Sensor Enabled Wearable RFID Technology for Mitigating the Risk of Falls Near Beds

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***Abstract*—The increasing ageing population around the world and the increased risk of falling among this demographic, challenges society and technology to find better ways to mitigate the occurrence of such costly and detrimental events as falls. The most common activity associated with falls is bed transfers; therefore, the most significant high risk activity. Several technological solutions exist for bed exiting detection using a variety of sensors which are attached to the body, bed or floor. However, lack of real life performance studies, technical limitations and acceptability are still key issues. In this research, we present and evaluate a novel method for mitigating the high falls risk associated with bed exits based on using an inexpensive, privacy preserving and passive sensor enabled RFID device. Our approach is based on a classification system built upon conditional random fields that requires no preprocessing of sensorial and RF metrics data extracted from an RFID platform. We evaluated our classification algorithm and the wearability of our sensor using elderly volunteers (66-86 y.o.). The results demonstrate the validity of our approach and the performance is an improvement on previous bed exit classification studies. The participants of the study also overwhelmingly agreed that the sensor was indeed wearable and presented no problems.**

I. Introduction

Falls occur commonly in residential care and hospitals, especially at night and in the surroundings of the bed [1]–[3]. Falls are costly as patients have a longer length of stay (LOS) at hospitals [4] and can result in anxiety, depression and a loss of independence; similarly, caregivers and nurses may also be affected by psychological trauma [5]. Monitoring the patient and recognizing their high risk falls related activities provide an opportunity to intervene and prevent a fall or provide immediate attention from a caregiver [6], [7] as opposed to falls detection [8], [9]. However, a fall detection strategy does not server as a falls mitigation strategy.

Previous studies were focused on detecting bed exits. In the case of methods in [6], [7], [10]–[12], these were based on one or multiple sensors strategically placed on or around the bed. Most of these methods involved pressure sensors achieving varying performance results as a consequence of the multiple types of sensing units employed. Furthermore, pressure sensors were found unreliable with patients lighter than 45.4 kg, a common weight for frail patients, but improved performance was achieved in combination with other sensors [12]. The location of these units (bed mats, bed rails, floor mats) makes them susceptible to constant mechanical stress, requiring regular maintenance and/or replacement. In addition, these units need thorough cleaning as they may be exposed to body fluids and/or other contaminated material.

Other studies focused on human activity recognition. These methods used different sensor systems, which can be divided either into worn sensors or environment sensors. However, a more accurate categorisation of these studies can be done based on their classification system: i)techniques based on threshold based algorithms; and ii)machine learning based approaches. From the former, in [13]–[16] sensors such as accelerometers and gyroscopes were used to extract physical features as input to a threshold based classification system as first proposed by Najafi [13]. Most methods required the use of bulky battery powered devices with multiple sensors that were attached to the subject's body. This approach implies heavy instrumentation of the subject which is not practicable with frail elderly subjects, and a high maintenance cost [13]–[15]. Furthermore, these methods relied on heavily preprocessed data e.g. multiple filtering stages, prior to the classification algorithms to isolate information content or extract desired features. This results in unwanted delays, added computational overhead and algorithmic complexity; all of which are detrimental to a responsive, scalable system [13]–[16].

Studies based on machine learning based classifiers, such as those of [17]–[22], included hidden Markov models (HMM), conditional random fields (CRFs) and support vector machines (SVMs). Generally, these methods demonstrated better performance than threshold based methods but to varying degrees of success. In the case of [17]–[19], these techniques suffered similar practical deficiencies as those of the threshold based methods i.e. battery powered equipment and subject instrumentation. In contrast, the methods in [20]–[22], all subjects were instrument free but the setting was around independent living, which is not the case for our target population. In addition, results showed great variability, this inconsistency affects the application of these techniques to elder care in a medical environment as result discrepancy leads to poor reliablity and lack of acceptance over time of a proposed strategy.

In order address the shortcomings of previous methods for bed exit detection, in this article, we propose an accurate, low

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computational overhead, low latency and low cost method for mitigating the risk of falls caused by bed exiting of elderly patients in hospitals and residential care environments. Furthermore, have addressed the issues of privacy concerns around using video based approaches [23] by indirectly inferring the activities of patients.

