Ambient Assessment of Daily Activity and Gait Velocity

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Abstract— **This paper describes novel ambient technologies for domestic gait velocity measurement and in-home daily activity monitoring. This was achieved through low cost, easily deployable passive infrared motion detectors and an unobtrusive wireless sensor network. This system was deployed in the houses of eight older adults (1 faller; 7 non-fallers) living independently over eight weeks. Inter-daily gait velocity and daily activity metrics were derived from this data set. Consistent daily rhythms were found, however no correlations to clinical or daily ethnographic data were found. Long-term data collection, particularly surrounding serious life events, would validate the ability of this system to highlight deviations in health status. This paper provides a framework for collecting, analysing and interpreting gait velocity and daily activity data.**

Keywords: gait velocity measurement; daily activity monitoring; unobtrusive monitoring; ambient sensors.

I. INTRODUCTION

The world's population is ageing and this trend is set to increase dramatically in the next 100 years. This impending demographic shift will be most acute in North America, Europe and Japan, placing a massive burden on healthcare systems. Modern technological approaches may facilitate more efficient delivery of healthcare. A move towards ambient, distributed and pervasive technologies to deliver healthcare more efficiently is proposed as a means of reducing the strain on traditional hospital based healthcare delivery systems. This will increase quality of life and independence of all patients, especially elders and those with chronic illnesses, and also serve to reduce the costs inherent in the current hospital-centric system. This will reduce the number of preventable visits to health-care professionals, provide accurate, reliable and useful clinical information and efficiently synchronise to electronic health records complimenting current health-care systems.

Falls in older adults are common and their incidence increases with age. Falls can lead to serious injury, hospitalisation, restricted mobility, and institutionalisation [1]. Various balance and mobility factors, particularly an impaired gait and mobility, an impaired stability when standing and slow voluntary stepping, have been shown to be associated with falls risk [2]. This has a negative effect on quality of life, leads to increased hospitalisation and is costly. In the community, the proportion of people who sustain at least one fall over a 1-year period varies from 28% to 35% in the over 65 age group to 32% to 42% in the ≥75 -year age group, with 15% of older people falling at least twice each year [3]. Incidence rates in hospitals are higher, and in long-term care settings approximately 30–50% of people fall each year, with 40% falling recurrently [4]. The cost of falls each year, among elderly people in the U.S. alone, has been estimated to be in the region of U.S. $20 billion [5]. The combination of high frequency and high susceptibility to injury in older people make falls a "geriatric giant" in their own right.

Common methods of falls risk assessment, including the Berg Balance Scale and the Timed Up and Go (TUG) test, are largely subjective, require clinically expertise to administer and are rarely used outside of clinical settings. While such tests do provide a cross-sectional snapshot into current health status, they do not provide an insight into circadian or inter-daily falls risk. These measurements are recorded in a clinical environment possibly resulting in data which is not representative of the real-world. For example, gait velocity measured in the clinic might not be representative of gait velocity measured in the home as patients may intentionally walk faster. It should also be noted that a changing gait is not pathological in itself; however a reduced health status may be inferred from impaired gait, slowing gait velocity or reduced daily activity.

The home-based objective measurement of gait velocity and daily activity, and their diurnal variations, might provide a more accurate assessment of falls risk. This paper describes the development and home-deployment of a low power unobtrusive wireless sensor network designed to measure gait velocity and daily activity in the home. This is achieved through a low cost, easily deployable passive infrared (PIR) motion monitoring system. An overview of the previous work done in this area is given in Section II. A description of the technologies developed and their deployment is given in Section III. Details of the gait velocity and daily activity information derived from the home-based deployment are given in Section IV. Some results are collated in Section V and a discussion is given in Section VI.

II. LITERATURE REVIEW

The clinic-based measurement of gait velocity has been well defined and its benefit, particularly for falls risk estimation, has been widely investigated. Various modalities for In-home gait velocity measurement are currently under development. A ceiling-mounted PIR-based motion detection system has been experimentally validated and compared to the clinical gold standard, a GaitRite Walkway System [6]. Advanced calibration methods ensured a high accuracy, however this may be unsuitable for mass deployment. An optical motion detecting system has been shown to measure self-selected gait velocity [7]. This technology continuously tracks the position of a person within a pre-calibrated environment (e.g. the main living area). Initial results report precise measurement of gait velocity suitable for long term

PervasiveHealth 2011, May 23-26, Dublin, Republic of Ireland

DOI 10.4108/icst.pervasivehealth.2011.246077

placement. However, it is unclear whether multiple systems are required per house and whether the cost per unit is prohibitive. This system has the ability to analyse the variability of gait velocity. Its unobtrusive nature is particularly suitable for monitoring older adults and sensitive populations.

