Visualisation of Movement of Older Adults within their Homes based on PIR Sensor Data

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***Abstract*—As the population lives longer, the number of people beyond the age of retirement is rising. Additional support is required to monitor the health of this aging population to ensure early detection of age related illnesses and accordingly to maintain wellbeing. Ambient sensors, such as those used in Great Northern Haven (GNH) residences, allow for continuous monitoring in an unobtrusive manner. In this paper we present visualisations of sensor data drawn from passive infra red (PIR) sensors located in three areas, i.e. the living room, hallway and main bedroom, in each of twelve independent living apartments. This representation of residents' movement can be used to infer changes in movement patterns over time.**

Keywords-AAL; visualisation; PIR sensors, aging in place

I. Introduction

It is a well discussed hypothesis that as people age it is crucial to employ regular monitoring in order for early signs of age related illnesses to be identified and treated [1, 2], ensuring wellbeing is maintained. As indicated in [3], subtle changes in a person's behaviour can provide early indications of age related decline. Integrating unobtrusive, ambient sensors into a person's living environment and supplementing with data analysis techniques may provide an efficient way to provide the necessary monitoring required for older people to "age in place". In this paper we describe the visualisation of data using passive infra red (PIR) sensors installed in twelve independent living apartments. The resulting visualisations represent movement levels of the residents over a period of 7 months and 17 days.

Great Northern Haven (GNH) is a purpose-built complex in Dundalk, Ireland which consists of sixteen independent living apartments. Each apartment has been integrated with a series of ambient sensors and actuators, 2240 within GNH overall, intended to monitor and support its residents. The integrated sensors include PIR sensors, contact sensors on all windows and doors, sensors on all light switches as well as electricity and water usage meters. This setup could be replicated easily in homes across the world. To date there are fifteen permanently occupied apartments, with residents aged 58 to 86. Among the permanent residents of GNH there is one multiple occupancy apartment, in which a married couple reside, with the remaining apartments being occupied singly, accommodating 10 men and 4 women. Pets are not allowed by the building management company. As a result the uncertainty which they could introduce is reduced. Residents suffer from a wide range of illnesses including heart conditions; diabetes; depression; bipolar disorder; with one resident having previously suffered a stroke and another having suffered from cancer. The sixteenth apartment is designated as a transition unit for falls prevention. As this apartment is only occupied for short periods it allows for it to be used for testing when vacant.

Existing ambient assisted living (AAL) research groups focus on the analysis of synthetically generated data or data collected within a lab environment over a limited period [4]. Others have installed ambient sensors within people’s homes for a period of a few months, presenting a limited dataset for behaviour monitoring [5]. Other research groups [6] focus on providing assisted living residences as an alternative for those who would otherwise have been moved to nursing homes. These provide researchers with less natural datasets which, it could be argued, are not representative of regular people aging in place. As GNH is the residents' permanent home this offers a valuable insight into older adults living independently. In this way, Great Northern Haven provides us with a novel dataset relating to older adults carrying out their normal daily activities.

The quality of the sensor data has been verified through a number of quality measures, discussed in section III. In this paper we focus particularly on PIR sensors which fire when movement is detected, remaining "on" as long as movement is being detected, before finally turning off 10 seconds or less after movement has stopped. Existing research groups [6] use PIRs that periodically fire, allowing them to represent movement using the number of sensor fires. The ability of our PIR sensors to remain "on" while movement is ongoing allows us to infer the number of seconds of movement more accurately. This results in a decidedly clearer picture of a person's movement within their apartment. It may be noted that while we initially focus on PIR sensors to detect movement our future work will involve the integration of further sensors to improve the inference of routine activities. For example, if movement is detected in the hallway, directly followed by the bathroom light being switched on, the bathroom door being closed and a period of inactivity in the hallway it may be inferred that someone is using the bathroom. The integration of data from sensors on doors and light switches, in addition to PIRs, can assist in determining when an individual makes a trip to the bathroom. While the integration of further sensors may improve activity recognition we acknowledge that not all individuals perform tasks how we might expect, as a consequence it may be difficult to definitively conclude that a

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certain activity is taking place and, in some cases, activities may be missed.

This paper is important in that it presents and discusses an approach to visualising movement based on real, extensive and reliable data for twelve single occupancy residential units in a traditional living environment. The visualisation of the movement time is presented on a room by room basis, which is particularly useful at identifying patterns in night time and sleep behaviour. Finally, the paper shows how the visualisations can help identify medium term changes in a resident's behaviour over time. Such visualisations could assist healthcare professionals in detecting deviations from normal behaviour. As such our future work will involve the use of cluster analysis to identify abnormal events, known as outliers. To ensure visualisations are a viable resource for healthcare professionals we plan to automate the process of clustering and visualising the resident's activities.