Firstly, our proposed approach utilizes a light, low cost, inexpensive, battery free RFID tag called Wearable WISP (Wireless Identification and Sensing Platform) or W^{2}ISP [24] (see Section II-A). This sensor is worn by elderly patients attached to their clothes (Figure 1(b)). Secondly, in order to improve the system responsiveness we keep the computational cost low by using a single accelerometer per person and minimum data preprocessing by eliminating filtering steps. Responsiveness is a key consideration because of the urgency of attending to a high risk situation (such as bed exiting) requires a prompt system response to provide a timely alert to a caregiver to proceed to an intervention in a hospital environment as described in [25]. Thirdly, to consider the dependency among consecutive activities, we use CRFs [26] to model and predict activities with flexibility of introducing various features to improve the performance of previous approaches [16]. Finally, since the use of video images for monitoring systems has been perceived as intrusive [23] to a patient's privacy, our approach preserves the privacy of a person. In summary, the contributions of this paper are as follows:

- We designed a simple approach for supporting bed exit classification using a single truly wearable device for the first time (to the best of our knowledge). The device is small, low cost, battery-less and can be worn continuously; moreover, the device relies on a single accelerometer sensor and is able to protect a patient's privacy.
- Utilize noisy and incomplete information effectively for activity classification by using conditional random fields based algorithm.
- Present a method that has been proven in elderly population as we have conducted extensive trials with elderly volunteers (66 to 86 years old), closely resembling the target population for this application as opposed to our previous trial using healthy adult volunteers [16].

The rest of the paper is organized as follows, Section II gives a brief overview the overall system and the data sources used; Section III describes the experimental settings and procedures, Section IV describes our experimental results and we present our conclusions in Section V.

II. System Overview

The proposed monitoring system consists on a wireless sensing platform, an activity recognition system (ARS) and a bed exit alert system (BEAS).

A. Wireless Sensing Monitoring Environment

The wireless sensor, W^{2}ISP [24], is a passive RFID tag based on the WISP developed in [27] (see Figure 1(a)). A W^{2}ISP includes a tri-axial accelerometer (ADXL330) and a microprocessor (MSP430F2132) and is powered by the electromagnetic (EM) energy radiated by nearby RFID antennae. The accelerometer works in low power mode and therefore requires minimum power to read the sensor. Although the low power operation mode increases read rate, it also introduces noise. The W^{2}ISP differs mainly from the WISP [27] in its wearability and increased read range as the tag employs an improved flexible antenna that isolates human body effects by using a conductive fabric. Experimentally, the sensor has reported a maximum read range of 4 m from [24] when attached over a person's chest area, on top of their clothing (see Figure 1(b)).

TABLE I
Parameters reported by a read event from the RFID Reader)

Parameter	symbol
Tag Identification	tID
Antenna Identification	aID
Acceleration on X* axis	a_v
Acceleration on Y* axis	a_l
Acceleration on Z* axis	a_f
Frequency Channel	fCH
Phase	ϕ
Received Signal Strength Indicator	$RSSI$

*X, Y and Z axes are relative to the sensor; vertical(v), lateral(l) and frontal(f) axes are relative to the subject.

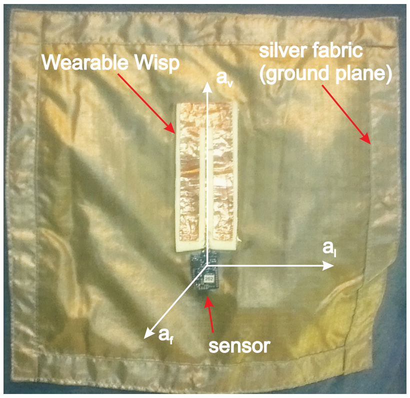
Three or four antennae located around the patient's room, directed mainly towards the chair, bed and walking area, due to the high risk of falls associated with these areas [1] are used to capture data from W^{2}ISPs. Antennae are powered by an Speedway Revolution reader operating at the regulated Australian RF frequency band of 920-926 MHz operating at a maximum regulated power of 1 W. Antennae were strategically located to closely simulate a real hospital room deployment (see Section III-A). Furthermore, the reader is capable of reading and discriminating multiple tags simultaneously. The information from the reader, shown in Table I, is reported to an in-house designed middleware which formats and timestamps the data for further analysis by the classification algorithms.

