Data Visualisation and Data Mining Technology for Supporting Care for Older People

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ABSTRACT

The overall purpose of the research discussed here is the enhancement of home-based care by revealing individual patterns in the life of a person, through modelling of the "busyness" of activity in their dwelling, so that care can be better tailored to their needs and changing circumstances. The use of data mining and on-line analytical processing (OLAP) is potentially interesting in this context because of the possibility of exploring, detecting and predicting changes in the level of activity of people's movement that may reflect change in well-being. An investigation is presented here into the use of data mining and visualisation to illustrate activity from sensor data from a trial project run in a domestic context.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Information Search and Retrieval – *Information filtering, search process, selection;* K.4.2 [**Computers and Society**]: Social Issues – *Assistive technologies for persons with disabilities*.

General Terms

Measurement, Experimentation, Human Factors.

Keywords

Older adults, independent living, assistive technology, visualisation, data mining.

1. INTRODUCTION

The number of older people in our society has experienced a dramatic rise, because the expected lifespan is longer than in previous decades. Therefore, many European, American and Far Eastern countries are starting to face a crisis because existing resources are inadequate to support essential health and social services for older people.

In 2005 it was estimated that there were about 12 million people in the UK over 60 years of age, of whom 752,000 were aged between 85 and 89, and 376,000 exceeded 90 years of age. According to Age Concern Scotland (2005), for example, there were over 1,097,026 people aged 60 or more in Scotland, representing approximately 21.5% of the total population [1].

In the UK, Age Concern estimated that there were approximately four people of working age (20-64 years) to each person over the age of 65 years by 2004. In comparison, in 40 years' time the proportion will be 2:1 [2]. In Scotland, the Scottish Executive reported that the total population aged 16-64 years is projected to decrease by 5% by 2019. As a comparison, the population aged over 65 is projected to increase by 26% by 2019 [3].

The ageing process is often accompanied by a loss of mental and physical abilities. These consequences contribute to an increased risk of accidents in older people's homes; hence there is a greater demand on formal health services as well as informal carers such as family, friends and neighbours [2]. Because of this shift, changes in the delivery of health and social services have taken place over the past 30 years. These changes have been created by government policy and concerns about the cost, workforce and community care service users.

Technology might enable carers to respond to a crisis and help prevent problems by providing early indications of deterioration in an individual's well-being and perhaps indicating where change is likely to lead to a deterioration in well-being. One possible solution is to build a model of people's lives that learns and reveals the individual pattern of "busyness" (overall activity) and give this information to inform the dialogue of care between home residents and carers.

The measure of activity, presence in locations and interaction with objects might provide information to assist understanding of patterns in people's behaviour. If there are regular patterns in the life of a person, changes to such patterns could suggest a change that should be followed up in a dialogue between a carer and that person – the dialogue of care. The question is whether it would be possible to build a busyness model of a person's life at various levels of granularity to describe individual lifestyle as an indication of well-being.

The incentive for this work is to provide domestic residents and carers, but particularly formal and informal carers, with information, so that they can provide care; and older people so they can 'self-care' and be confident to continue to live at home.

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1.1 Costs of Residential and Community Care

The Scottish Executive modeled eight scenarios to project costs of residential and community care services. The base model scenario was intended to show what could happen if everything were to remain as it is today. The fourth scenario considered this hypothetical situation: "people receiving over 20 hours of community care a week are accommodated in a residential care home". The fifth scenario considered what would happen if 1% of people receiving informal care received formal care instead [3]. The following were the projected costs for each scenario (Table 1).

Table 1. Projected costs in Scotland (in £ millions p.a.)

Projected costs (m)	2004	2019	2004-2019
Base Model			
Residential care home	261.0	484.0	85%
Community home care	202.0	361.0	79%
Scenario 4			
Residential care home	261.0	570.0	118%
Community home care	202.0	285.0	41%
Scenario 5			
Residential care home	261.0	666.0	155%
Community home care	202.0	416.0	106%

Source: Adapted from First Report for the Range and Capacity Review: Projections of Community Care Services Users, Workforce and Costs (2004) [3].