The suitability of these technologies for long term deployment is central to their development. The ceiling-mounted PIR system measured gait velocity of fourteen older adults, seven cognitively healthy and seven with mild cognitive impairment (MCI), living independently in the community over a mean duration of 315 days [8]. A higher variation in the median walking speed and also a higher variability in daily activity patterns in the MCI group compared to the cognitively healthy controls. PIR sensors were deployed throughout the homes of 53 cognitively healthy elderly adults for approximately one year [9]. The Mini-mental state examination (MMSE) was measured before and after the study. Participants who showed a cognitive decline (MMSE < 24; n=6) at the end of the study were found to have a significantly lower number of outings as well as having a decreased indoor movement compared to individuals who remained cognitively healthy (MMSE $\geq$ 24; n=44). A PIR based system capable of extracting spatiotemporal patterns typical of daily activity was deployed in a domestic environment for thirty days [10]. In this study, a relatively large number of 15 motion sensors were deployed in the environment. This resulted in a descriptive model of their frequent daily activities and patterns, such as *sleep ->bath -> breakfast*. Longitudinal analysis of such data, collected over extended periods, could provide valuable insights into health status and wellness.

III. Methods

A. Subjects

Data was collected from eight (1M, 7F) older adults (aged 67-87). Patients were recruited as part of a wider study on aging (www.trilcentre.org) and each received a comprehensive psycho-social assessment including a 3m over-ground walking trial across an electronic walkway (GAITRite Inc.). Patients walked at a self-selected comfortable walking speed, these data are used here as a baseline for habitual walking speeds. 1 patient had self-reported history of falling ('fallers') in the past 5 years, whereas 7 patients had no history of falls ('non-fallers'). Inclusion criteria were patients aged 60 years and older and able to understand the instructions. The system was deployed over an eight week period.

TABLE I. PARTICIPANT DEMOGRAPHICS AND FUNTIONAL CHARACTERISTICS

ID	Age	Sex	#PIRs	#PIR Hits	#Days	#Vel. Rail Hits	Mean Gait Vel. (m/s)	St Dev Rail Vel. (m/s)	GAITRite Vel. (m/s)
074	84	F	4	1511	39	178	1.03	0.59	0.94
140	87	F	6	6094	36	614	0.97	0.76	0.42
149	83	F	6	160	7	11	1.07	0.55	0.49
300	70	F	7	8720	41	273	0.71	0.46	0.44
321*	72	F	6	6377	49	598	0.85	0.52	1.31
378	70	F	8	5736	45	458	0.34	0.22	0.67
386	83	M	8	1861	29	0	-	-	0.95
409	67	F	6	7077	43	384	1.2	0.92	1.4

* indicates faller

B. Data Acquisition

Data were collected from PIR sensors in two configurations:

1. Dwell sensor – individual PIR sensors strategically placed to determine frequency/duration of activity in the detection area or 'dwell-zone' of a given sensor
2. Velocity rail sensor – three equally spaced, collinear PIR sensors mounted on a bespoke plastic rail.

1) Dwell Sensor: Each dwell sensor consisted of a Shimmer wireless sensor [11] with a PIR daughter board (Panasonic NaPiOn Passive-Infrared motion sensor). Motion events were timestamped using the 32.768 kHz piezoelectric crystal on the Shimmer, and recorded temporarily onto RAM as movement was registered by the PIR motion sensor. Data from each sensor were collected from multiple locations within each home and transmitted wirelessly on an hourly basis, via the low-power 802.15.4 radio to a central aggregator within each house. Multiple units were deployed in the home of each participant. The exact number of PIR Shimmers deployed in each home, was dependent on the size and layout of each house (see **TABLE I**). Each PIR Dwell Sensor was placed on the ceiling over frequently passed locations such as the lintel of the bathroom door. The field of view of the PIR is conical in shape and by default covers a large area. An aperture covering was used to restrict the 'dwell-zone' of each PIR. In laboratory tests it was found that each PIR sensor continued to fire even after the person has exited the dwell zone of the PIR. However, it was found that the initial triggering time of the PIR dwell sensors could be relied upon.

