Behaviour Modelling for Detecting the Onset of Dementia using Ambient Intelligence

Nidal AlBeiruti and Khalid Al-Begain
Centre of Excellence in Mobile Application and Services
Faculty of Computing, Engineering and Science
University of South Wales, United Kingdom
{ nidal.albeiruti, k.begain }@southwales.ac.uk

***Abstract* — Using technology to provide sustainable proactive care for elderly people is an emerging and evolving field of research. Ambient Intelligence (AmI) solutions can be used to collect data from different sensor modalities installed inside homes. The collected data can help to support decision making for clinicians and carers. In addition, it can provide family members with reassurance about their relative's wellbeing. Behavioural models can be inferred from the collected data. Several currently available solutions try to detect activities before building behavioural models. Our approach is using Hidden Markov Models to build behavioural models directly from raw sensor data without the need of detecting activities first. The model depends on using simple and non-invasive binary sensors. The model is designed to detect abnormalities, sudden or gradual, in daily behaviour which may be considered an indicator of dementia. The model is tested using a real data set and evaluated using generated data.**

Keywords- Ambient Intelligence; Hidden Markov Models; Behavioural Modelling

I. INTRODUCTION

Elderly people become frail and more prone to illness and chronic diseases as they age. As a result, their need for support and care grows with time. Particularly in developed countries, the demography is changing since the ratio of elderly people out of the population is growing steadily as a natural result of the increase in life expectancy. The health care is developing and thus the people are living longer. Providing care for elderly is an imperative and time-critical however expensive service that consumes a substantial amount out of any government's budget which endures intimate scrutiny under the current economical austerity measures. In the field of Gerontology, the concept of aging-in-place has developed over the years enabling the elderly to stay autonomous and independent at their home as much as possible before institutionalizing or hospitalizing them in a specialized facility.

The paradigm of assisted living (AL) environments can be defined as providing care to people in their homes or in specialized care facilities, supported by technology [1]. Assisted living is augmented by adding ambient intelligence (AmI) which refers to the emerging field in computing of applying automated reasoning utilizing artificial intelligence techniques in order to understand people's behaviour within their surroundings whether it was in occupational, home or medical environments [1]. In social computing, the merger between assisted living and ambient intelligence created the emerging paradigm of Ambient Assisted Living (AAL). AAL environments harness the vigorous progress in the fields of sensing and wireless sensor networks as well as the versatile fields of software and hardware. In addition, it is supported by the robust developments in the communication arena which enables offering new opportunities to wider population as long as the technology is continuously transforming to be ubiquitous, pervasive and definitely mobile [1].

Smart home or house is used to refer to solutions in any living or working environment that was designed and implemented carefully and specifically with the main goal of assisting people in performing frequent and daily activities [2]. In some scenarios, the smart home can handle the control issues in situations related to comfort and leisure. Smart homes and their appliances can be devised with biomedical monitors, actuators and sensors that collect data using a network to a home gateway. The smart home may dispatch processed or unprocessed data to a remote data centre that may be responsible for instigating a help, care or emergency procedure [2]. Smart homes may include assistive technologies that are designed to serve elderly or disabled people that may include very simple facilitating solutions such as specially designed can openers or complex technological solutions such as harnessing robotics for example [3]. Assistive technologies help the targeted groups by providing assurance and safety and by enhancing impaired physical functions in order to assist in doing activities of daily life (ADL). In addition, assistive technologies help in assessing the cognitive capabilities of elderly in their homes by monitoring, or actually telemonitoring, their daily activities [3].

By using technology within the AAL paradigm, this paper is about using cutting-edge technologies for telemonitoring daily behaviour to handle detecting the onset of cognitive decline which may be a strong indicator of dementia within elderly people inside their dwellings' environment. This paper is an extended paper with additional results; the original paper is available in [4]. The additional results include evaluation of the resulting standard behavioural model's capability of identifying between normal and abnormal behaviour.

A. *Cognitive Decline and Dementia*

According to the report published by the Alzheimer's Research UK, dementia describes a group of symptoms that happens as a result of the brain cells' death or stopping working properly which leads to a progressive decline in cognitive capabilities such as memory, understanding, orientation, thinking, calculation and judgement [5]. Although there is no cure for dementia itself as a disease [6], it is easy to understand the importance of early diagnosis of the onset of dementia when considering the fact that those people diagnosed will be expected to live for three to nine years only [5]. Therefore, it is a time-critical job, considering the neurodegenerative prognosis of dementia [7], to try to enhance their life style in any proportion out of the limited time left. From another perspective, early diagnosis will enable starting proactive planning to facilitate treatment, compensation and coping.

In fact, each dementia patient in the UK costs the economy about £27,647 per year [5]. Therefore, early diagnosis by telemonitoring their daily behaviour in home settings will have a very positive impact on the economy by saving significant amounts. For example, between the year 2010 and 2021, assume that the forecasted increase in the number of people who will be suffering from dementia (increase from 821,884 to 940,110 citizens [5]) is equally divided between the twelve years to be 9852 citizens per year. If 10% only were successfully early diagnosed that they might suffer from dementia and then they are referred accordingly in order to mitigate or inhibit the symptoms for one year only, this will save the economy more than £27 million per year.

In [8], the authors are focusing on Alzheimer disease which accounts for approximately 50% of dementia cases. They suggest that in the early stages of the disease it may stay stable for several years. This phase is referred to as mild cognitive impairment. However, detecting this onset of dementia can provide a good opportunity to identify the cause of dementia since it can be sometimes reversible. In other irreversible cases, medication and disease management can help the patient to have a better life for the relatively limited time remaining for him in this life in the case of elderly people.

