (considered as the time corresponding to the maximum of $sin\,\theta$). The transition duration (TD) is the time interval estimated from the beginning of the leaning forwards phase (P_1) to the end of the leaning backwards phase (P_2). Hence $\mathrm{TD} = t_{p_2} - t_{p_1}$, where t_{P_1} and t_{P_2} are the time related to P_1 and P_2, which are estimated as the time corresponding to the two nearest minima of $sin\,\theta$ before and after t_{PT}, respectively. Unlike the approach in [6] which relied on a gyroscope to evaluate θ accurately, we only require an estimate. The value of θ can be estimated because the contribution of acceleration components from the posture transition can be assumed to be negligible compared to that of gravity. Therefore $\theta \cong tan^{-1}\left(z\text{-}axis_{acceleration}/x\text{-}axis_{acceleration}\right)$.

In [6, 7] the vertical displacement of the sensor at the end of the SiSt and StSi transition is used to differentiate between the two PTs. However, the WISP tag based approach could not be used to reliably report the vertical displacement because of the intermittent replies from the WISP and the partial concealment of the WISP from the antenna collecting the data from the WISP during the SiSt and StSi transitions.

However, we were able to study the RSSI (received signal strength indicator), which is the strength of the signal reflected from the WISP and detected at the antenna, as a method of estimating the distance of the person to the antenna and hence whether the person is standing or sitting at the end of the PT. RSSI is reported by the reader in steps of 0.5 dBm for each received signal from the WISP. A sensor at any given time will have different RSSI readings reported by different antennae and therefore each antenna is a reference point for location and displacement of the WISP. RSSI based method has several downsides as it is affected by the environment such as the electromagnetic properties of objects in the surroundings and multipath effects [15]. However we found that in short range measurements RSSI was adequate to successfully discriminate between SiSt and StSi transitions.

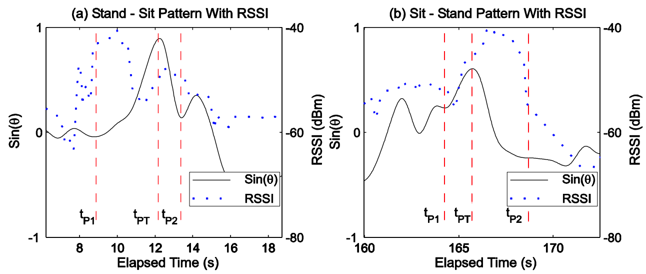


Figure 3: Detection of Sit-to-Stand posture transitions showing $sin\,\theta$ (solid black line) and RSSI values (dashed blue line).

To classify between these two transitions, we employed a threshold based approach using the information from TD, $\sin\theta$ and the received signal strength indication (RSSI). After filtering $sin\,\theta$ to remove noise using a band pass direct-form II second-order Butterworth filter with cut-off frequencies at 0.04 and 0.7 Hz, the aforementioned three components are evaluated.

First, a true PT has a TD above 1.725 s and $sin\,\theta$ larger than 0.275 at t_{PT}. Second, the RSSI (inversely proportional to the quadruple of distance [15]) indicates that the distance variation from the antenna due to the displacement of the body will result in the RSSI reading decreasingly or increasingly depending on the location of the antenna relative to the person. In this environment, antennae are located above 2 m over floor level. As a result, when standing, the distance from the WISP to the antenna is shorter than when the person is sitting, causing a negative gradient during a StSi and positive gradient during a SiSt transition (see Fig. 3).

C. Getting In and Out of Bed

A classification algorithm for getting into and out of bed events was developed from the early work in [6]. The lying state was discriminated from sitting or standing by analysing the acceleration readings from the anteroposterior axis (x_g) where readings of approximately 0 and 1g correspond to lying and standing or sitting respectively. The signal was filtered with a direct-form II second-order Butterworth low pass filter with cut-off frequency at 0.16Hz, eliminating noise and other components such as walking.