2) Velocity Rail: Three PIR dwell sensors were mounted, equally spaced on a horizontal custom built rail which allowed the estimation of habitual in-home velocity as shown in Figure 1. Each of the three PIR dwell sensors were triggered sequentially as a person walked past the rail. Each rail was 2m in length except where the layout of the particular house confined this length. All events on each PIR sensor events were synchronized relative to one Shimmer and logged along with a timestamp onto an SD card. These data were transmitted hourly to the central aggregator. Valid gait velocity data was recorded on seven of the subjects; data collection errors resulted in no gait velocity measurements being recorded from one patient.

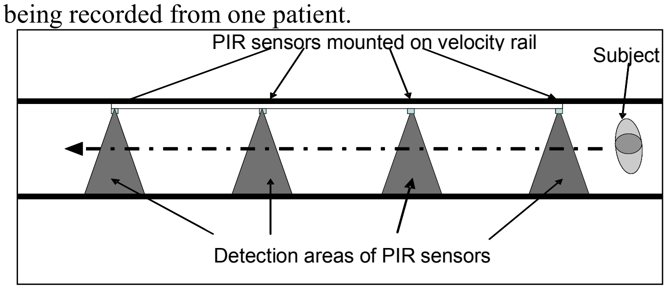

Fig. 1. Velocity Rail Schematic.

C. *Analysis*

1)*Data Gait Velocity Algorithm:* As the distances between the first and second, second and third, and first and third PIRs are known, the time between each PIRs first trigger time can be used to calculate velocity as a person walks past the rail. The mean of these three velocity values was recorded as the gait velocity for a given gait event. The PIR dwell sensors registered motion detection beyond the initial triggering and continued to fire after the patient left the detection area of the PIR. Thus, only the first triggering of each individual PIR was used. The following checks were used to ensure valid walks: a) all three PIRs must trigger consecutively in the correct order, b) packets from each PIR are consecutive and any walk containing missing PIR motion event packets are discarded, c) a refractory period in assessing gait velocity is implemented, and d) gait velocity must be less than 4 m/s. Full details concerning the PIR Dwell Sensor data collected can be found in Table II.

4) Collection Unit and Communications Protocol: Data were collected on the aggregator (*Dell Inspiron 1501 laptop*) running custom UDP server software over the 802.15.4 radio. . To ensure low powered operation on the sensors a protocol was defined to accept the transfer of data hourly from each pre-defined Shimmer existing within the environment, keeping the radio active for a minimal amount of time. A custom syncing packet was sent to the aggregator unit at the beginning of the hourly data transfer from each PIR dwell sensor. This process was used to time-lock the PIR Dwell event data with the aggregator's internal clock. All PIR dwell event data within the environment were timestamped relative to this computer. Data were transmitted during separate pre-defined windows of time because all transfers shared the same 802.15.4 RF channel. Each device and the data collection equipment were checked remotely from a backend console that communicated with all home aggregators. This allowed for the monitoring of the operating status of deployed equipment and for fixing any technical issues that arose during deployment.

5) Ethnographic and patient diaries: Each patient was asked to provide self-reported scores (1-5) for mood, dizziness, energy, steadiness and wellness both in the morning and in the evening. Other information was also recorded in a diary including amount time spent out of the house, details of any visitors coming to the house, details of any falls occurring and any changes in daily routine. Space was also provided for any other comments the participant may have such. These data were reviewed manually during analysis.

IV. Data Analysis

A. *Velocity Rail*

1) Gait Velocity per patient per day: The mean gait velocity for each patient per day was derived from the velocity rail. The mean and standard deviation of gait velocity per day was calculated as shown in Figure 2. These data were highly variable and no discernible patterns across days were evident.

2) Gait Velocity per patient per hour: Circadian variations in gait velocity were also investigated (Figure 3 illustrates circadian variations). The mean velocity and standard deviation can be seen over each day. No discernible patterns were evident across all data, although some subjects did show a slower gait velocity early in the morning and before bedtime. There was a mean of 12.5 gait velocity events recorded over 7 subjects over 201 days. No valid gait velocity data was recorded for one patient.

3) Longitudinal Distribution of Gait Velocity Measurements: The distribution and magnitude (mean velocity per hour) of gait velocity measurements over a day can be seen in Figure 4. A period is evident during the final ten days of data collection where no valid gait velocity measurements were recorded by the velocity rail. Upon examination it was found that this was due to errors in the communications protocol. As expected, no gait velocity events were recorded between the hours of 2am and 8am. The magnitude of the gait velocity for each hour is shown in the colour bar. If no gait velocty is recorded this is because no gait velocity hits were recorded as seen over all hours towards the end of the recording period in Figure 4.