In Fig. 1, from [8], scores from the Mini-Mental State Examination (MMSE) were used to visualize the progression along the years. It is obvious that detecting dementia in early stages is very difficult since symptoms can be very subtle.

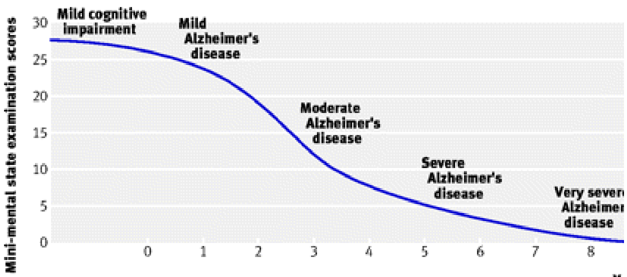

Figure 1. Symptom progression in Alzheimer's disease (Source [7]).

The duration of the mild cognitive impairment and the mild Alzheimer disease phases can last for less than 2 years. If the disease was detected in those phases the curve line deterioration will be much smoother than what it looks like in the moderate Alzheimer phase. This can enhance the patient's life for a couple of years before reaching the inevitable severe Alzheimer phase. The nature of the subtle degradation of this disease will have its implications on the detection methodology used in the case of behavioural monitoring or telemonitoring.

Based on one of the well-known nursing management standards for disturbed behaviour in aged care facilities; Poole's Algorithm [9], dementia is the last option to check after all other possibilities based on the elderly people's behaviour. These possibilities include delirium, depression or mental disorder. The importance of Poole's Algorithm to this research comes in twofold. First, it underlines the importance of monitoring the behaviour of elderly people since it can be a strong indicator of the onset of delirium, depression and dementia. Second, it underlines the importance of instigating support and care each time an abnormal behaviour is detected. In the algorithm diagram [9], anytime an aggressive, confused or inappropriate behaviour is noticed, the algorithm will end up by instigating supportive communication and care techniques. Therefore, in the case of telemonitoring, it is important to raise alerts to the care providers in case any abnormality is detected.

II. Related Work

There are different techniques to model human behaviour for different purposes such as for crowd modelling, sports, work flow efficiency and medical applications. For ambient assisted living environments, sensor firings and readings are grouped to form actions or movements that when grouped together will form recognizable activities. The series of concurrent and subsequent activities will form the behaviour. Some activities will be composed of sub-activities which gives behaviour a hierarchical perspective. Based on the Britannica Encyclopaedia [1], human behaviour is: "The potential and expressed capacity for physical, mental, and social activity during the phases of human life". However, in this paper, the physical behaviour is used to assess the mental capacity.

It is expected that an ensemble of different sensor modalities or even a solution with single modality binary sensors will produce huge data. Monitoring this data and trying to find similarities or abnormalities between different sets of data is a laborious job if it is to be done manually which may result in biased decisions as well. This data processing task can be automated, hence, the importance of machine learning techniques. Machine learning is about analysing large-scale data automatically by aiding, understanding and mimicking humans [10]. Machine learning is highly connected with Artificial Intelligence (AI) field, but machine learning is more related and about processing data to produce and adapt models. The very well-

[1] http://www.britannica.com/EBchecked/topic/275332/human-behaviour

known fields in machine learning are supervised learning and unsupervised learning. However, other fields or types of machine learning include anomaly/novelty detection, online/sequential learning, query/active learning, reinforcement learning and semi-supervised learning [10]. Machine learning utilizes the statistics field and probabilistic models to generate its final models. A more technology-based survey about proposed solutions to handle detecting the onset of dementia specifically is available in [11].

A. Behaviour Modelling

Based on [12], the probabilistic models the can be used for behaviour profiling include Hidden Markov Models (HMM), Hierarchical approaches, Conditional Random Fields (CRF) and Dynamic Bayesian Networks (DBN). However, the authors recommend using HMM when the application is about modelling behaviour based on discrete location. In addition, they consider, anomaly detection as a subset of those behaviour modelling techniques.

Actually, in [13], there is an accepted categorization of activity recognition and behaviour modelling techniques. It categorizes these techniques into three categories, namely generative modelling, discriminative modelling and heuristic/other approaches. This categorization applies to data-driven approaches. There are other techniques that are knowledge-driven.

1) Generative Modelling.

Generative modelling techniques include HMMs and DBNs. Actually, HMMs are the popular technique used in this field [13]. For example, in [14], the authors used Radio Frequency Identification (RFID) tags and readers to collect data in dense sensing mode. The components were designed by Intel Research Seattle and are called Wireless Identification and Sensing Platform (WISP). For mapping identified objects into high-level daily activities, they used first-order simple HMM. In another kind of solution [15], the authors proposed a framework to visualize and model behaviour based on HMMs. They suggested using a blob sensor node and a wearable sensor. They avoided labelling data into activity categories in order to respect the patient's privacy. The blob sensor node was used in their previous work [16] which models behaviour using HMM as well. HMMs have been used in systems that include multi-modalities including cameras. For example, in [17], the proposed system's design relies on the data fusion originating from wearable and ambient sensors. It utilizes cameras in addition to ear-worn accelerometer and gyroscope. Although the system uses cameras, the solution respects subject's privacy. Utilizing the optical data flow from four cameras, a 3D posture is extracted using probabilistic methods (HMM). In another solution, utilizing real data sets, in [18], they used HMMs for recognizing Activities of Daily Life (ADLs). They utilized their collected six real datasets from smart apartments. In their sensor selection part, the importance of motion sensors is clearly shown and they show that it formed the greatest value for activity recognition. Some efforts were done to filter the inputs of HMMs in order to have better results, for example, in [19], HMMs are used to generate models of behaviour which can be used to detect abnormalities and trends. They utilized belief values in order to accept or reject observations to be used in the behavioural model. HMMs have been used as well with other techniques as in [20], they use unsupervised HMM to discover and track activities within a smart environment. Using unsupervised model enables them to elude the annotation of data that is required by other approaches. However, before using the HMM to identify activities they extract activity patterns using Discontinuous Varied-Order Sequential Miner (DVSM) combined with a clustering algorithm. Other variants of HMMs where used, including Hidden Semi-Markov Models (HSMMs) as in [21] or Coupled Hidden Semi Markov Models (CHSMM) as in [22]. Actually Coupled Hidden Markov Models (CHMMs) are considered a simple DBN extension of HMMs [13].