The remainder of the paper is structured as follows. In section II we will consider related research. In section III we will discuss the data analysed with particular focus on data quality. We will present our visualisations in section IV, which we will discuss in section V after which we will present our conclusions in section VI.

II. Related Research

Living labs have been developed in recent years in response to the demand for ambient assisted living. They allow smart home technologies to be integrated, tested and deployed within a controlled environment which has a similar setup to a regular apartment or house. Some examples of living labs include MavHome [7], Gator Tech Smart house [8] and PlaceLab [9].

Ongoing research taking place in Orcatech [10] relates to the unobtrusive monitoring of motion [11] and sleep patterns [12]. In [11] the authors describe the unobtrusive monitoring of elders using motion and contact sensors in order to determine location, walking speed and daily activities to facilitate the detection of early changes in cognitive function. An individual was monitored over a period of several months, with particular focus on the period between the time the individual got up and 12pm. The raw data was analysed to eliminate errors, which may result from simultaneous transmission by multiple motion sensors. Although it appears to be an effective means for monitoring motion, evaluation over a longer duration is required to determine if it fulfils the authors objective of detecting early changes in cognitive function. In [13, 14] the authors describe the use of four ceiling mounted PIR sensors used to analyse gait. The use of four sensors within the same room, providing the solution to one problem, is an impractical and expensive long term resolution.

In [15] the authors present activity recognition of data collected within three disparate setups: the two story home of two adults and their pet; CASAS smart home testbed [5]; and three single occupancy apartments within an assisted care facility. These datasets cover a period of between two and three months. Activity recognition was carried out and visualisations representing activities of daily living were presented. Uncertainty was introduced by working with multiple occupancy. While the on-campus testbed provides a controlled environment for observation and detection of activities of daily living it doesn't offer a true representation of people's routine activities.

The work ongoing at University of Missouri (MU) [6, 16, 17] is most closely related to our work. Their data comes from a 31 unit facility housing older people who would have otherwise had to move to a nursing home (residents' demographics have not been presented). Consequently they are required to provide on-site support from healthcare professionals, such as nurses and physical therapists. They also have staff responsible for maintenance, housekeeping, transportation and dining services and social activities are scheduled regularly. The authors represent all motion sensor events within one visualisation [6]. This doesn't allow for the identification of the location of movement in the house. The introduction of multiple occupancy as well as pets brings with it uncertainty. In [17] the authors present an algorithm to identify, and resultantly remove, instances of multiple occupancy. It is suggested that it is not as effective if the visitor is not highly active and as a result may miss some visitor events. As such the removal of visits improves uncertainty but does not eliminate it completely. If multiple occupancy occurs regularly it may result in certain periods being ignored. In addition, various questions relating to data validation do not seem to have been addressed by the authors in the published literature. The authors have not put forward the quality measures considered; each sensor's expected output; and their degree of error. If verification has taken place, they have not stated if these quality measures have been achieved for all data considered.

Our setup differs from those presented in that the residents live independently—without support from medical practitioners. Various social clubs meet on a weekly basis and excursions are organised every six weeks. These are available to the residents of GNH although attendance is optional. Subsequently attendance by residents has been poor to date. This results in data which closely relates to real life setups. While the residents may have visitors, we feel they would most likely be present during the day. Hence our future focus will relate to night time behaviour.

III. Data Analysed

As mentioned previously, for the purposes of this paper we consider twelve single occupancy apartments. The participants included 9 male and 3 female residents, aged between 61 and 86 years. Three apartments have been excluded from our study. One as a result of multiple occupancy, while two others were unoccupied for the period being considered. Given the scope of the paper we consider visualisations for three residents in particular which most clearly portray diverse activity levels and routines among residents.