TABLE II. PARTICIPANT GAIT VELOCITY CHARACTERISTICS

ID	Age	Sex	#Rail Hits	#Days	GaitRite Velocity	Mean of Daily Rail Velocity	Mean SD of Daily Gait Velocity
074	84	F	178	35	0.94	1.03	0.59
140	87	F	614	36	0.42	1.23	0.76
149	83	F	11	1	0.49	1.95	0.55
300	70	F	273	38	0.44	0.88	0.46
321	72	F	598	32	1.31	0.83	0.52
378	70	F	458	24	0.67	0.29	0.22
386	83	M	-	0	0.95	-	-
409	67	F	384	35	1.4	1.33	0.36

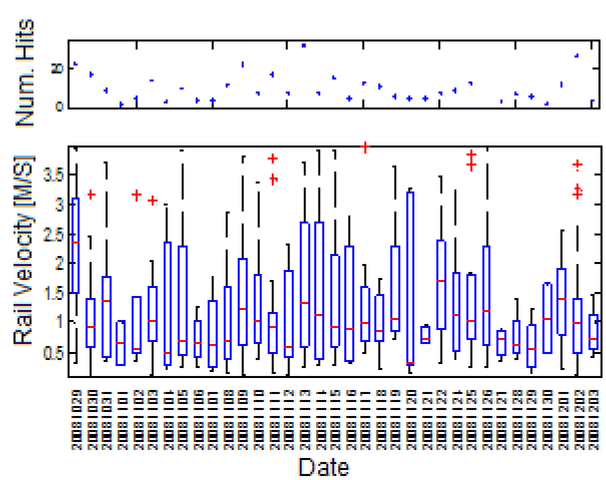

Fig. 2. Gait Velocity per Patient per Day for subject 409.

B. PIR Dwell Sensors

1) PIR dwell sensors: The PIR dwell sensors were deployed at highly frequented locations within a house. Between 4 and 8 PIR Dwell Sensors were installed in the environment on either ceilings, lintels of doorways or in the velocity rail. A PIR dwell sensor 'hit' occurs when motion is first detected by that sensor. A refractory period was used to concatenate multiple hits within a limited time span as these would result from the same set of movements. Full details concerning the PIR Dwell Sensor data collected can be found in Table III.

2) Dwell Time: The time taken to travel through a PIR Dwell Sensor's detection area was proposed as a method of estimating velocity and was referred to as 'Dwell Time'. It was found upon initial investigation that the entry time into dwell zone was accurate and reliable. However, the exit time could not be located as the PIR Dwell Sensor continued to fire after the patient had left the dwell zone. 'Dwell Time' was not examined subsequently.

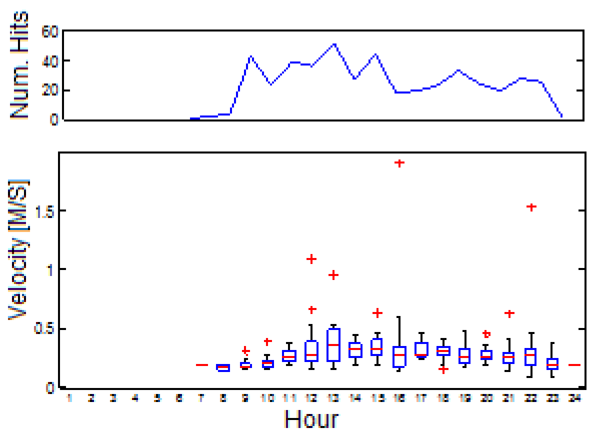

Fig. 3. Gait Velocity per Patient per Hour averaged over all Days for subject 378.

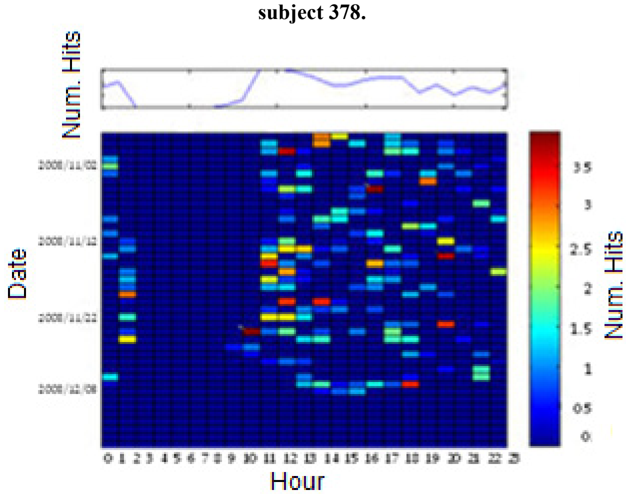

Fig. 4. Longitudinal Distribution of Gait Velocity Measurements for subject 409.