2) Discriminative Modelling.

Discriminative modelling techniques mainly use CRFs and Support Vector Machines (SVMs). In [23], for activity recognition purposes, the authors compare HMM as a generative model with CRF as a discriminative model. They used one simulated dataset and another real world dataset to do their experiments. They concluded that CRF achieved better that HMM. However, they stated that HMMs performed better than CRFs when the feeding data included the idle activity. In [24], authors have summarized their experience about activity recognition and discovery. Using three datasets for activity recognition, they show that Support Vector Machines (SVMs) scores the highest average followed by HMM, then Naive Base Classifier and at last is CRF. They stated that each one of them has advantages and disadvantages and the task will help to decide which one to choose. For activity discovery, they used pattern recognition. Part of a framework for activity recognition, in [25], they use SVMs and CRFs on two ready-published datasets. CRFs are used for predicting future actions. They concluded that CRF outperforms HMMs when compared using F-measure.

3) Heuristic/Other Approaches.

The authors of [26] used a linear model based on a linear function to model the walking speed of 27 elderly people. They used eight unobtrusive Passive Infra-Red sensors that are arranged in a line and fixed in the ceiling. They suggest that detecting the change in walking speed will lead to early detection of cognitive decline in elderly, foresee disability, or anticipate risk of future hospitalization. Also, monitoring walking speed, in [27], they collected data for 418 days (monitoring 18 elderly people unobtrusively) and used wavelet analysis to figure out the differences by comparing day-to-day activity. To examine the trends in the resulting variance, they used mixed model repeated-measures analysis of variance (ANOVA). They divided the participants into two groups: those with mild cognitive impairment and those who are cognitively healthy. The classification criterion was based on CDR (Clinical Dementia Rating) scale and MMSE (Mini-Mental State Examination). Similarly, in [28], they used mixed model analysis of variance to infer the activity level of 14 participants and they compared that to the MMSE level of those participants. In their implementation, Ultra-Wide band wrist-worn radio transponders (Ubisense 2.0) were used. These transponders are capable of measuring unconstrained locomotion every 0.43 seconds up to an accuracy of 20 cm.

In another example, in [29], the researchers setup five passive infrared sensors in each of the 14 subjects' homes over three months. Those sensors monitored how many times the subject get out of the home and monitored the sleep time and rhythm. They used standard deviation and correlation to compare two groups of subjects which are the mild cognitive impairment group and the control group. Another technique was proposed in [30] where the authors presented a software tool called SAMCAD II which uses pattern recognition in order to assess behavioural rhythms. They used the Circadian Activity Rhythms (CAR) methodology in order to infer baseline behaviours and the changes that happen later which may be an indicator of a chronic disease.

B. *Smart Homes*

Building on ambient intelligence solutions and ambient assisted living environments, smart homes have been investigated by different research groups. The groups included in their investigations the use of smart homes' environments for telehealth/telecare solutions as well. Examples of those research groups are: CASAS smart home [31], MIT House_n and PlaceLab [32], Georgia Tech Aware Home [33], MavHome [34], Welfare Techno house in Japan [35], the Gator Tech Smart House [36] , The ORCATECH Living Laboratory (OLL) [37], and iSpace/iDorm [38]. A list of the published datasets generated from some of these smart homes from the aforementioned groups and other groups is available from BoxLab [39] .

III. BEHAVIOUR MODELLING

A. *Sensor Type Selection*

Based on the literature review and the experience that the research team have built from visiting different related facilities, a group of design goals were selected and are cherished throughout the whole project. Actually, the selected design goals can serve as guidelines for designers who are working on all projects within the field of Ambient Assisted Living (AAL) or telemonitoring specifically. The selected guidelines are: simple, unobtrusive, cost-effective and non-invasive. These guidelines can be considered as required characteristics of the resulting solution. A detailed description of those guidelines in addition to a comprehensive framework for such solutions will be published separately when they are more complete.

Accordingly, several sensor types were considered. However, Passive Infra-Red (PIR) sensors were selected because of their availability and simplicity [40]. PIR sensors are binary sensors, which means that the sensor can be either on or off. This can restrict the amount of information that can be extrapolated out of such sensors. Additionally, other candidate types of sensors were considered, such as the utilities meters for water, electricity and gas consumption. However, this research aimed at checking whether it is possible to infer behaviour based on a very simple sensor such as the PIR sensor only.