B. Classification Problem

We must consider two key issues related to our classification system. First, we need to understand the sequence of activities comprised in bed exiting. Based on observations of elderly subjects we considered the sequence of states:

- Lying
- Sitting on bed
- Out of bed.

Secondly, we need to acknowledge the limiting nature of RFID technology. The effects of variable distance to antenna, destructive interference due to multipath, RF band interference and occlusion by RF opaque objects such as the human body, cause irregular, incomplete and noisy readings which are delivered to the ARS. Hence, the sequence of activities from the sensor that describe a bed exit can be discontinuous



(a)

(b)

Fig. 1. (a) Wearable WISP showing sensor and accelerometer axes, (b) Elderly volunteer with Wearable WISP attached to garment.

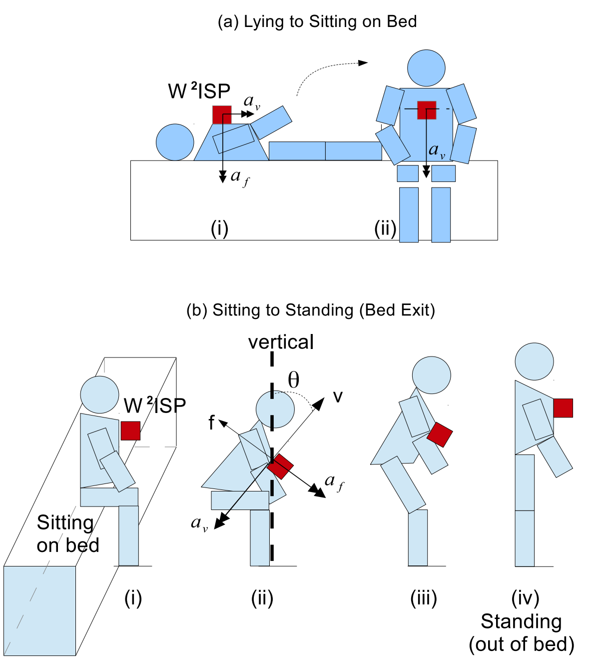


Fig. 2. Process sequence for (a)Lying to sitting, (b) Sitting to standing

(e.g. Lying to Out-of-bed). In addition, we have to consider sensor noise due to the sensor working on inadequate power.

Finally, we can indicate that a bed exit event is recognized as such if an Out-of-bed activity has been predicted, given that the previous activity was either Sitting-on-bed or Lying.

C. Activity Recognition System

Given an observation sequence $X = (x_t)_{t=1}^{T}$, where $x_t \in \mathbb{R}^d$ and T is the length of the sequence. The Activity Recognition System (ARS) is to predict the associated activity sequence (*i.e.* label) $Y = (y_t)_{t=1}^{T}$, where $y_t \in \{1, \cdots, C\}$. Here C is the number of activities (classes).

Here we use CRFs to build our ARS (activity recognition system), because CRFs naturally model the dependencies of the activities in one sequence. CRFs assume the conditional distribution from exponential family below [26],

$$p(Y|X;\lambda) = \frac{1}{Z(X,\lambda)} \exp\left(\sum_k \lambda_k \sum_{t=1}^{T} F_k\left(y_{t-1}, y_t, X, t\right)\right) \quad (1)$$

$$Z(X,\lambda) = \sum_Y \exp\left(\sum_k \lambda_k \sum_{t=1}^{T} F_k\left(y_{t-1}, y_t, X, t\right)\right), \quad (2)$$

where F_k are the feature functions and $\lambda = (\lambda_k)_k$ are the weight vector. $Z(X, \lambda)$ is a normalization constant. The parameter λ of the CRF can be learnt via maximizing the likelihood. Here we use Limited-memory BFGS (LBFGS) [28] to maximizing the likelihood. Given X and λ, ARS predicts the label Y,

$$Y = \operatorname*{argmax}_Y p(Y|X;\lambda), \quad (3)$$

where we use the Viterbi algorithm to get the maximal assignment for the label Y instead of exhaustive search.