TABLE III. PARTICIPANT PIR DWELL SENSOR CHARACTERISTICS

ID	Age	Sex	#PIRs	#PIR Hits	#Days	Mean #Hits per Day	SD #Hits per Day	Min #Hits per Day	Max #Hits per Day
074	84	F	4	1511	39	37.8	33.5	4	124
140	87	F	6	6094	36	171.6	89.7	57	404
149	83	F	6	160	7	22.2	14.1	8	43
300	70	F	7	8720	41	214.3	146.4	41	952
321	72	F	6	6377	49	129.6	49.8	43	243
378	70	F	8	5736	45	128.4	53.8	50	268
386	83	M	8	1861	29	63.3	41.8	1	166
409	67	F	6	7077	43	166.9	67.7	3	294

3) PIR dwell sensor hits per Day per Patient: The total number of PIR dwell sensor hits per day per patient was extracted from the data set. An example of this can be seen in Figure 5. Towards the end of data collection the patient was away from the house for two days. This can be seen by the very low number of PIR dwell sensor hits in Figure 5.These sensors quantified levels of daily activity within the home, however due to the unique nature of each house no cross comparison across patients could be made. An investigation into the variation in daily patterns within each patient's data was performed and no discernible patterns were evident.

4) Location Specific PIR dwell sensor hits: The locations of PIR dwell sensor hits were also examined. An example of this can be seen in Figure 5. The sensor placed at the lintel of the kitchen door suffered from data collection errors resultant due to the zigbee communications protocol. Data integrity checks were performed every two weeks during this study. The variation in the amount of activity at a particular location did not result in any discernible pattern.

5) Circadian Distribution of PIR dwell sensor hits: Estimations of the circadian aspect of daily activity, within the home, were derived using this system, see Figure 6. However, it must be noted that a very limited number of PIR dwell sensors were deployed in each house and as such this may not be fully descriptive of daily activity.

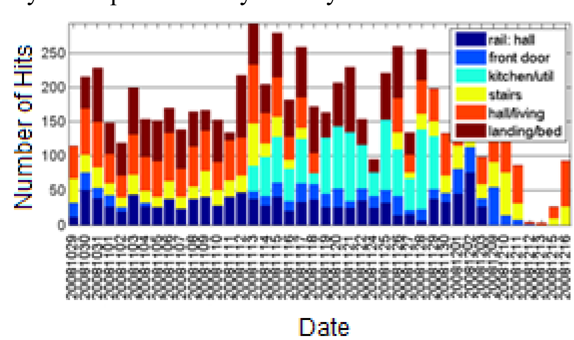

Fig 5. PIR dwell sensor hits per Day, Separated into PIR Locations for subject 409.

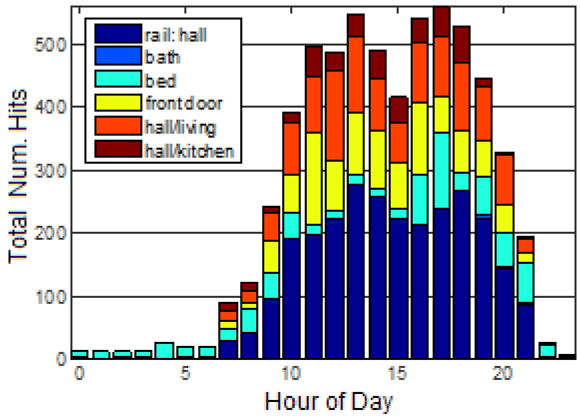

Fig 6. Circadian Distribution of PIR dwell sensor hits for Subject 140.

6) Longitudinal Distribution of PIR dwell sensor hits: Methods of describing and visualising the mean daily activity patterns of an older adult in their home are described above. A longitudinal description of their daily activity is given in Figure 7. An actogram representation of this activity is given in Figure 7A, while a polar plot is also shown to represent this data well. Toward the start of data collection, a significant number of PIR dwell sensor hits were reported over a twenty hour period. Upon further investigation,it was found that this was due to a faulty PIR sensor which continually reported motion.