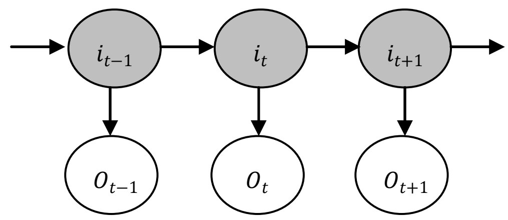

Figure 2. A visual representation for a first-order Hidden Markov Model where the nodes in gray are the hidden states and the white nodes are the observed symbols.

Since PIR sensor firings can be correlated with the location of the subject within the home, the model that will be generated will be a location-based model and will measure the movement between sensor nodes utilizing the count of sensors' firings and their sequence. Given the suitability of HMM for discrete location-based behaviour modelling as stated in [12], HMM were used in the suggested model.

B. *Hidden Markov Model (HMM)*

The HMMs are generative probabilistic models [21], [41], [42]. As the name suggests, there are two faces for this model, an observed face, resembled by observed symbols, and a hidden face, resembled by hidden states. The number of possible hidden states is N and the number of possible observed symbols is M. The observation sequence O can be defined as $O_{1:T} = \{O_1, O_2, \dots, O_T\}$ where the length of the sequence is T and where O_t is the observation symbol at instant t such that $O_t \in \{1 \dots M\}$. Sometimes O_t can be a single symbol or it can be a vector of symbols $\vec{O}_t$. The hidden states sequence I can be defined as $I_{1:T} = \{i_1, i_2, \dots, i_T\}$ where the length of the sequence is T and where i_t is the hidden state at instant t such that $i_t \in \{1 \dots N\}$. Generative models define the joint probability between the hidden and the observable $p(I_{1:T}, O_{1:T})$. The relation between the hidden states and the observed symbols can be visualized as demonstrated in Fig. 2.

An HMM is comprised of three matrices as demonstrated in equation 1 below. The HMM model is called λ.

$$\lambda = \{A, B, \pi\} \tag{1}$$

Based on the notation used in this paper, the first matrix is A, which is the transition probability matrix between hidden states. The second matrix B is the emission probability matrix. The third matrix π is the starting (or initial) hidden state probability matrix. The definition of each matrix [41] is presented in the three equations below.

$$A = \{a_{ij}\}\ where\ a_{ij} = p(i_{t+1} = j \mid i_t = i)\ \text{where}\ i, j \in \{1..N\} \tag{2}$$

$$B = \{b_j(O_k)\}\ where\ b_j(O_k) = p(O_k\ \text{at}\ t \mid i_t = j)\ where\ O_k \in \{1..M\} \tag{3}$$

$$\pi = \{\pi_i\}\ where\ \pi_i = p(i_1 = i)\ \text{where}\ i \in \{1..N\} \tag{4}$$

In a first-order HMM there are three assumptions:

- First one is the inherited Markovian assumption which is about the dependency between hidden states such that the transition probability to state *i* depends only on one state *j* which directly precedes state *i* as clarified in equation 2 above, hence the name first-order.
- The second assumption is the stationary assumption such that the transition probability from state *i* to state *j* at time t_1 is the same at t_2 and does not change with time.
- The third assumption is the output independence assumption such that the observed emission of a symbol *O* at state *i* is independent from the previous observed emission in previous states and depends only on state *i* as demonstrated in equation 3 above.

Using HMMs can help solve three problems [41]:

- The evaluation problem: Given a model λ, how to calculate the probability that a sequence of observations *O* was generated by that model which means finding $p(O|\lambda)$. This can be solved by the Forward-Backward Algorithm.
- The decoding problem: Given a model λ and a sequence of observations *O* how to find out a sequence of states *I* that maximizes the joint probability $p(O,I|\lambda)$. This can be solved using the Viterbi Algorithm which utilizes the Maximum Likelihood (ML) algorithm.
- The learning problem: Given a sequence of observation *O* and/or a sequence of states *I*, how find parameters for a model λ that maximize the probability of $p(O|\lambda)$ or $p(O,I|\lambda)$. This learning or training problem can be achieved utilizing the Baum-Welch Algorithm which is an Expectation Maximization (EM) algorithm.

C. Model Design

There were four options in designing the model in order to achieve the ultimate goal of detecting abnormality. First option was to model the location of the subject based on the triggering PIR. This option will entail having rooms as states where the subject moves between rooms will form the transitions. Since this option has evolved later on to take the sensor instead of the room, there was no need to consider uncertainty if two sensors fire together. Second option was the subject's state model or modelling the change, where there were three states: normal, mild change and severe change. The third option was about having active, quiet and outside states which will need defining the activity level thresholds. The fourth option was to infer activities and then try to model the behaviour similar to the solutions suggested in the literature as discussed in subsection A in section II. Actually, inferring activities included some error margin and resulted in some generalization of the original sensor firings. Given the requirement of using simple sensors and the limited features that the type of sensor utilized provides, the decision was made to proceed with the first option which is about modelling the user location based on the PIR sensor firings. This decision was supported as well by the fact that it is hard to provide a threshold-based model to identify between the wellness (or even activity level) of the subject given the myriad number of possible illness cases.

The initial first option assumption of modelling location evolved to model the sensors as states since some rooms may contain more than one sensor and by adopting this technique the implementation of the solution can proceed without even doing the semantic labelling of sensors to associate them with locations or even objects. Actually the nature of the PIR sensors as binary sensors facilitated adopting this technique and resulted in having the sensor as the state and the emission symbol at the same time in the model. Based on this, if the number of sensors is N, matrix B in the model will be an NxN identity matrix. In addition, matrix A will be of size NxN as well and will contain the probability of a sensor firing after another sensor. For π, the decision was made to make it an $Nx1$ matrix containing $1/N$ in each entry which means giving equal initial probability to start with any sensor. However, this simplification can be changed later on to reflect the real case that some sensors will have higher probability to start with rather than other sensors in a specific home environment.