D. Model Setting

We consider a CRF model based on the sequence of states determined in Section II-B (Figure 3). Observations are extracted directly from the reader reported data, we consider for each observation the following data $[a_v, a_l, a_f, RSSI, aID]$. The value of RSSI is of interest as an indicator of relative distance to surrounding antennae, a higher RSSI value to a certain antenna would indicate the tag is in closer vicinity than to an antenna with a lower RSSI to the same tag. In addition, we consider the body tilting angle θ towards the front and back from the vertical reference (see Figure 2(b)). The angle θ is a rich source of information for body posture and transition [13], [14], [16], which is approximated from current acceleration values $\theta = arctan\left(\frac{a_f}{a_v}\right)$; furthermore, we consider the $sin(\theta)$ as alternative to θ as is proportional to θ and range limited to [-1,1].

Acceleration and $sin(\theta)$ are continuous signals with infinite amount of possible state sequences; therefore we quantized both signals to steps of 0.05(g for acceleration), and constrained these signals to the range of [-1,1]. This range is enough to include all activities of interest as acceleration values exceeding this range are unlikely for elderly patients with the exception of falling, which can reach high acceleration values.

We include the time difference $(\triangle t)$ between an observation x_t and its prior x_{t-1}. Similarly, this information is quantized into steps of 0.025 s as the minimum $\triangle t$ between consecutive

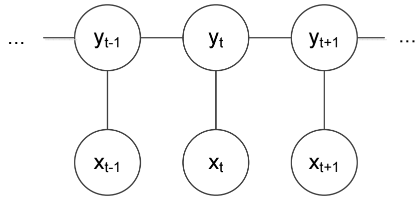


Fig. 3. CRF model: Sequence of labels y_t depend on sequence of observations x_t; in our case y_t can take values: Lying, Sitting on bed or Out of bed.

observations and limited to a maximum $\triangle t = 10$ s, as we consider this time sufficient for a person to be in a steady state.

E. Bed Exit Alert System

We evaluate the recognition of bed exit events in the sequence of observations in an alert setting context. The Bed Exit Alert System (BEAS) is to provide an alert signal, provided the current ARS output $y_t = \{\text{Out-of-bed}\}$, and previous output $y_{t-1} = \{\text{Lying, Sitting-on-bed}\}$, independent of the number of consecutive readings in the current state.

We consider this approach because few identification errors scattered along a test sequence can trigger multiple alarm errors as opposed to multiple recognition errors in a sequence batch that can trigger a single alarm error. This is because we make a prediction per each sample observation. Since the nature of this system is to notify caregivers/nurses of a high risk activity being performed, the alert signal needs to be triggered once only. That is only the first predicted Out-of-bed label in an input sequence after a Lying or Sitting-on-bed state triggers the signal, regardless of the duration of the state.

F. Baseline Method

Our proposed bed exit classification algorithms is evaluated against a threshold based classifier recently developed in [16] to recognize bed exits. This method considers acceleration data processed in multiple stages and was evaluated using only healthy adult volunteers [16].

This algorithm recognized bed exit events after detection of a lying to sitting on bed and sitting to standing postural transition (PT) sequence. The first transition used filtered vertical acceleration (a_v) data while the second considered filtered $sin(\theta)$ where θ is the body tilting angle with respect to the vertical. Another parameter considered was the change in RSSI values with respect to a fixed antenna. As a person sitting or standing becomes farther or closer to the fixed antenna, a perceivable negative or positive difference in RSSI, respectively, is observed.

III. Experimental Setting

A. People and Location

We conducted a trial with fourteen elderly volunteers from 66 to 86 years old. The trials were performed at a clinical room which was instrumented with antennae positioned to closely resemble a hospital room deployment; i.e. antennae were located in non-obstructive positions on the walls and ceiling. For this reason, most some activities resulted in the patient being away from the direction of maximum radiation from reader antennas or being too far from the closest antenna. This constraint affected the frequency of samples collected as well as resulting in incomplete data segments.