7) Interdaily Circadian Stability Index: A stability index of the circadian rhythms,in terms of daily activity, of the older adults were calculated using the number and circadian distribution of PIR dwell sensor hits. This index was modified from inter-daily stability metrics which use wrist actigraphy to examine the changes in total daily activity over time [12]. In this analysis, the variances of hourly number of PIR dwell sensor hits was calculated per seven days of data and subsequently normalised by the total number of PIR dwell sensor hits over those seven days. This was defined as the inter-daily circadian stability index. Significant changes in total daily activity, and the distribution of this activity throughout a day, may be representative of a reduced health status. This data is presented in Table IV. An outlier can be seen in week 1 for patient 300. Upon investigation it was found that this deviation in circadian stability related to a faulty sensor, see Figure 7.

8) Location of PIR dwell sensor hits: The total daily activity,and distribution of activity throughout a day, of an older adult may remain the same. However variations in the location of activity may provide valuable insights, such as an increased use of the bathroom throughout a day or excessive time spent in one location, indicaing possible injury or impairment. The average location of PIR dwell sensor hits over the entire data collection period for a patient can be seen in Figure 8.

9) Room Transition Information: The PIR dwell sensor data contain information about how the participant moves about the home. This can be extracted by tracking consecutive firings of the PIR dwell sensors over the recording period. Room transition information between PIR dwell sensors were investigated in order to examine common room transitions/habitual pathways. The usage of these pathways and also the time taken to travel between each PIR dwell sensor pair were calculated. A room transitioning quasi-velocity measurement was calculated as the inverse of the time

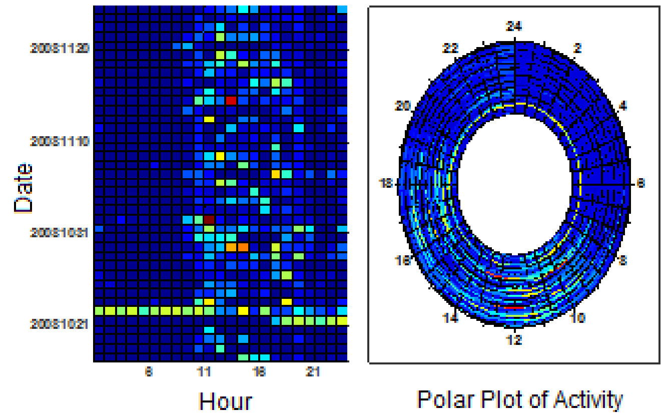

Figure 7. Longitudinal Distribution of PIR dwell sensor hits. (a) Actogram of PIR dwell sensor hits for subject 300 on left, (b) Polar plot of PIR dwell sensor hits on right.

TABLE IV. INTER-DAILY CIRCADIAN STABILITY INDEX

Sub ID	Age	Sex	Interdaily Circadian Stability Week 1	Week 2	Week 3	Week 4	Week 5
074	84	F	1.49	1.33	3.21	1.76	0.78
140	87	F	2.17	3.57	2.67	1.78	1.66
149	83	F	-	-	-	-	-
300	70	F	5.08	2.22	2.94	1.95	2.32
321	72	F	1.39	1.01	1.36	1.63	1.52
378	70	F	1.67	1.67	0.76	1.26	-
386	83	M	1.28	1.22	1.29	0.82	-
409	67	F	1.8	1.53	2.34	2.27	2.34

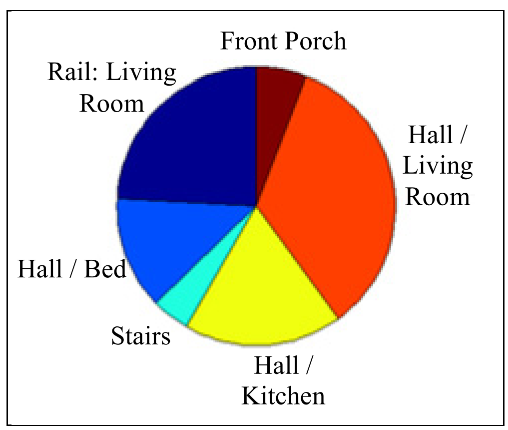

Figure 8. Location of PIR dwell sensor hits for subject 321.

taken to travel between two PIR dwell sensors. To ensure validity, each sensor was required to have fired continuously for at least ten seconds. A PIR room transition was defined to occur when two sensor hits occur within a limited time frame (empirically chosen to be 600 seconds). Data generated using these conditions, from patient 300, are presented in Figure 9; the relevant house floorplan for these data is given in Figure 10. The average time taken for room transitions are given in Figure 11.