PTs of sitting-to-lying and lying-to-sitting were detected based on threshold values before and after the event. The sitting-to-lying PT was detected using the pattern of the derivative of x_g. Here t_{PT} is the estimated time at which sitting-to-lying occurs and corresponds to the minimum of the derivative of x_g while t_{P_1} and t_{P_2} are the times corresponding to two nearest maxima of the derivative of x_g before and after t_{PT}, respectively. This PT was correctly classified as such if the mean of x_g before and after its t_{PT} was above $0.7g$ and below $0.4g$ respectively.

D. Mobilizing without a Walking Aid

Walking was detected by analyzing the vertical acceleration component every 5 seconds; the signal was filtered to distinguish the stepping patterns by isolating signals within 0.62 and 5 Hz approximately. To detect a walking period, negative peaks below a threshold of -0.05 g were considered as possible steps if 2 or more consecutive steps with intervals between peaks of 0.25 to 2.25 seconds were present in the window time.

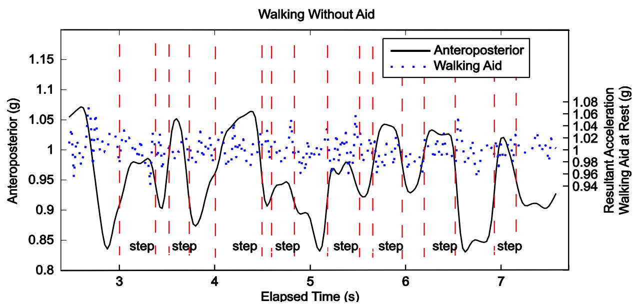


Figure 4: A person walking without a walking aid

Activity of a patient walking without an aid was detected if a person was found to leave or enter a room without their walking aid. A person identified as moving through a threshold without also simultaneously detecting the walking aid moving across the threshold signalled the positive identification of a subject mobilizing without a walking aid. Inference was achieved by using the tag direction algorithm which indicated the direction of movement and the resultant acceleration a_R reported by the WISP attached to the walking aid which indicated whether the aid was being used. A value of for a_R around 1 g (gravity) confirmed that the walking aid was not being used (as shown in Fig. 4) where a_R is given by $a_R = \sqrt{a_x{}^2 + a_y{}^2 + a_z{}^2}$.

TABLE 1. SENSITIVITY AND SPECIFICITY RESULTS

PT	Sensitivity	Specificity
Sitting down on a chair (standing-to-sitting)	92.2%	97.9%
Getting up from chair (sitting-to-standing)	90.4%	94.0%
Getting into bed (sitting-to-lying)	100%	100%
Getting out of bed (lying-to-sitting)	100%	100%
Entering a room/restroom	100%	100%
Leaving a room/restroom	100%	100%
Walking without a walking aid	100%	100%

V. RESULTS

Performance was evaluated using sensitivity and specificity measures (see Table 1). Overall, subjects performed 197 PTs including StSi, sitting-to-lying, lying-to-sitting and SiSt with 99 lying conditions: supine and prone position and left and right side lying. Relatively high sensitivity and specificity for detection of getting into bed as well as getting out from bed were obtained (see Table 1). We also demonstrated a high accuracy (100%) in identifying PTs related to mobilizing.

VI. CONCLUSIONS

Our work shows that WISP tags have the potential to provide a technological intervention to prevent falls in acute hospitals. We have shown that their performance is comparable to the existing systems using wearable and battery-powered sensors for human activity monitoring [4-8], but without the drawbacks of user involvement, expense, and maintenance. Currently our team is developing a wearable, concealable and flexible antenna to allow the development of a more ergonomic WISP with increased read range. We are also currently working with clinicians at the Geriatric Evaluation and Management (GEM) unit at the Queen Elizabeth Hospital, South Australia to conduct a clinical trial to validate our approach with frail patients and clinical staff.

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