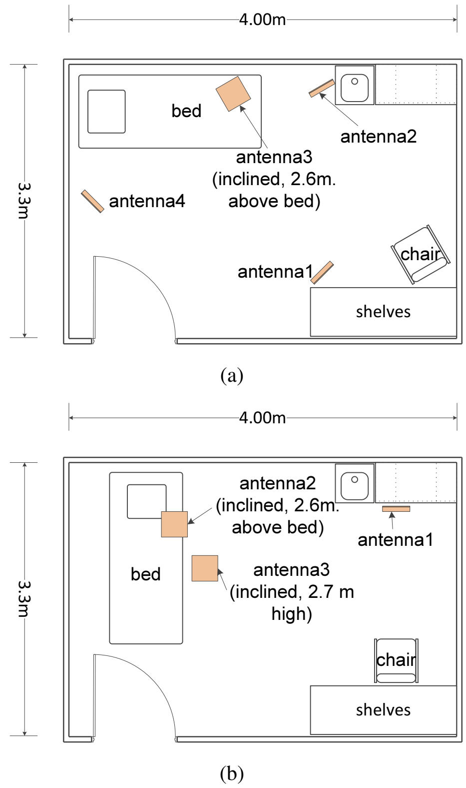


Fig. 4. Different room configurations used for trials (a): First room configuration (*RoomSet1*), (b): Second room configuration (*RoomSet2).*

We considered two different room configurations as practical deployment options. Antennae were strategically located to best fit each of the room arrangements with the constraint of ceiling and wall positioning of antennae. The first room configuration (*RoomSet1*), included one antenna at ceiling level (*antenna3*), and three antennae located on walls, which directly covers the bed area and most of the room area. The second room configuration (*RoomSet2*) included two antennae at ceiling level (*antenna2* and *antenna3*) and dispensed with one wall level antenna, this disposition covered the area of the bed, its vicinity and covered the area over the arm chair as shown in Figure 4.

B. Experimental Procedure

Each volunteer wore a garment with the sensor attached over the sternum, as shown in Figure 1(b). Each subject was directed to perform an average of five sets of activities. Each set of activities included a mixture of the following:

- Lying on bed (in any position of the subject's choosing such as to the side or supine position), sitting on bed, getting out of bed, getting into bed

TABLE II
RoomSet1 AND *RoomSet2* GENERAL INFORMATION.

Characteristic	RoomSet1	RoomSet2
Number of antennae	4	3
Number of activity sets	60	27
Number of subjects*	10	5
Number of observations	52459	22619

*one subject participated in both datasets

- Sitting down on arm chair, getting up from arm chair, sitting on arm chair
- Walking

There were no additional instructions given about the mannerisms for conducting activities and thus resulted in different gait, speed and posture transition time for each subject. Volunteers were also instructed to lie down comfortably. They were either in supine position or on their sides. All the activities were annotated by an observer in real time.

We evaluated two datasets each corresponding to the deployments illustrated in Figure 4. Table II describes the differences in for both datasets. Data from both datasets was used to generate the features described in Section II-D before being processed by the classifier for automatic activity recognition.

We evaluated the performance of the system, accuracy, sensitivity and specificity given in (4), (5) and (6) respectively, to correctly predict observation labels and alert in case of bed exit events. The ARS (activity recognition system) performance was evaluated via a 10-fold cross validation of our two datasets; BEAS (bed exit alert system) was evaluated using ARS test data output from the 10-fold partitioning.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}.100 \quad (4)$$

$$Sensitivity = \frac{TP}{TP + FN}.100 \quad (5)$$

$$Specificity = \frac{TN}{TN + FP}.100 \quad (6)$$

In (4), (5) and (6), for any given activity of interest, true positives (TP) refers to labels correctly classified as the activity of interest; true negatives (TN) are labels of other activities correctly excluded; false positives (FP) are all false alarms or other activities wrongly classified as our activity of interest and false negatives (FN) are all misses or observations of our activity of interest wrongly labelled.

IV. RESULTS

A. Reading Rate Variations

The experimental results are largely dependant on the timely powering of the sensor as explained previously (Section II-B). The translation and body motion of the sensor bearer creates variations in readings due to distance changes to antennae and other factors such as multipath. These factors affect the reading rate due to inadequate power to operate the sensor as well as the resulting extended power-up time.