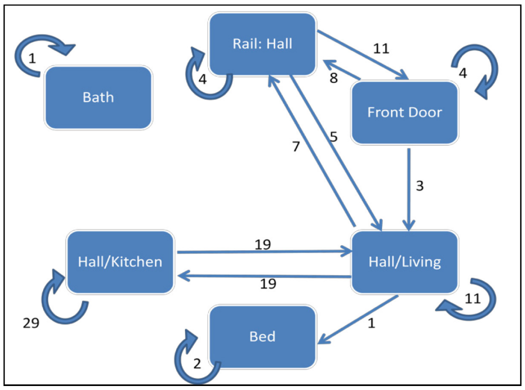

Figure 9. Room Transition Information for patient 300 over the entire recording period. The number of transitions between rooms is highlighted.

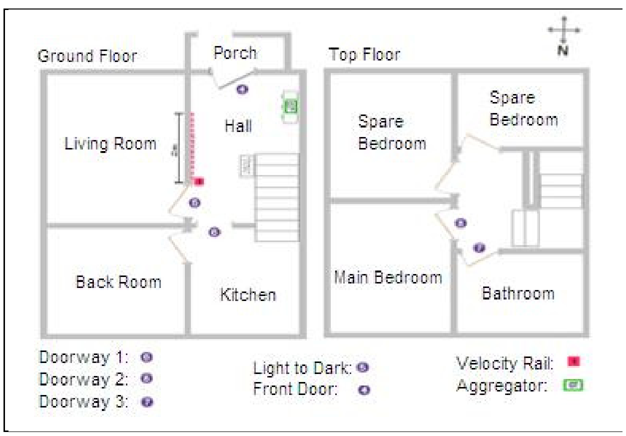

Figure 10. House Layout for Patient 300

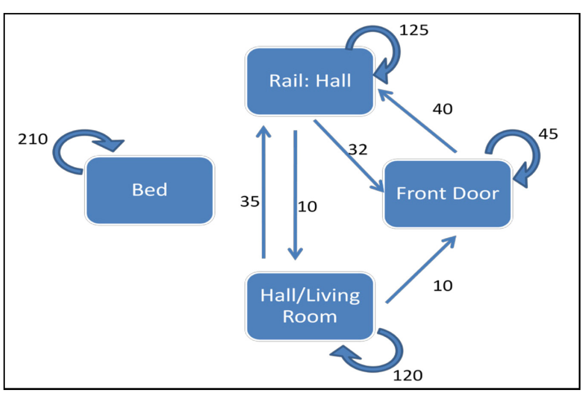

Figure 11. Room transition information for patient 140 over the entire recording period. The time taken to transition between rooms is highlighted.

C. *Ethnographic Information*

Mood, dizzy, energy, steadiness and wellness subjective data were collected twice daily (morning and evening) using a diary. Little variability was found in these data over the data collection period for each patient. This low variability suggests these metrics are ineffective; however this may be due to several other reasons. These include participants retrospectively filling out entries for multiple previous days at once to appear to adhere to the prescribed protocol, participants entering high scores falsely in order to appear healthier (to others and to themselves), or a participant's lack of understanding of the metrics.

V. Results

A number of hypotheses were tested for significance using the collected data set.

1. The velocity value produced by the rail velocity did not significantly correlate to a PIR room transitioning quasi-velocity measurement (the inverse of the time taken to travel between PIR Dwell Sensors).
2. The velocity rail data (both velocity and number of hits) did not correlate to any of the ethnographic metrics.
3. The number of hits on the velocity rail was not correlated to the number of PIR dwell sensor hits.
4. The room transitioning quasi-velocity or velocity rail velocity did not significantly correlate to ethnographic data or clinical data (including age, body mass index, timed-up-and-go test, activities of daily living (ADL) index, instrumented ADL index, and the mini-mental state examination).
5. Any of the PIR-derived activity metrics did not significantly correlate to ethnographic or clinical data.
6. A correlation suggesting significance was found between mean gait velocity and age, however further investigations would be required to substantiate this claim.
7. No significant difference in gait velocity or variation of gait velocity was found between the faller and non-fallers.

VI. Discussion

The deployment, amongst an independent elderly population, of an in-home gait velocity and daily activity monitoring system is discussed in this paper. A velocity rail was developed using three equally spaced PIR dwell sensors, and a logical algorithm to extract the gait velocity of a patient walking past. An ambient, low-power network of PIR dwell sensors measured activity within the home for a mean of 36.13 days over eight people. All metrics were analysed on a per-day basis, averaged per-hour, longitudinally and, where applicable, on a per-location basis. Higher-level metrics including the stability of circadian activity were extracted using this system as well as information regarding the transition between locations, including a quasi-velocity metric. A framework for recording gait velocity and activity metrics was also developed.