The PIR sensors were originally located in the corner of the living room, facing the main entry point to the apartment and in the corner of the bedroom. While these picked up on most movement within the rooms they missed out on transitions between rooms. Consequently movement from the living room through the hallway into the bedroom was often missed. The location of these sensors was changed on 18th April 2011. The new placement, visible in Fig. 1 above the living room door,

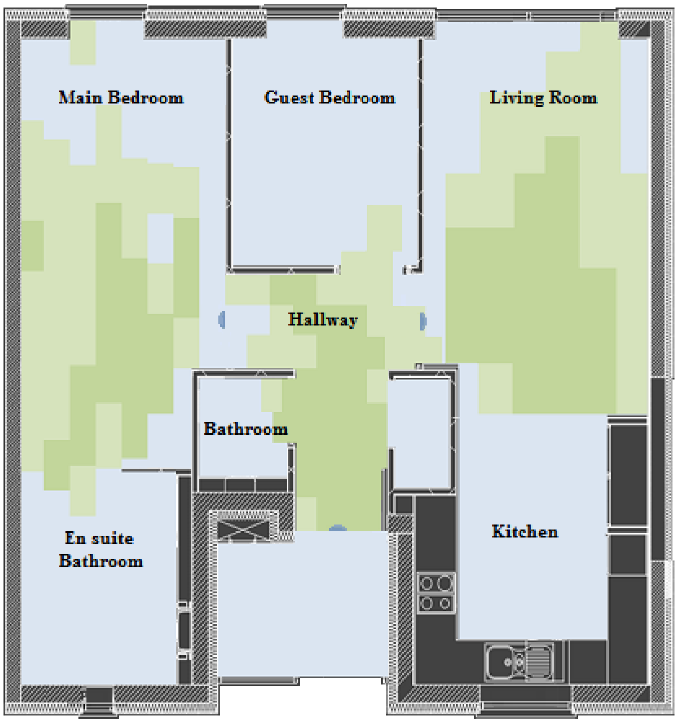

Figure 1. Visibility of the PIR sensors throughout GNH apartments

above the main hallway door and above the bedroom door, recognises these transitions between rooms. While data has been collected from GNH apartments over a period of 20 months, beginning in June 2010, for the purpose of this paper we consider the period after the sensors were relocated between 19th April and 5th December 2011.

Fig. 1 shows the visibility of the PIR sensors throughout the apartment. Each of the PIRs is denoted by the dark blue semi circle, with the curved end pointing out into the room. The darker green areas are visible to even the subtlest of movements, the PIRs pick up movement to the lighter green areas but not subtle movements within these areas and the pale blue areas are blind to the PIR. Furniture is normally placed in the blind areas in the living room, hallway and bedroom. The kitchen, guest bedroom and two bathrooms are blind to the PIRs.

Significant validation has been carried out on all sensor data to ensure a high quality of data is maintained. The following paragraphs outline some of the validation checks performed.

The first of these quality measures relates to data loss, specifically in verifying that none of the days included in the visualisation is missing data. Each apartment has one electricity sensor which should periodically fire every 12 seconds. By verifying that each individual electricity sensor has approximately 7200 records for each day this provides strong validation as to whether data has been lost or not. If there are significantly less electricity records it could mean that the system crashed and will result in other sensors suffering from similar data loss. Any day which doesn't comply with this measure was excluded from the dataset. Resultantly 3rd May was excluded from our analysis as data loss was experienced during the two hour period between 10am and 12pm.

Our second quality measure relates explicitly to verifying that the PIR sensors were working correctly for each day. PIR sensors may be verified against each other. For instance no two sensors should pick up the same movement. Secondly, transitions between rooms should be detected. If, for example, movement ceases in the living room we would expect the PIR in the hallway to detect movement prior to the PIR in the bedroom. The PIR sensors used in all apartments in GNH output values of 1 or 0. Each PIR sensor should fire with a value of 1 when movement is detected, changing to a zero value after motion has stopped. The data included in the visualisation has been verified to ensure that a value of 0 should always follow a value of 1. The PIR sensor issues an end of movement output value of 0 exactly 10 seconds after the last detected movement. This cutoff time was validated experimentally. In calculating the movement time we have subtracted 10 seconds from each PIR firing interval to ensure the time duration covers only real movement.

IV. VISUALISATION

We use density map visualisations [6, 17, 18] to illustrate the extent of movement of each of twelve GNH residents. One hour blocks depicted the clearest representation of extent of movement, as well as being most effective in portraying deviations from normal behaviour. Therefore we chose to present the days movement by hour (horizontal-axis) and day (vertical-axis), but also by sensor location, i.e. living room, hallway and bedroom. Each week is grouped from Monday to the following Sunday, the transition is highlighted by a thin red horizontal line signifying the beginning of each week. Eight hour blocks are grouped using vertical grey lines. Each box is coloured to indicate the duration (in seconds) of movement within that hour, white corresponds to the shortest amount of movement possible per hour, i.e. zero seconds; while black corresponds to the longest amount of movement possible per hour, i.e. 3600 seconds. Fig. 2 portrays visualisations of all PIR sensors relating to two GNH residents over a period of one month (June 2011). The two most notably distinct patterns between individuals are movement during the hours of sleep and periods of inactivity. We next introduce and discuss the visualisations for two sample residents for a single month.