TABLE III
ANTENNA RANGE FROM COLD START (METERS)

	Response Time Window (s)	
Deviation angle from antenna front (degrees)	2	5
0	1.5	2.0
30	1.37	1.58
60	0.92	1.35
90	0.40	0.47
[90 180>	0	0

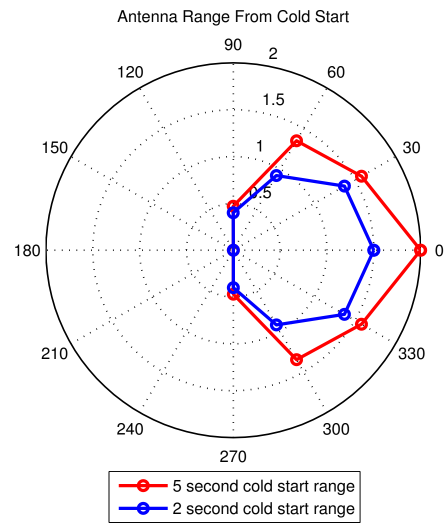


Fig. 5. Antenna range from cold start for two time windows: 2 s (blue) and 5 s (red). Distance measured in the horizontal plane in meters.

We have tested the read range of the W^2ISP from a cold start measures from our critical antennae (those located on the ceiling) over two fixed time windows (see Table III). A cold start is where the reservoir capacitor of the Wearable WISP has been discharged after a time t^* without RF exposure (in our case $t^* \geq 10$ s). We evaluated read range using a ceiling mounted antenna and a W^2ISP located at 2.5 m and 1.4 m, respectively, above ground level. The antenna had an inclination of 50° from the vertical. We considered measurements every 30° from the front of the antenna and two time windows of 2 and 5 s for the sensor to gather power and respond at maximum distance to the antenna as shown in Table III and Figure 5. The sensor can send information from cold start 1.5 m away from the antenna in less than 2 s when directly in front of the antenna; an increase of deviation from the front of the antenna results in a shorter range for the sensor to be able to respond in that time window.

B. Experimental Results

The manually labelled data (truth) was compared with predicted data. Table VII shows overall accuracy for both datasets, and a percentage comparison of the composition of both datasets in terms of collected observations. We can observe that both datasets achieved high overall accuracy. In the case

TABLE V
NEAR BED RELATED ACTIVITY RECOGNITION IN BOTH DATASETS

Activities	RoomSet1 (%)			RoomSet2 (%)		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
Lying	99.62±0.25	99.74±0.21	99.43±0.59	97.45±4.08	98.15±4.17	94.66±5.71
Sitting on bed	96.37±1.94	92.51±6.11	97.78±1.07	94.67±6.55	78.28±11.42	96.08±5.35
Out of bed	96.62±2.02	87.97±4.99	97.76±2.09	96.07±5.64	71.84±12.61	98.04±3.33

TABLE IV
ARS OVERALL ACCURACY AND RELATIVE COMPOSITION OF EACH LABEL IN RESPECTIVE DATASETS (%)

	RoomSet1	RoomSet2
ARS Overall Accuracy	96.34±1.94	94.14±6.56
Composition for Lying	59.04	88.67
Composition for Sitting on bed	28.86	7.11
Composition for Out of bed	12.09	4.21

TABLE VI
BED EXIT RECOGNITION IN BOTH DATASETS, RESULTS IN %

Method	Dataset	Accuracy	Sensitivity	Specificity
BEAS	RoomSet1	84.55±6.78	78.24±12.6	87.33±5.35
	RoomSet2	86.9±8.85	90.14±13.47	86.57±11.11
Baseline [16]	RoomSet1	68.28±5.9	14.45±15.4	91.14±5.85
	RoomSet2	69.6±8.36	19.02±19.72	93.36±4.8

of *RoomSet2* the highly accurate result is partly due to the greater composition of Lying observations ($> 88\%$). Samples from lying states achieve a greater prediction accuracy than other labels in that dataset (see Table VII). This disparity in observations is also due to the lack of observations (sensor reads) in positions other than lying attributed to the change in antenna disposition. The lack of reads result from the distances between the W^{2}ISP wearer and antennae being maximised as the antenna facing the subject sitting on bed (*antenna4* in *RoomSet1*) is moved to being almost on top of the subject (*antenna3* in *RoomSet2*) as seen in Figure 4. From this ceiling position, readings can be hindered due to obstruction by folds in the clothing breaking the ground plane of the sensor or other body parts such as the head obstructing RF signals.

In addition, we have to consider the reduced number of antennae. The likelihood of having a feeding antenna in range to generate a response from cold start reduces as the subject moves from one position to the next, as demonstrated in SectionIV-A.