Under these assumptions, the annual cost for residential care home in the fourth scenario is projected to increase to £570 million, £86 million more than under the base model. The cost for community home care is projected to decrease by £76 million from the base model. Under scenario five, by 2019 the residential care home cost is projected to increase to £666 million per annum, £182 million more than the base model. The cost for community home care is projected to increase to £416 million, £55 million more than the base model.

In general, the base model scenario seems to be the most feasible from the economic point of view. However, the cost for community home care is significantly cheaper in the fourth scenario than the base model. This means that the role of the community care services is expected to increase in the future in providing health and social services to the elderly.

2. BACKGROUND

The following literature suggests that assistive technology might support the independence and well-being of older or disabled people:

- Porteus and Brownsell [4] stated that lifestyle modelling and activity monitoring are specifically concerned with the use of technologies to help elderly and disabled people to live independently;
- Fisk [5] stated that activity monitoring includes the monitor-ing of general or specific activities and physiological factors, environmental conditions (temperature, humidity) in order to identify situations related to the inhabitant and the dwelling;
- Hine et al. [6] stated that lifestyle modelling consists in the correlation of specific activities with patterns of well-being like eating and social interaction. These activities can be visualised at different levels of granularity and changes of activity could reflect changes in well-being.

In the context of support for independent living and autonomy of older people, a number of initiatives have taken place, including: feasibility studies to test technology in supporting older and frail people [4]; ubiquitous computing and an intelligent environment that consisted in sensor networks, human computer interfaces and computational perception to recognise people's movements and their interaction with objects with the aim of improving the quality of life of older people [7]; tracking of people's movement and activities with video cameras and PDA to empower people with information that help them to make decisions [8]; multimodal systems that included audio, video and speech recognition to allow the residents to interact with the system [9,10]; embedded sensors in the floor that provided accurately the location of the older person at home with the aim of increasing the independence and quality of life of older and disabled people [11]; pervasive technology focus on helping people suffering from cognitive deficits to plan, remember and complete activities inside and outside the house [12]. The objective of the latter project [12] was to promote a person's autonomy, to reduce hazards and risks and to help family and carers to be in touch with the older adult.

From the care point of view, Anchor Trust in association with British Telecom were interested in knowing the feelings of participants, both older people and carers, during a study conducted in Liverpool [4]. Another project concerned in this aspect was at Georgia Institute of Technology [13], who designed a digital portrait as an interface to keep an open channel of communication between parents and children. The portrait's frame showed the resident activity through butterfly icons that changed their size according to the level of activity.

From the physiological point of view, research at Massachusetts Institute of Technology (MIT) [8] was focused on health care strategies including monitoring, compensation and prevention to motivate changes in people's behavior like consuming healthy food and increasing exercise routines.

From the computational aspect, various data analysis techniques have been used including clustering, mixture models [14] and rule-based algorithms [15] to detect people's patterns of behavior; OLAP technologies to visualize activities of daily living (ADLs) [16]; classification rules [17] to identify deviation from normal patterns of behavior; sophisticated data mining techniques and machine learning algorithms like Markov chain and Bayesian models to discover changes of lifestyle related to a person's well-being [18,19].

3. RESEARCH OBJECTIVES

The research described here attempts:

- to understand older people's lives and visualise positive or negative changes;
- to anticipate changes in an effective way before quality of life has deteriorated.

There are two different basic approaches:

1. Monitoring of Activities of Daily Living (ADLs). This looks at specific activities, such as having a bath or having break-fast.
2. Measuring of Activity ("busyness"). This counts the number of sensor firings for a specific time period and location, for example in the kitchen during the cooking time period.

Some research projects based on the first approach used video cameras [7,8] to record people's movements and others employed devices like PDAs [14] to register people's activities. These techniques might be too intrusive from the ethical and privacy point of view. The second approach might be less intrusive.