A. Sleep

In Fig. 2 we see that resident A consistently goes to bed between 11pm/12am and 8am/9am. The sleep schedule of resident B, however, is much more changeable, with their bed time generally ranging from midnight to 4am until 8am to 11am. While resident A appears to have a consistent duration of sleep resident B's again is quite varied. It is, however, apparent that resident A has more movement than resident B throughout the night. This regular movement is clearly visible in the visualisation of resident A in the form of yellow coloured blocks. This is particularly evident in the early part of the night and may result from the resident finding it difficult to fall asleep, alternatively they may result from the resident reading or watching television in their bedroom before going to sleep. Movement ranges from less than a second of movement to 170 seconds of movement suggesting that, while movement is

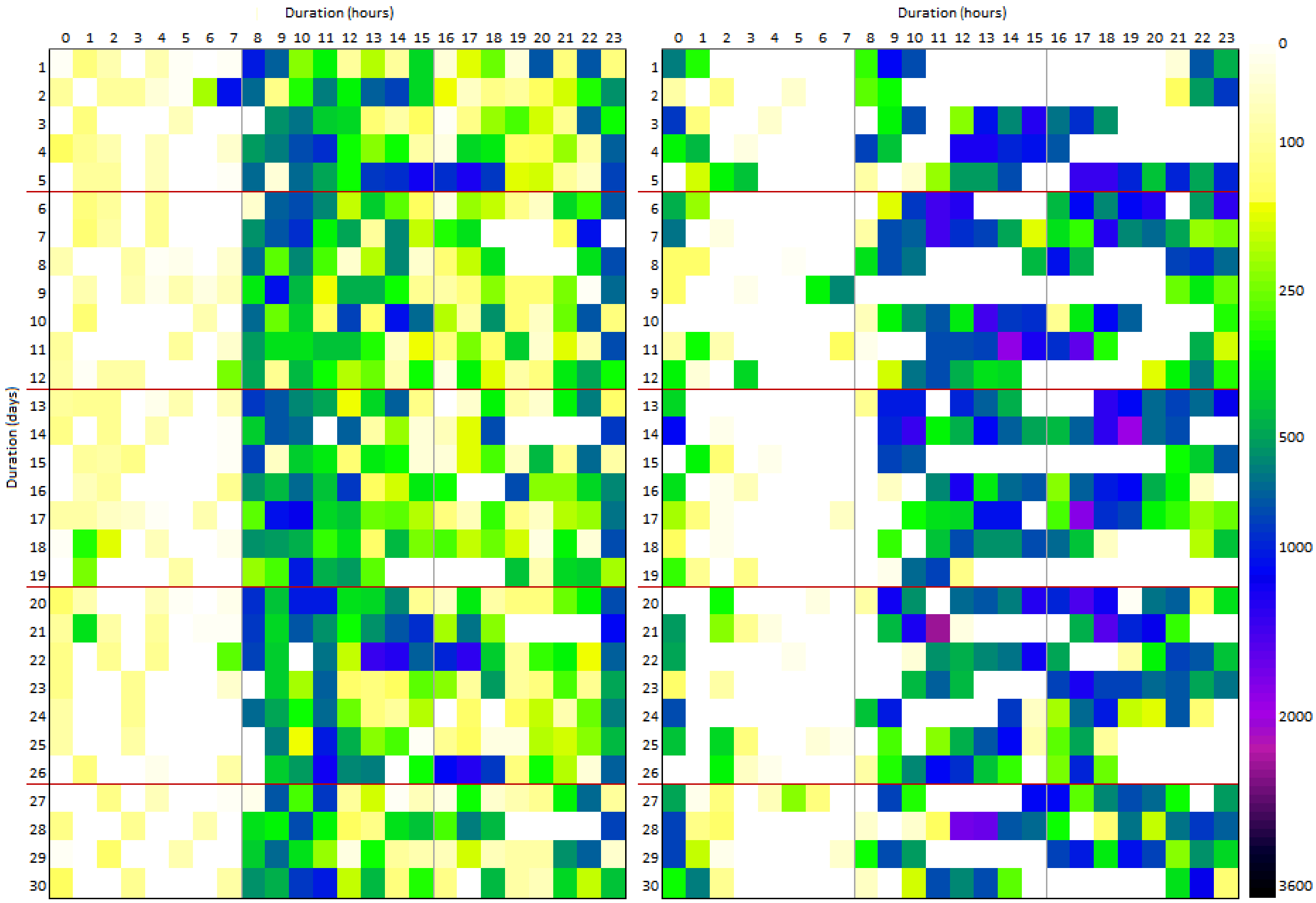

Figure 2. Visualisation of all PIR sensor data for two residents: resident A (left) and resident B (right) in June 2011 *(0 represents 0 seconds of movement in an hour, 3600 represents 3600 seconds [total movement] of movement in an hour)*