In order to build the model, the incoming sequence of sensors triggered will be used as the observations *O* to learn the HMM parameters as a learning problem as described in subsection B in section III above. These observations will be divided based on an equal time-window *t*, for example, a day time-window. Therefore, similar to equation 1, the resulting model for a time window *t* can be expressed as $\lambda_t = \{A, B, \pi\}$. When a new time window (*t+1*) sequence is ready and available, it will be used to generate λ_{t+1}which is the model for (*t+1*) time window only.

Now the standard/normal model will be built and fixed every number of time-windows (e.g. every 14 days) or whenever a carer finds appropriate which is part of giving the carer more involved role in building and tailoring this model. The carer can as well include or exclude days in building the standard model based on assessing the actual situation for that time window. If a time window was deemed appropriate to be included in the standard model, its model will be the standard model if it was the first time window or its sequence will be used to train the previous standard model if a previous standard model exists. This process will result in a standard or normal model λ_{st}, where t is the sequence number at which the standard model has been built.

When the standard model λ_{st} is established and new observations O_{t+1} arrive in a different time window, there are two methods that can be used:

- Calculate the log-likelihood that O_{t+1} was generated by the current standard/normal model λ_{st}.
- Build a model λ_{t+1}, as described previously, using the O_{t+1} and compare the resulting model with the available standard/normal model λ_{st}. To compare two HMMs, the Kullback-Leibler distance will be used as advised in [41].

(a) (b)

Figure 3. (a) Comparing new time-window observations with the standard behavioural model λ_{s0} . (b) Comparing the new time window model with the standard behavioural model λ_{s0} using a distance measure.

Actually, both methods generate a distance like measure for a specific time window t, therefore the resulting distance is called d_t . Based on a one-day time window, Fig. 3 (a) and (b) below demonstrates the two methods above.

Since each time the comparison happens, a distance or log-likelihood is calculated, the kept standard/normal model will be represented by a tuple called S_i as shown in equation 5 below where λ_i is the HMM standard/normal model, μ_i is the mean value of the distance or log-likelihood until i, and $\sigma_i$is the standard deviation until i.

$$S_i = \{\lambda_i, \mu_i, \sigma_i\} \qquad (5)$$

Recording more than one standard model tuple S that includes the latest value of the mean and standard deviation as well, will enable detecting sudden abnormality by comparing it to the latest standard model and will enable detecting gradual change in behaviour by comparing to a previous group of standard models, this is demonstrated in Fig. 4 below.

For abnormality, a function is defined called $\beta(d_t, S_i)$ such that $\beta \rightarrow \{0;1\}$ where 0 means normal and 1 means abnormal. Equation 6 and 7 provide the definition of the abnormality function for Kullback-Leibler *k* and log-likelihood *l* respectively.

$$\beta_k(d_t, S_i) = \begin{cases} 0 : d_t \leq (\mu_i + \sigma_i) \\ 1 : d_t > (\mu_i + \sigma_i) \end{cases} \qquad (6)$$

$$\beta_l(d_t, S_i) = \begin{cases} 0 : d_t \geq (\mu_i - \sigma_i) \\ 1 : d_t < (\mu_i - \sigma_i) \end{cases} \qquad (7)$$

IV. The Experiment: Results and Discussion

After collecting raw sensor data in a lab environment in order to understand and study the technology and analyze the implications of handling the data until it is transformed into a suitable format, the main experiment was done in order to implement the solution in a real home, collect data, process data and build a behavioural model. However, due to the complexity, whether it is technical or ethical, associated with implementing the system in a real environment, the research team opted to use one of the already available data sets. Therefore, the behavioural modelling was done on the selected data set. The following will provide description and details about the experiment and will show the results accordingly.

During the conducted literature review, multiple already available datasets were considered. These datasets are published online for usage under different licenses and requirements. Actually, these datasets are very vital to the progress of research in this field and those behind them should be thanked for making these dataset available. The datasets were used by the publishing research groups for purposes that are sometimes very different from the purpose of this research. In addition to the datasets from the groups mentioned in section II (subsection B), additional datasets where considered from Tiger Place at University of Missouri: Instrumented assistive living, and Tim Van Kastreen: University of Amsterdam: Activity Recognition Dataset.

During going through the aforementioned datasets, the design goals, mentioned in section III in Part A, were considered. This meant that only datasets that have PIR readings in it were included. The nature of PIR does not

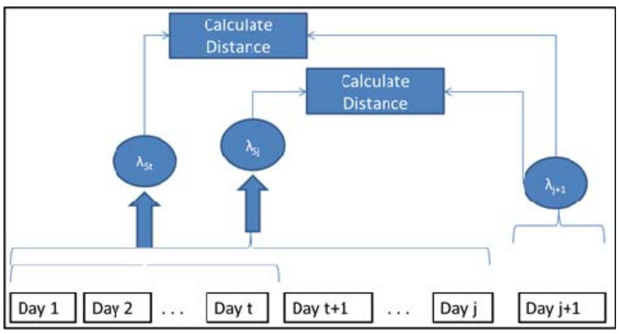

Figure 4. Comparing a new behavioural model with more than one standard behavioural model to detect sudden and gradual change.