Comparison of both datasets clearly indicates that *RoomSet1* data achieves better accuracy ($\geq 96\%$), sensitivity ($\geq 88\%$) and specificity values ($\geq 97\%$) as shown in Table V. All states achieved high accuracy values ($> 94\%$), particularly in *RoomSet1*, in which sensitivity values were noticeably higher than those in *RoomSet2*. These results indicate that the system is able to differentiate between subjects Lying and Sitting-on-bed, which is an added advantage in patients that are not supposed to get up from bed unsupervised, especially at night time where a Sitting-on-bed state implies that the patient is probably attempting to go to the toilet. Another important issue to notice is that in all cases the level of specificity or false alarms is relatively low ($\geq 94.6\%$), explicitly in *RoomSet1* where specificity ranges from 97.8% to 99.4%.

TABLE VII
BED EXIT RESULTS FROM PREVIOUS STUDIES

Study Author	Sensitivity(%)	Specificity(%)
Hilbe [11]	96.0	95.5
Bruyneel [10]	91.0	100.0
Ranasinghe [16]	90.4	93.8

We evaluate the BEAS performance using ARS predictions. The results are shown in Table VI where accuracy for both datasets is $> 84\%$. Results indicate that *RoomSet1* deployment achieves lower performance than that of *RoomSet2*. However, these results seem to contradict those of individual label predictions where *RoomSet1* achieved higher performance values for all labels when compared to data from *RoomSet2*. The explanation lies in the higher numbers of scattered label recognition errors resulting in increased FP and FN values in *RoomSet1*. Furthermore, in *RoomSet2*, the low composition of Out-of-bed observations does not reduce performance of bed exit classifications as only one predicted label is enough to trigger an alarm.

We compare these results with those of the Baseline method applied to both datasets. We notice that accuracy and sensitivity values are much lower than those of BEAS because the baseline method requires detection of PTs in order to perform its threshold based classification. The method fails to detect most PTs due to incomplete data from elderly subjects, producing many FNs.

Furthermore, our proposed bed exit classification algorithm achieved a low false alarm rate (specificity $> 86\%$). This result is important as a high false alarm rate can cause frustration in caregiver staff affecting the acceptance of the intervention. Although the baseline method depicts a larger specificity, it is only because of a general failure to detect possible events to evaluate rather than the classifier not producing FPs.

Moreover, we compare these results with previously developed fall prevention devices [10], [11], [16] shown in Table VII. Hilbe et al. [11] achieved sensitivity and specificity values in the order of 95%. The system is composed of a pressure sensor mounted on the bed rails; however, bed rails are not recommended as a method to prevent falls as it may increase the height of a fall and the risk of related injuries

[3], [29]. Bruyneel et al. [10] used multiple sensors (presence, movement, temperature) built in a bed mat. This method achieved no false alarms but has an increased associated cost due to demands of servicing and cleaning as the product is exposed to body fluids from patients. Moreover, mats are prone to displacement due to body movement and this method confirms a bed absence signal after a 2 minute delay. Similarly, in the baseline method [16] a 20 s data segmentation strategy is employed resulting in maximum response delays of 20 s. In contrast to these methods, our proposed system achieves comparative results and offers additional advantages as it is wearable, wireless, inexpensive, maintenance free and free of heavy data cleaning and conditioning steps such as filtering; therefore, free of processing delays that might withhold the timely execution of a high risk alarm [10], [16].

C. Wearability of the Wireless Sensor Equipment

This section investigates the users perception on the wearability of the device among the elderly volunteers. A short questionnaire filled out by each subject after their trial. The questionnaire was designed based on the work of [30] which identified several factors for evaluating wearable sensors. In our study, we focused on the use of the equipment and the restrictions on freedom of movement of the user while wearing the equipment. The questions were awarded a score from an 11 level point system (0-10). Although the questions are formulated in either positive or negative statements, in all cases a score of 10 demonstrate complete satisfaction on both question sets. The questions for measuring the wearability of the W^{2}ISP were:

1) Wearing the equipment was no problem.
2) I just forgot I am wearing it.
3) I am satisfied using the equipment.
4) I find the equipment easy to use.

The specific questions for measuring freedom of movement were:

5) How did you experience wearing the equipment while performing activities?
6) Were you hindered by the equipment while walking?
7) Were you hindered by the equipment while sitting?
8) Were you hindered by the equipment while lying?