present, it is not a significant amount. The green peaks represent a larger amount of movement. They are visible between 1am and 2am on 18th, 19th, and 21st of June and peak to between 249 and 379 seconds. This behaviour is inconsistent with resident A's normal night time pattern and as a result it should be examined in more detail. Following a correlation between visualisations of individual PIR sensors, see Fig. 3, it appears that it largely results from movement within the bedroom, with the exception of 18th June where movement is detected within the hallway and living room, as well as the bedroom.

In examining the night time behaviour of resident B, while movement seems irregular, it appears to be normal for the resident in question. An abnormal event is evident on 27th June, whereby there are very few hours where no movement is visible. This is inconsistent with their regular behaviour. Movement is evident between 3am and 6am, with a peak in movement of 236 seconds between 4am and 5am. When verified against the individual PIR sensor visualisations for this duration it appears that resident B moved from the bedroom, through the hallway, to the living room, movement was then detected between the living room and hallway before the resident finally returns to the bedroom.

B. *Periods of inactivity*

Resident A seems to have continuous periods of inactivity within the home on Tuesday evenings from 7pm until 10pm/11pm as well as some Wednesday evenings, occurring almost every week for the period depicted in Fig. 2. It can also be clearly seen that resident A appears to spend one Sunday afternoon, 19th June, inactive for five continuous hours which may suggest they have left the house for this duration. Aside from this resident A seems to be inactive, maybe leaving their apartment, for one or two hours several times per week.

Resident B's routine looks very different, appearing to have extended periods of inactivity on several days per week spanning into the afternoon. This consistent inactivity suggests that the resident may be away from home for this period, with outings on the 1st, 8th, 13th, 15th, 20th and 29th corresponding to attendance at scheduled social events. There are similar extended periods of inactivity evident one or more evenings per week, suggesting that the resident may be away from home during these periods also.

C. *Movement within and between rooms*

We will now consider resident A's movement between and within individual rooms in more detail, see Fig. 3. The