3.1 Activities of Daily Living (ADLs)

The concept of ADLs has been used since 1963, when Katz et al. [20] proposed the Index of Independence in ADL. The index is based on the measure of biological and psychological functions, which summarise the overall performance in six areas: bathing, dressing, going to the toilet, transferring, continence and feeding.

In 1969 Lawton developed two scales to measure two domains of functioning of older people [21]. The first scale was an adaptation of the model of activities proposed by Lowenthal named Physical Self-Maintenance Scale (PSMS), measuring self-care ability in areas of toileting, feeding, dressing, grooming, locomotion and bathing. The second scale named Instrumental Activities of Daily Living (IADL) focused on measuring a set of more complex behaviours including: telephoning, shopping, food preparation, housekeeping, laundering, use of transportation, use of medicine and ability to handle finances. This scale had different ratings for males and females.

In 1980 Roper, Logan and Tierney proposed a nursing care model based on the functional status of a person. This model has been refined several times since then. The final publication (2000) took into account five concepts: activities of living, lifespan, dependence and independence continuum, factors influencing ADLs and individuality in living [2]. The model includes:

- Maintaining a safe environment;
- Communicating;
- Breathing;
- Eating and drinking;
- Personal cleansing and dressing;
- Controlling body temperature;
- Mobilising;
- Working and playing;
- Expressing sexuality;
- Sleeping;
- Dying.

Each stage of a person's lifespan (infancy, childhood, adolescence, adulthood, senior citizenship) influences the individual behaviour. At different stages of the lifespan, there is continuous change and every aspect of living is influenced by the biological, psychological (intellectual and emotional), socio-cultural (spiritual, religious, philosophical and ethical), environ-mental and politico-economic (legal) circumstances encountered.

The dependence and independence continuum in the ADLs varies according to age. In old age the loss of independence can be equally gradual and it rarely occurs for all of the ADLs.

The individuality in living is actually the relationship between the other four concepts mentioned before (activities of living, life-span, dependence and independence continuum and factors influencing ADLs), and the experience of each individual. Each person carries out each ADL differently, determined by stage of life, the degree of dependence or independence and the biological, psychological, socio-cultural, environmental and politico-economic factors.

A conceptual model of personal well-being was described by Sixsmith et al. in 2007 [22]. This model took into account five concepts: personal factors, context factors, activity, experience and well-being. The following aspects were considered:

- Having good social relationships with family, friends and neighbours;
- Participating in social and voluntary activities, and indivi-dual interests;
- Having good health and functional ability;
- Living in a good and safe home and neighbourhood;
- Having a positive outlook and psychological well-being;
- Having an adequate income;
- Maintaining independence and control over life;
- Expressing sexuality and feelings.

Sixsmith et al. [22] reported that there were some ADLs such as preparing food, eating, sleeping and receiving visitors that have a strong relationship with people's well-being.

3.2 Busyness

This research project is based on the approach of measuring activity and is attempting to answer whether it would be possible to build a busyness model of a person's life at various levels of granularity to describe individual lifestyle as an indication of well-being.

Busyness as a concept is a measure of overall movement and activity within a dwelling, and of interactions with objects. This potentially preserves the privacy of the occupant to a greater degree than would be the case if specific activities were being identified, measured or inferred.

The measure of activity, presence in locations and interaction with objects in a private dwelling, without attempting to infer specific activities, might provide information to characterise an individual's lifestyle. The nature of the busyness, the count of movements or interactions, builds a busyness model of a person's life. This, in conjunction with contextual information could give indications of well-being.

4. DATA AND METHODOLOGY

A telecare project was conducted by an interdisciplinary team, among the objectives of which were to evaluate the feasibility of using various sensors to provide lifestyle patterns of older people, and to understand the role of technology in home-based care.

As part of the above project, a pilot study of flats at a residential care home was conducted for some 9 months. Each dwelling was installed with a set of sensors (passive infrared sensors (PIRs), pressure sensors, door contacts and electrical sensors) optimised to measure the activity of the resident based on known interests and habits, following discussion with each of the residents. Data were recorded from these sensors and contextual information from the lives of the residents also noted during the study. The resulting data were made available for analysis for this research.