Long term analyses will be able to investigate any correlation between deviations in these metrics from baseline with overall health status.

This system was implemented using an 802.15.4 ZigBee communications protocol. All data was transferred using the same frequency staggered in time. This led to a strict setup protocol resulting in difficulties during data collection. Another source of error resulted from out-of-range PIR dwell sensors continuously attempting to connect to the basestation. This resulted in interference with other PIR dwell sensors in-range and led to multiple sensors failing. A resolution to packet interference could be found using a frequency hopping protocol although this may reduce the battery life of each wireless sensor. Testing should be carried out in simulated or test environments over a similar duration as the study. While experimental testing of this system (including the protocol) was successful, a well defined installation procedure must be carried out to ensure valid data collection. However, it must be noted that such experimental testing cannot cater for all real-world eventualities.

Similar research by OHSU details similar PIR-based gait velocity measurement systems [8,13,14]. Calibration of this system results in a high accuracy when compared to the GAITRite Walkway System [6]. However this is not efficiently realisable for large scale deployment as each system must be individually calibrated prior to operation in each environment with each particular participant. An extension of this system estimates bed entry/exit times [15]. However, it must be noted that this relates to the time at which activity in the house declines, not specifically to when sleep begins/ends.

There is an inherent difficulty in ensuring that all movement profiles under analysis relate specifically to the particular resident under analysis, and not visitors or other residents in the environment. Radio frequency identification (RFID) has provided a means of circumventing this issue, however its long-term practicality or suitability for sensitive populations is questionable. In respect of this a fully ambient system was developed. Older adults living alone were included in the study and daily records of visitations were kept in an attempt to ensure valid data collection. However, this places a reliance upon retrospective diary entries, which inherently is not ideal. The accuracy of retrospective entries relates to how far back in time the visitation entry refers to from when the entry is logged by the participant. This can be further complicated by compliance issues, such as the participant entering data relating to previous days and reporting the current date falsely in order to be seen to adhere to the prescribed protocol. This problem is symptomatic of ambient monitoring systems in general and a well defined and thought-out methodology must be designed in order to ensure that results are not negatively affected.

No significant correlations existed in this data set between health status (inclusive of clinical and ethnographic data) and gait velocity measurements or the derived metrics of daily activity. This may be more indicative of the overall positive health status of the participants in this study during the recording period. In order to clinically validate the benefits of this system, the collection of data surrounding both serious life events and longitudinal declines in overall health status is required. A longer term study over a larger cohort, such as that presented by Suzuki et al. [9], would provide more definitive results. The mean in-home gait velocity measurement did not show a strong correlation to the clinical gold standard (GAITRite Inc. Walkway System). This suggests that a clinical assessment does not provide an adequate estimate of the degree of diurnal and daily variation in gait speed. The participant's velocity is different when measured in the clinical setting than that measured in the home as seen in Table II. This may be due to inter- and/or intra- daily variations. The clinical measurement of gait speed may suffer from the white coat effect (i.e. the patient may walk faster in the clinic as they are being watched by a healthcare professional). Similarly other inter- and intra- variations were found, such as deviations in the minimum and maximum number of hits per day, in activity monitoring, and in the distribution of the activity. These are likely reflective of the participant and their life during the recording period. A longer study duration over a larger cohort will provide a deeper understanding of how daily activity and gait velocity relate to the health status.

An ambient monitoring approach to in-home monitoring provides minimal intrusion, is more suitable for sensitive populations and also requires less user interaction minimising user non-compliance. However, such technology suffers from an inability to distinguish participants (a problem inherent to its unobtrusive and non-contact design). The benefit of in-home self selected gait velocity monitoring remains under analysis, despite gait velocity being indicative of pathological changes. A long-term data set collected over various cohorts would inform us of the association between falls risk, overall health status and wellness with gait velocity and daily activity. This paper presents an easily deployable system capable of longitudinally analysing gait velocity and daily activity information. A number of metrics and visualisations of this data is also presented.

ACKNOWLEDGMENT

This research was completed as part of a wider programme of research within the TRIL Centre, (Technology Research for Independent Living). The TRIL Centre is a multi-disciplinary research centre, bringing together researchers from UCD, TCD, NUIG & Intel, funded by Intel, GE and IDA Ireland. (http://www.trilcentre.org). We also acknowledge the help and support of the staff of the TRIL Clinic, St James, hospital, Dublin and the participants involved in this study.

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