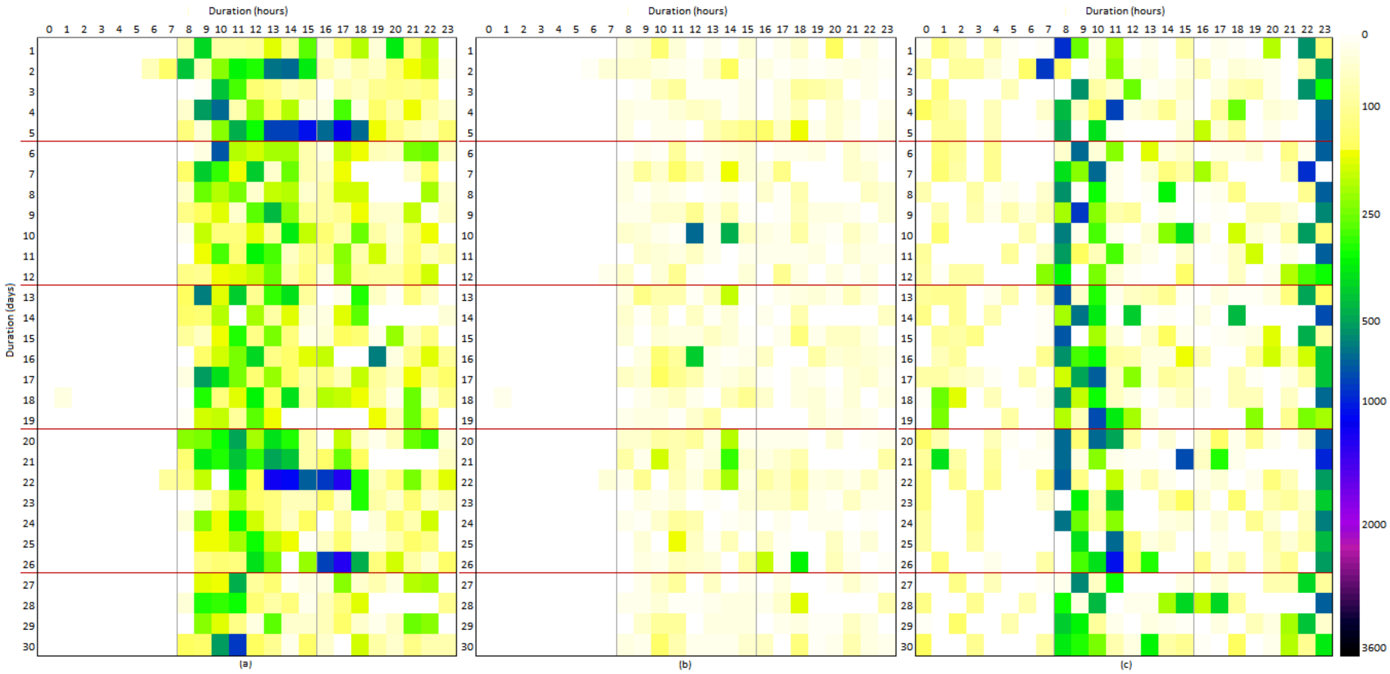

Figure 3. Visualisation of PIR sensor data in the living room (a), hallway (b) and bedroom (c) for resident A in June 2011 *(0 represents 0 seconds of movement in an hour, 3600 represents 3600 seconds [total movement] of movement in an hour)*

resident's movement is represented using the PIR in the living room (a), the PIR in the hallway (b) and the PIR in the bedroom (c). From looking at the period between 12am and 8am in (a) and (b) it is clearly identifiable that the resident doesn't generally move between rooms at night. There is some slight movement visible within the bedroom (c) at night, significantly increasing at 7am/8am. There is a significant amount of movement in the bedroom (c) between 7am/8am and 9am/10am, movement between the hallway (b) and the living room (a) is also evident within this period. Movement gradually increases in the living room (a) and decreases in the bedroom (c) between 9am and 11am. Towards resident A's bed time, i.e. 10pm to midnight, the movement decreases in the living room (a) and begins to increase once again in the bedroom (c).

It is apparent that the resident spends the majority of their waking hours within the living room, although there is a clear pattern of movement between rooms relatively frequently throughout the day. Increased movement is visible between rooms and particularly within the bedroom (c) on several days prior to periods of inactivity. This is particularly evident on 7th June between 4pm and 5pm, 17th June between 6pm and 7pm as well as 22nd and 28th June between 5pm and 6pm. Several of these events correspond to the periods of inactivity, mentioned in section B, relating to Tuesday evenings which reinforces the idea that resident A may spend Tuesday evenings away from home.

D. Changes in night time behaviour

We next present data for a third resident, C, to show changes in behaviour. Fig. 4 effectively depicts changes in the night time behaviour patterns of resident C over a six week period. The resident appears to regularly move between the living room (a), hallway (b) and bedroom (c) at night in the period between 1st and 18th August 2011. The movement levels within the bedroom, in particular, show a significant amount of movement within this period, ranging from less than a second to 415 seconds per hour. Inactivity is visible over the following days, with only two days with any visible activity, between 18th and 26th August, suggesting that the resident is away from home for this period. We see that the resident returns and stays overnight on 26th August, this is clearly visible as there is movement within the bedroom (c) throughout the night. Resident records have established that the resident was in hospital for this period. The movement levels during the few days directly following the hospital visit increase significantly. This abnormally high level of movement suggests that the resident had a visitor during this period. Night time behaviour has also changed dramatically when compared with the period prior to the hospital visit. Movement between rooms has reduced with only one hour where movement is detected at night on 31st August and 1st and 8th September. The movement levels in the bedroom (c) have also been reduced significantly to between zero and 154 seconds indicating that the resident is consistently sleeping better. Analysis over a longer period supports this suggestion.

V. Discussion

The visualisations not only indicate significant dissimilarity between residents they identify differences within each individual's behaviour. This is acutely apparent in Fig. 2 but is also evident subtly through day-to-day changes in behaviour in the visualisations of other residents. Analysing a resident's behaviour after a hospital visit, as identifiable in Fig. 4, has the potential to enable healthcare professionals to identify a patient's progress remotely. Visualising data in this way could result in considerable time savings for healthcare professionals.