The methodological approach of this research included the following activities:

- Construction of a data warehouse;
- Preparation of data;
- Visualisation of data with OnLine Analytical Processing (OLAP) technology, to explore a person's busyness at different levels of granularity;
- Building of a data mining model to seek patterns and unexpected features in the data sets.

4.1 Data Warehouse

Data from sensors were gathered continuously into a local database and consisted of the following attributes: timestamp when the sensor was firing, sensor ID, and state of the sensor (ON/OFF). This information was then collected into a relational database and organised into a data warehouse.

4.2 Data Preparation

Data preparation consisted of the segmentation of the daily activity by time zones as defined in Table 2.

Table 2. Segmentation of time into zones

Zone	Hour
Sleeping	00:00 – 7:00 a.m.
Early morning	7:00 – 9 a.m.
Late morning	9:00 – 12:00 p.m.
Lunch	12:00 -4:30 p.m.
Afternoon	4:30 – 7:00 p.m.
Evening	7:00 – 10:30 p.m.
Late evening	10:30 – 12:00 midnight

4.3 OnLine Analytical Processing (OLAP)

OLAP technology was employed to visualise data from the data-base and to explore the level of activity within the dwelling. The analytical process followed these steps:

- Building a data cube: Data from the data warehouse were organised into a multi-dimensional data model in order to provide facilities for summarisation and aggregation at different levels of granularity (general and specific) [6]. The data cube was aggregated by room (bedroom, hall, kitchen and living room), time zone, week (5-24) and weekday;
- Data analysis: Charts representing daily sensor firings seg-mented by zones, from week 5 until week 24 inclusive, were visually explored. In addition, contextual information describing the dates of various events in the participant's life, such as changes in medication, was analysed;
- Trend analysis: A polynomial trend line was used to reveal the underlying trends of changes in busyness in the life of the person. Over time the trend lines showed change, and how great the change had been. The reliability of the trend line is given by its correlation factor R2. At this stage in the exploration it appeared that R2 >= 0.1 was revealing interesting trends that were sufficiently reliable to be considered by carers.

4.4 Change of Medication

The results reported in this paper were based on data from one of the flats, whose resident had some changes in medication that were accompanied by observed changes in busyness.

The participant was suffering from non-insulin-dependent diabetes. For some time the participant's blood sugar levels were consistently outside the desired range. As a result of this, the medical doctor took a decision to change the medication in week 9. Unfortunately this change of medication did not bring expected positive results and the participant's blood sugar level remained high. Therefore, in week 16 the doctor decided to change the medication for the second time (see Figure 1).

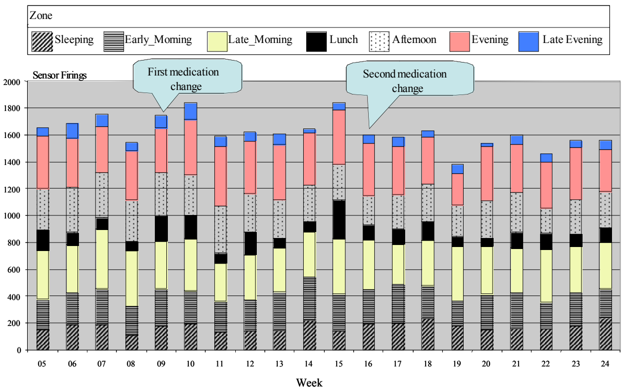

Figure 1. Sample of busyness by time zone

4.5 Building a Data Mining Model

Another technique to help to inform the dialogue of care and to alert the domestic residents and carers about change is to look for occasions where the regular pattern has been broken. If the life of an older person can be shown to have patterns, certain rules might confirm that. If those rules are broken, this can suggest the need for a discussion between the older person and carers to check if these changes are significant and if action is required.

A data mining tool was employed to build a data model. The purpose of this supervised learning model was to identify some rules and to discover distinctions between rooms, using data which especially highlighted a normal pattern of busyness.