DOI 10.5013/IJSSST.a.15.05.01

ISSN: 1473-804x online, 1473-8031 print

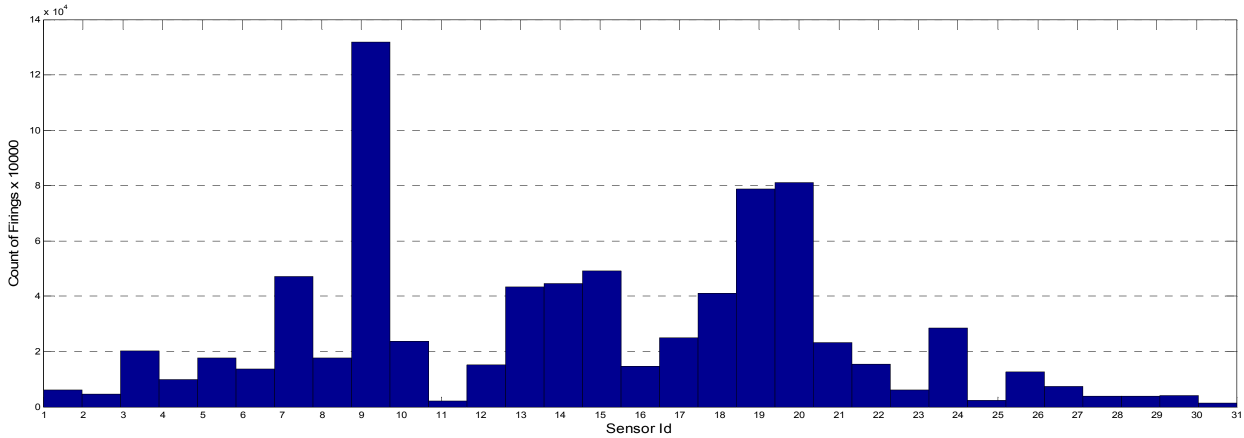

Figure 5. The count of sensor's firings for each sensor in the used dataset.

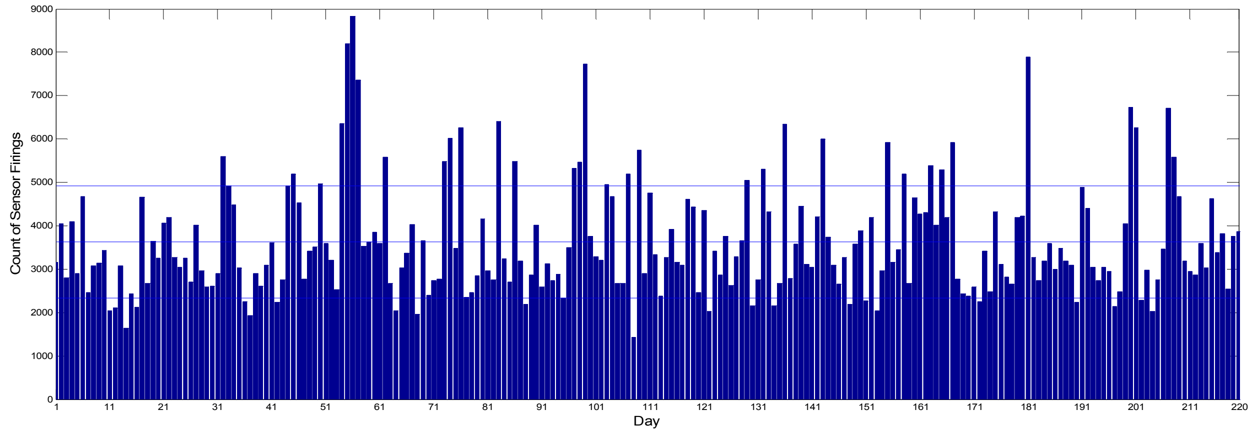

Figure 6. The total count of sensor's firings for each day in the dataset.

allow distinguishing between different people in front of it [40]. Therefore, datasets that are gathered based on one person living alone were considered. In addition, the documentation associated with each dataset was an important factor to ratify its usability.

Based on all of these factors, the dataset from CASAS [31] was selected. The selected dataset name is Aruba and it was recorded during 219 continuous days. It has a total number of records of 1,719,558. The dataset recorded firings from 31 motion sensors (PIR), 3 door sensors, 5 temperature sensors, and 3 light sensors. The PIR sensors firings accounts for %92.82 of the dataset which is 1,596,142 records. The subject who triggered the sensors was one female who lived alone but she had her children and grandchildren visiting sometimes. One more advantage of this dataset is that there is another subsequent dataset which contains similar sensors' settings but it recorded firings for 407 days, that dataset is called Aruba2.

The most identifiable issue with the selected dataset was the problem of flight delays in the arrivals of sensors' packets to the gateway. Therefore, some sensors may have been triggered on but they have returned off after another sensor is triggered on.

The first challenge was to transform the dataset into a more suitable format and during this task some data cleansing was required to handle for example invalid records that have an 'ON' but no 'OFF' record. In such records, the time was set manually in some cases or the whole record was deleted in other cases. In order to manage the data more effectively and to finish formatting it properly, the dataset was loaded into an Oracle XE database. In the database, time format conversion problems were handled and the main task was to build a new table showing one record only for each sensor firing containing both the on and off time. This will enable calculating the duration of the firing and thus assessing the amount of movement that happened. Therefore, the dataset was separated into two different tables, one that contains the 'ON' records and another table that contains the 'OFF' records. Actually, the powerful database engine used enabled rejoining those tables together and calculated the elapsed firing time for each sensor's firing. When data was ready in the required format, it was exported into Matlab in order to start the next step. Each firing record contains an id, a number representing the time when the sensor is triggered and another number representing the time when it was switched off, the elapsed time which is the result of subtracting the third field from the second one, and finally the sensor (motion sensor) number. The count of firings for each sensor is presented in Fig. 5 which shows that sensor 9 accounted for the highest count of firings, while sensors 11,