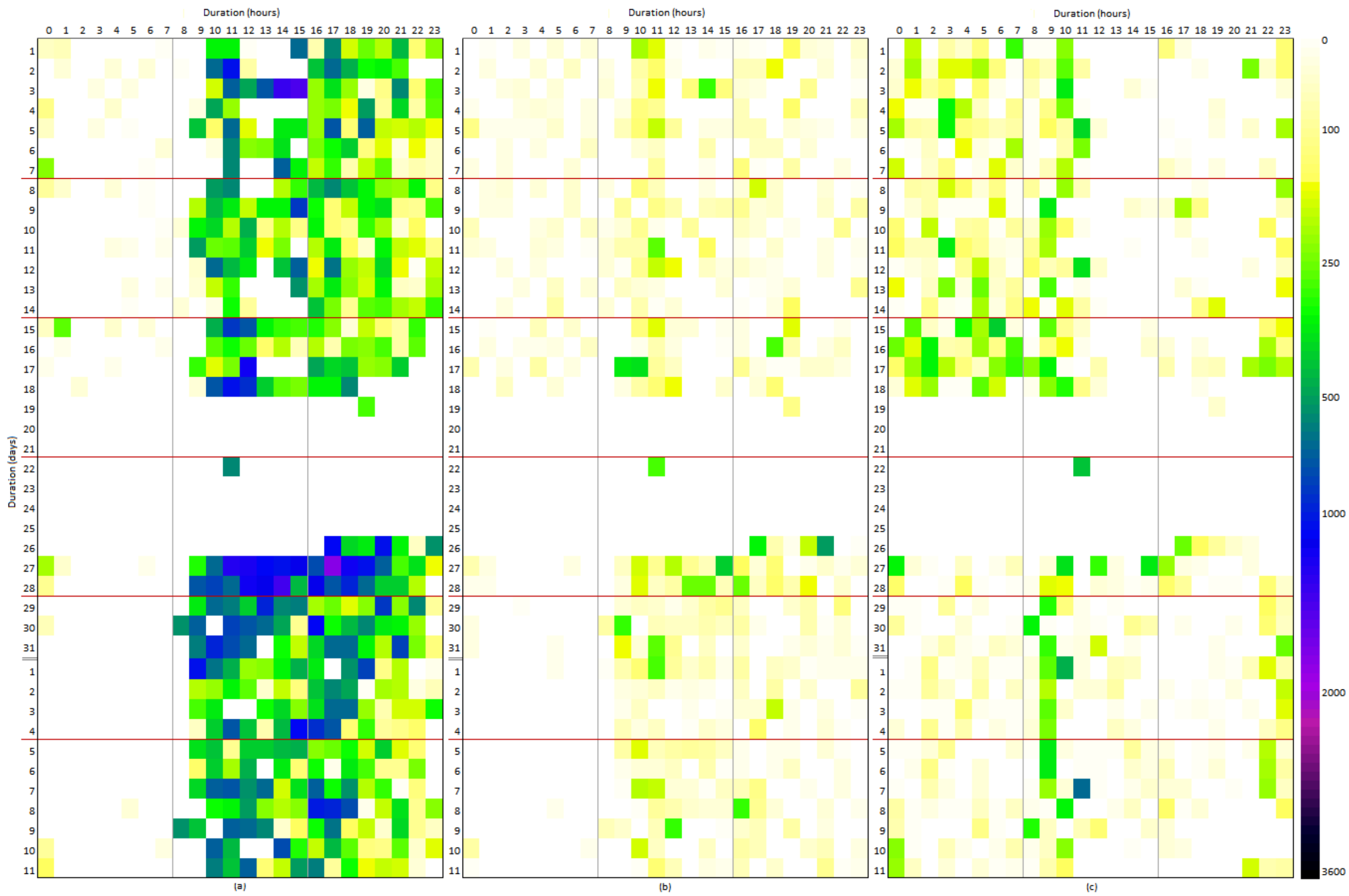

Figure 4. Visualisation of PIR sensor data in the living room (a), hallway (b) and bedroom (c) for resident C over a six week period, between 1st August and 11th September 2011 *(0 represents 0 seconds of movement in an hour, 3600 represents 3600 seconds [total movement] of movement in an hour)*

Common age related illnesses such as cardiovascular disease, diabetes mellitus, lower urinary tract obstruction, anxiety or primary sleep disorders, and behavioral and environmental factors may be identified by minor changes in behaviour [19]. Nocturia is one example of a common symptom of each of the above illnesses, appearing as a continuation of day time urination pattern. It presents sufferers with an increased risk of falls [19]. It also has possible implications on a resident's quality of sleep and cognitive function. Early detection and treatment by healthcare professionals is essential. Abrupt changes in behaviour can indicate immediate health complaints. The visualisations provide valuable insight into both gradual and abrupt behaviour changes.