The data mining process followed these steps:

- Data selection: Data that showed a normal pattern of busyness was used in the classification algorithms presented here. The data was split into training (66.66%) and testing (33.33%) data sets, using 8 weeks (17-24) and 4 weeks (5-8) respectively as suggested by Han and Kamber [23].

Table 3. Example of training data aggregated by day

Location					
Bathroom	Bedroom	Hall	Kitchen	Living room	Zone
2	20	3	1	1	Sleeping
3	11	4	4	12	Early_Morning
6	9	9	1	38	Late_Morning
1	0	2	1	6	Lunch
2	7	3	6	33	Afternoon
1	6	2	4	47	Evening
1	9	2	0	0	Late_Evening

- Table 3 displays the location attributes: bathroom, bed, hall, kitchen and living room (considered as inputs) and the attribute zone (output). An individual row is an instance of data. For example, the second row shows the sensor firings in the bathroom=2, bed=20, hall=3, kitchen=1 and living room=1. This level of activity corresponds to a single day period in week 23;
- Algorithm selection: Weka [24] software was employed to train and test the data model because it offers several algorithms to classify and predict data such as C4.5 (pruned and unpruned trees), regression trees (Reptree) and Naïve

Bayesian trees (NBtree). The pruned C4.5 decision tree algorithm was selected because it produced the most accurate and simple rules;

- Data classification and validation: Different training and testing data sets were used for several times, until the results produced an understandable and simple set of rules. In addition, the set of rules was selected by choosing the model with the highest accuracy percentage on the test data.

5. RESULTS

5.1 OLAP Results

The data showed some changes in busyness in the sleeping and evening time periods, around the time when changes in medica-tion were also happening.

There was a slight increase in firings on the lamp in the living room in the period between weeks 13 and 16 in relation to the preceding and following periods (see Figure 2). It was known that this lamp was used while doing crosswords and Sudoku in the evenings. This probably reflects a change in this entertainment activity. Next, there was a slight increase in busyness in the kitchen between weeks 14 and 16 in comparison with the period before (weeks 5-13). After week 17 the trend line decreased as shown in Figure 3. There was a moderate decrease in firings on the bed sensor in the bedroom after week 15 compared to the preceding weeks (see Figure 4). Additionally there was a fluctua-tion in data during the observed period in the hall, reflected in the increase in sensor firings between weeks 9 and 11 and between weeks 13 and 18 (see Figure 5); the hall is a transit space, reflecting movement from one part of the flat to another. An increase in busyness had also occurred between weeks 9 and 15 in the bathroom relative to the preceding weeks.

All these results revealed interesting fluctuations in the data that may or may not be important in themselves; taken together they reveal changes in busyness in the household. The cause of any change is usually a matter of interpretation, but the evidence of change can be made available for discussion between the resident and the carer, thus helping to stimulate and inform the dialogue of care between them.

5.2 Data Mining Results

After using the decision tree algorithms to produce a set of rules, those representing unambiguous events were selected. The rules came out as in Table 4.

Rules 1 and 3 confirmed that during the late evening and sleeping time period this participant was more likely to be in the bedroom than in the living room as would be expected. Sleeping at night is a normal pattern in people's lives associated with well-being. Other important rules were 2 and 6, which showed the living room as the busiest place during the lunch and evening periods. Being in the living room at lunch and evening is associated with eating, having a rest or having social interaction.

Table 4. Rules generated using decision trees algorithms

id	Rule (volume of sensor firings)	Output	Instances	Correctly Classified
1	Living <=0 AND Bed[1-8]	Late Evening	33/1	32
2	Living[1-10] AND Bed <=4 AND Kitchen <=4	Lunch	37/4	33
3	Living <=10 AND Bed >12	Sleeping	48/3	45
4	Living >10 AND Hall <=6 AND Bed <=1 AND Kitchen >1	Afternoon	42/4	38
5	Living[11-22] AND Hall <=6 AND Bed[2-14] AND Kitchen >5	Early Morning	26/2	24
6	Living >29 AND Hall <=6 AND Bath <=3 AND Bed >7	Evening	20	20
7	Living >10 AND Hall >6 AND Bath >3 AND Kitchen <=6	Late Morning	37/3	34
	Total number of instances		380	330

One of the measures used to evaluate the results of the classification algorithms was the accuracy, defined by the number of instances correctly classified divided by the total number of instances [23]. The accuracy of the algorithm with training data was 86.84 % (330/380) and 72.58 % (135/186) with testing data.