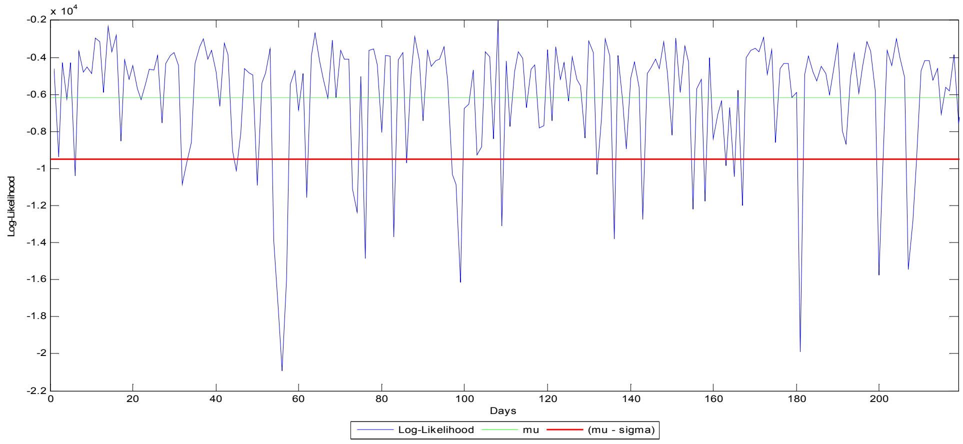

Figure 7. The log-likelihood for each day compared with the standard behavioural model

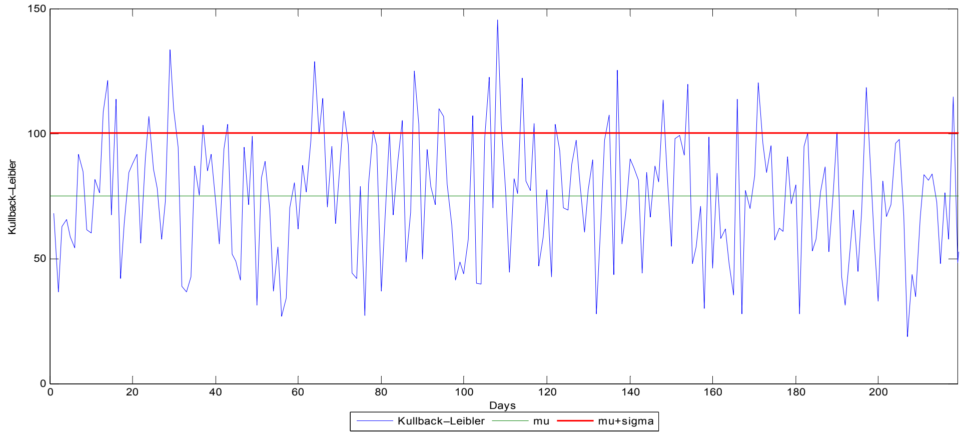

Figure 8. The Kullback-Leibler distance for each day compared with the standard model

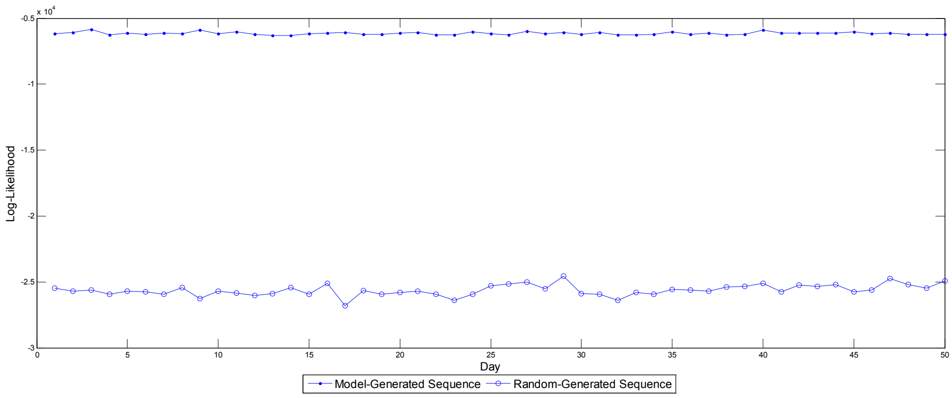

Figure 9. The Log-Likelihood distance for model and random generated sequences

25 and 31 have the least count of firings. In Fig. 6, the number of sensor firings' count for each day is demonstrated. The average number of PIR sensors firings for each day is 3626.75 event/day. The figure also shows that on day 109, the least number of firings had been recorded.