The visualisations may also illustrate subtle changes such as the extent to which a resident moves throughout the day. When considered on a daily basis, this facilitates in identifying whether an individual has a strong or weak routine. Determining an individual's routine can assist in calculating when a change occurs and, more importantly, to what extent. As such visualisations have the potential to assist in determining abnormal events that require further examination. We acknowledge that our research is at an early stage and there is much to be done.

A. Limitations

Having verified that all sensor data included is technically accurate it should be noted that some areas of the apartment are blind to the PIR sensors, see Fig. 1—if a resident is moving within a blind area the PIR sensor will not identify this movement. The PIR sensors are located over the door in the living room, hallway and main bedroom, hence some rooms are out of range of the PIR sensors, i.e. the kitchen, bathroom and guest bedroom. Aside from these rooms there are certain areas of the living room, hallway and bedroom where movement will not be detected by the sensors. These blind areas are not commonly used by the residents as they are generally located along walls and areas which contain furniture. The exception is the kitchen area and there are plans to add further PIR sensors to this area. We believe that the absence of this limited amount of movement would not impact significantly on the behaviour patterns presented. Furthermore as our focus is on night time activity, and movement between rooms, the impact is minimal.

A limitation of our work is that we have not used other sensor information to accurately establish periods where residents are away from home. In our visualisations any movement corresponding to either movement in a blind area or movement outside the home is represented in the same way, as a white/pale block. While some of these occasions are obvious from the visualisations it is difficult to identify shorter absences from the apartment due to the scale of the visualisation, i.e. periods of activity are shown in one hour blocks. Information relating to time outside the home will be integrated in the near future. This will add valuable insight into the resident's movement patterns throughout the day. Our future research focuses on night time behaviour which is unlikely to be overly affected by events relating to time outside the home.

In the case of multiple occupancy it is very difficult to link sensor triggers to specific individuals. A key requirement for all ambient sensor systems is to ensure that an accurate account of the residents' movements is retrieved. As we use PIR sensors we cannot isolate the origins of the movement. This lack of recognition of the resident makes it difficult to interpret the reason for high levels of activity. Uncertainty may be introduced when a home has multiple residents, as well as periods when visitors are present. In these cases it becomes difficult to differentiate between the resident's movement and that of their visitor—appearing as an increase in activity. Consequently increased movement levels may result from increased activity by the resident themselves or alternatively they may result from the presence of visitors.

As visitors are more likely to be present during the day, we believe that the visualisations have greatest potential to provide insights into night time behaviour. This is the planned focus of our future research. As an aside, the development of an iPad survey app, which will be filled out daily by each resident, will verify whether the residents have had visitors or not. This will assist in understanding and analysing visualisations.

VI. Conclusion

In summary, the visualisations presented in this paper consider a period of 7 months and 17 days, however, data collection is ongoing. The planned integration of an iPad survey to record the residents' health and wellbeing on a daily basis will support in the analysis of visualisations. To reduce uncertainty we propose to focus on night time behaviour. We believe residents are unlikely to leave the house and may have fewer visitors during this time period. The initial focus will relate to several behaviours in particular. Specifically the time the resident goes to bed/gets up; the number of times the resident goes to the bathroom and the number of major night time disturbances experienced by the resident. As a preliminary step we intend to focus on the development of algorithms to recognise such behaviours. Following this a cluster analysis will be performed to establish whether the residents have consistent patterns, whether they deviate from these patterns and to what degree. Major deviations will be incorporated into the visualisations. It is planned that the resulting visualisations will be validated by healthcare professionals.

This paper presents visualisations representing PIR sensor data in order to show the extent to which the residents of the Great Northern Haven move throughout the day. The use of such visualisations allows for their patterns of behaviour to be identified. They also provide insight into how the residents use their homes. This depiction of normal behaviour has the potential to facilitate the detection of abnormal events. It may also make the recognition of gradual changes in behaviour possible. Future work must focus on verifying the usefulness of the visualisations in a rigorous scientific manner, and on the development of clustering algorithms for automated identification of potential changes in behaviour patterns. A further validation will be required to determine the visualisation's ability to identify activity patterns and changes in patterns relating to routine behaviours. Finally, we plan to automate the process of visualising and clustering the resident's activities to ensure that it is a viable solution for healthcare professionals.

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