5.3 Discussion

Considering this and data analysis from the five other participants in the study, some rules to describe people's lives were found, but these residents were not as regular as some other people have been seen to be. Heatley et al. [25], for example, reported that people have consistently accurate patterns of well-being (eating, sleeping, toileting and having a shower).

Decision tree algorithms were used to see how good the rules were, but in some cases the rules were not strong enough. Further data are needed in order to build a more solid model of people's lives. Deviations from rules might be useful for detecting signs of forthcoming problems. Reflecting the fact that the life of a person can be rather irregular, the rules need to be relaxed, to be more fuzzy, operating within limits rather than thresholds. Older people are likely to be regular in some aspects of their lives, however, for example in making weekly telephone calls to close relatives.

6. NEXT STEPS

Future work will investigate other approaches to try to discover regular patterns and ways to interpret and present outcomes. Examples of avenues to follow are:

1. To find some rules for locations to see if there are some regularities associated with specific locations in the house, for example the living room, the kitchen, or the bedroom.
2. To try clustering algorithms in order to find when an activity takes place or to describe the busyness associated with a particular event during a day. For example, busyness in the kitchen followed by busyness in the living room then in the kitchen which describes the patterns of busyness associated with the lunch-time period.

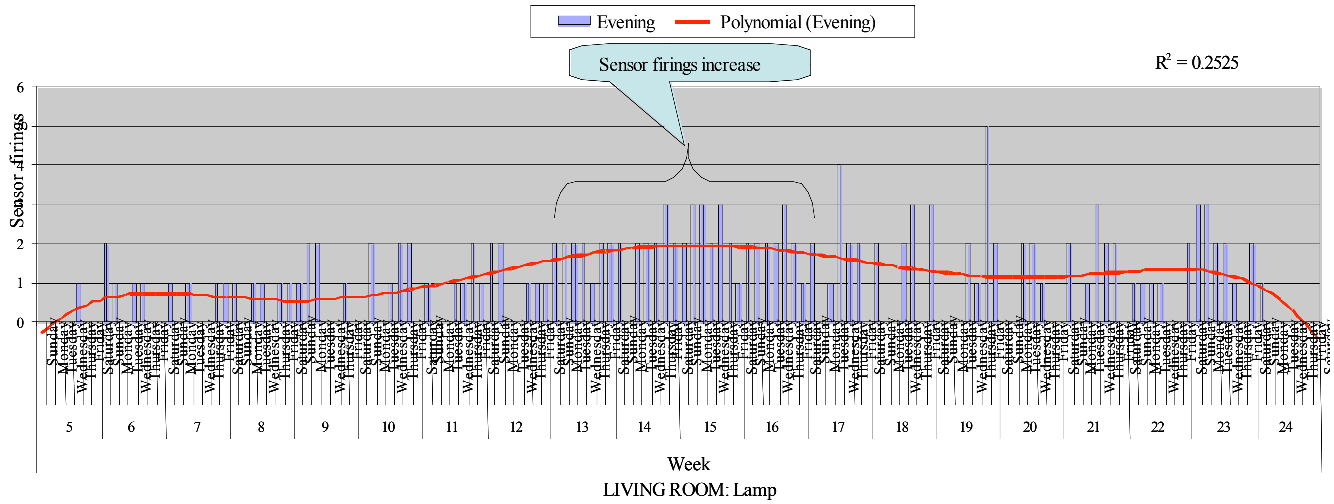

Figure 2. Living room lamp (electric sensor) busyness during the evening time period