The tabulated results (Table VIII) show great satisfaction towards the equipment and its wearability. In particular the results indicate that the elderly volunteer participants were not constrained or obstructed by the device while performing their activities. The system achieved average scores of 9.8 and 9.7 for both question sets. In general female subjects provided higher scores on all questions than male subjects with the exception of Question 8. Furthermore female responses to Question 8 has the largest SD as well as the lowest score, perhaps indicating that females may have felt some discomfort when lying with the sensor attached over the breast bone. However, further studies (such as a focus group) will be required to develop a more definitive conclusion. Overall, these results overwhelmingly support the use of the W^{2}ISP as a wearable and easy to use device, suitable for use with elderly.

TABLE VIII
SCORE AWARDED TO EQUIPMENT ACCEPTANCE AND FREEDOM OF MOVEMENT: AVERAGE ± SD

	Trials Population		
Question	Overall	Males	Females
1	9.88±0.48	9.5±1.00	10±0.00
2	9.7±0.84	9.5±1.00	9.76±0.83
3	9.76±0.66	9.5±1.00	9.84±0.55
4	9.88.±0.48	9.5±1.00	10±0.00
Average Equipment	9.8±0.63	9.5±1.00	9.9±0.5
5	9.7±0.68	9.5±1.00	9.76±0.6
6	9.88±0.48	9.5±1.00	10±0.00
7	9.88±0.48	9.5±1.00	10±0.00
8	9.29±1.57	9.5±1.00	9.23±1.73
Average Freedom of Movement	9.69±0.92	9.5±1.00	9.75±0.92

V. CONCLUSION

In this article, we provide a novel approach to bed exit classification for mitigation the risk of falls. We considered the use of raw signals i.e. with no preprocessing such as filtering, to achieve bed exit alarming capability. We proposed a classification algorithm based on CRFs to correctly predict the label of each observation and ultimately distinguish whether the subject has exited the bed using these labels. The system was successful evaluated using two datasets.

The results demonstrate that the proposed system has similar performance as more expensive, bulky bed exit alarm systems requiring regular maintenance.In addition, our proposed classification algorithm is a significant improvement over the threshold based algorithm. Furthermore our approach achieves high accuracy with incomplete and noisy raw data.

Furthermore, the system can be developed for real time processing as the proposed classification algorithm is capable of making a prediction for every observation. In addition, the system is capable of multi-tag reading, thus, capable of multi-patient monitoring and alarming. In terms of responsiveness our system provides minimal delay, however this does not guarantee a prompt intervention from respondents (carers). Further trials are needed to establish the effectiveness of our approach as a falls prevention strategy.

The use of two room configurations shows that the use of more antennae does not necessarily improve the overall performance of the system. The use of a more focused antenna placement as in *RoomSet2* where antennae were particularly oriented towards high falls risk locations such as the bed and chair achieved higher performance as opposed to *RoomSet1* which covered a wider horizontal plane. Furthermore having a unnecessarily larger area of coverage also lead to more scattered errors due to the relatively large numbers of readings obtained from locations outside the vicinity of the bed. However having a more a more focused area of coverage makes the system more sensitive to a varying room configurations. However, given that clinical rooms in the same hospital or residential care environment have similar layouts, classifier can be trained to adapt to new conditions.

This research also demonstrates the feasibility of using the Wearable WISPs as an activity monitoring device. The use of such device is clearly advantageous as an inexpensive, wireless, maintenance free device can easily be discarded when exposed to a high risk infection environment unlike using bed rails or bed mats. The feedback given from participants in the study confirmed the device to be wearable and non-obstructive.

A practical implementation of the solution will however imply a one time infrastructure cost of deploying commercial UHF readers and antennae. Nevertheless, RFID hardware prices have been falling as RFID technology is more widely adopted. The only recurrent cost component is the tags, however, the cost of the tags are continuing to diminish. At present the W^2ISP is expected to cost around \$2 to \$3 when mass produced [24], [31].

Finally, our group is currently working on collecting information from real patients in their clinical environment to verify the performance of this study with real patient data. Our future work will also involved extending the classification algorithms to include the prediction of other risk related activities such as getting up from a chair, going to the toilet and walking without a walking aid. In order to improve classification accuracy we are currently considering support vector machine based algorithms that incorporate learning so that we can move towards a system that evolves over time.

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