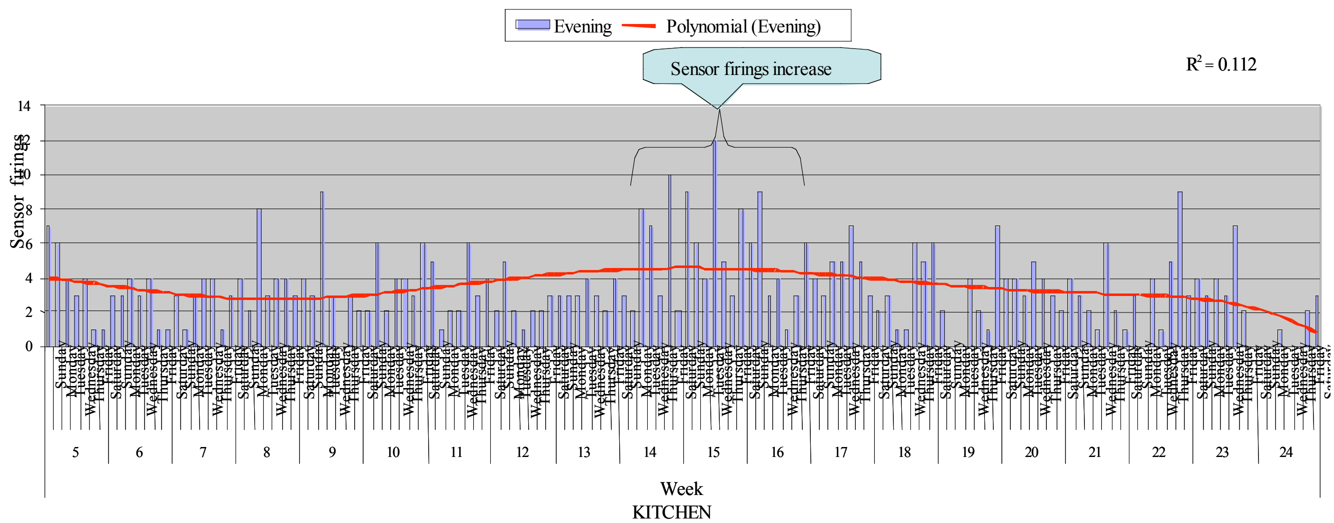

Figure 3. Kitchen busyness during the evening time period

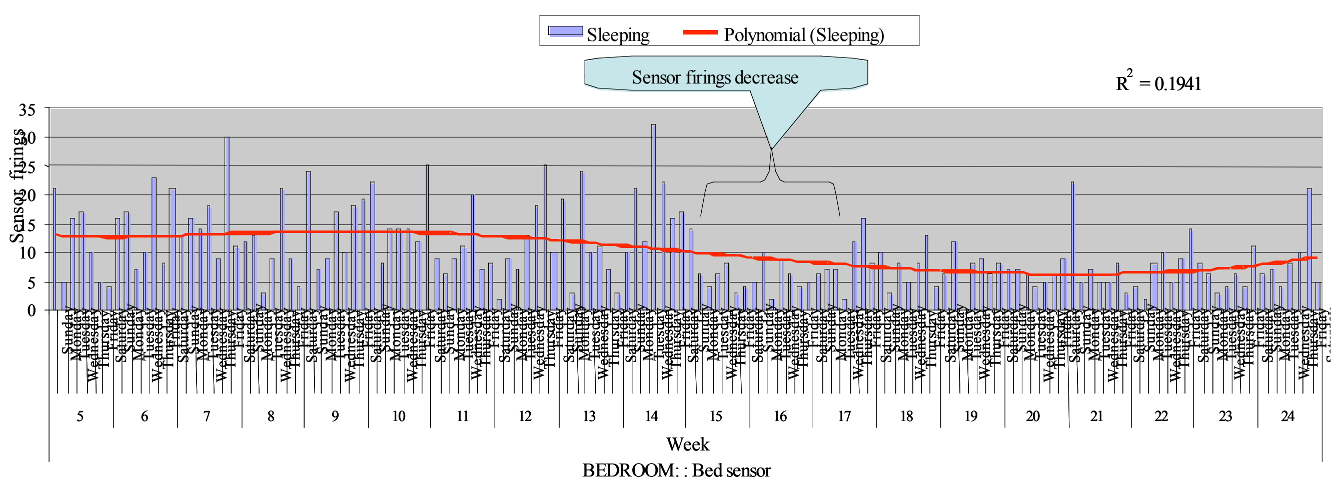

Figure 4. Bedroom (bed sensor) busyness during the sleeping time period

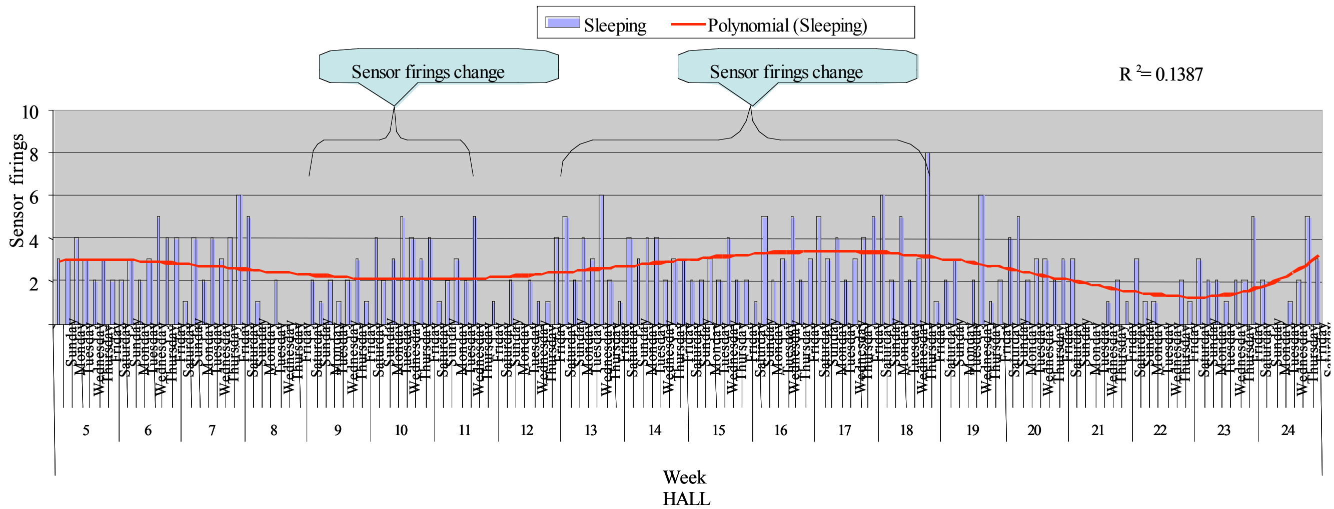

Figure 5. Hall busyness during the sleeping time period

3. To try some learning algorithms such as time-series or probabilistic models to compare with the results from decision trees and clustering.
4. To detect deviation of events that do not fit the expected patterns from an analysis of longitudinal trends.
5. To build an individual model of a person's life taking into account all the characteristic aspects as an individual. For example, whether a person depends on an occupational therapist or is healthy and independent.
6. To investigate the rate of trend changes.
7. To build interfaces to show this information in ways that communicate most intuitively to residents and carers.

7. CONCLUSIONS

The outcomes of this investigation indicate that data mining and OLAP offer interesting possibilities for exploring and detecting changes in the level of activity of people that may reflect changes in well-being. Changes in busyness are visible and detectable from the busyness data gathered in domestic environments, despite irregularities in people's behaviour. Appropriately presented, these could help to inform the dialogue of care. It was also seen that older people may not have very regular lives, however, and the focus of such techniques in future should be to concentrate on those aspects that are regular and have a relationship with well-being, for example sleeping, preparing and eating food, and making telephone calls to close relatives and carers. Continuing research needs also to investigate the optimal size of data set for data mining on lifestyle information of the kind seen here.

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