Within Matlab, the data was transformed to generalize the date in order to group records in a specific time window. In this experiment, that time window is a day. Therefore, the 'Date/Time ON' field was used to divide the dataset into subgroups where each group belongs to a single day. The whole dataset was then used to build a behavioural standard model as described in section III part C. As a result, we had a fully trained model for the all 219 days. Next, the resulting model was used as a standard model λ_{st} to be compared with the same dataset days one by one. Fig. 7 shows that the built model could identify some days as being abnormal using the

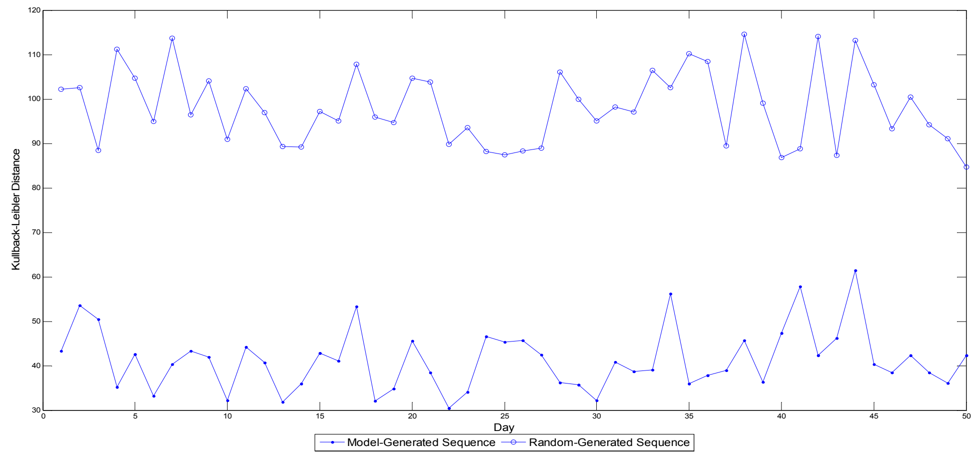

Figure 10. The Kullback-Leibler distance for model and random generated sequences

Log-likelihood to compare the standard model λ_{st} with sensors' firings from each day of the dataset.

The green line in the figure shows mean value (μ) of the Log-likelihood while the redline shows a one standard deviation (σ) value subtracted from the mean. The standard model was successful in identifying 32 days as abnormal days. Repeating the same comparison but using the Kullback-Leibler distance, shows again that it can be used as well to identify abnormal days (34 days) as demonstrated in Fig. 8 where the green line represents the mean (μ) and the redline is a one standard deviation (σ) added to the mean (μ).

The same standard model λ_{st} generated from all days was used to evaluate the model and the results by simulating generating a sequence of events (sensor firings) from the standard model itself. The length of the generated sequence was selected to be similar to the average of sensors firings per day from the dataset (3626.75 event/day) approximated to 3627 event/day. The number of days generated was 50 days making 50 sequences. The resulting generated sequences represent normal behaviour that follows the standard behaviour and should be identified as normal. From another side and using the same parameters above, sequences of random numbers were generated to represent random or abnormal behaviour. The random numbers are generated following a discrete uniform distribution over an interval between 1 and 31 representing the 31 PIR sensors. When comparing both sequences to the model using the Log-Likelihood and the Kullback-Leibler distance, the two sequences are significantly different. As demonstrated in Fig. 9 and Fig. 10, both log-likelihood and Kullback-Leibler distances show that the random generated sequences are far from the model generated sequences and they can be easily identified, which means that the random sequences generated do represent abnormal behaviour and, principally, the inferred standard model can successfully detect abnormalities in daily behaviour.

V. CONCLUSIONS

Telemonitoring systems, that are unobtrusive, simple, cost-efficient and nonintrusive, will support the achievement of the aging-in-place concept. Dementia is one of the important challenges that need to be monitored. Daily behaviour rhythms' changes can be an indicator of something going wrong that may be the onset of dementia. Utilizing ambient intelligence and by telemonitoring for proactive care, it is possible to utilize law resolution binary sensors (i.e. PIR) to build a behavioural model.

The behavioural model proposed in this paper can be used to monitor daily behaviour. Using the model, it is possible to detect gradual and sudden abnormal behaviour based on distance measures or log-likelihood, and by keeping more than one standard/normal behavioural model. The proposed model was tested using a real dataset. It was evaluated by comparing generated normal days from the model to abnormal days that are generated from random sequences. The suggested model's sensitivity was enough to successfully identify abnormal days.

The model grants carer an interactive role during building the standard model about which days to include or not include. This hybrid-style model that empowers carers can provide more true positives (higher system sensitivity) and will increase its acceptability during implementation as a decision-support system.

REFERENCES

[1] M. Mulvenna, W. Carswell, P. Mccullagh, J. C. Augusto, and H. Zheng, "Visualization of Data for Ambient Assisted Living Services," IEEE Commun. Mag., vol. 49, no. January, pp. 110–117, 2011.

[2] M. Chan, D. Estève, C. Escriba, and E. Campo, "A review of smart homes- present state and future challenges.," Comput. Methods Programs Biomed., vol. 91, no. 1, pp. 55–81, Jul. 2008.

[3] M. Chan, E. Campo, D. Estève, and J.-Y. Fourniols, "Smart homes - current features and future perspectives.," Maturitas, vol. 64, no. 2, pp. 90–7, Oct. 2009.

[4] N. AlBeiruti and K. Al-Begain, "Using Hidden Markov Models to Build Behavioural Models to Detect the Onset of Dementia," in 2014 Sixth International Conference on Computational Intelligence, Communication Systems and Networks, 2014, pp. 18–26.

[5] R. Luengo-Fernandez, J. Leal, and A. Gray, "Dementia 2010: The economic burden of dementia and associated research funding in the United Kingdom," 2010.

[6] Alzheimer's Research UK, "Treatments for dementia," 2010. [Online]. Available:

http://www.alzheimersresearchuk.org/siteFiles/resources/documents/ARUK_Treatments_for_dementia.pdf. [Accessed: 04-Jan-2012].

[7] Alzheimer's Research UK, "All about dementia," booklet, 2010. [Online]. Available: http://www.alzheimersresearchuk.org/siteFiles/resources/documents/ARUK_All_about_dementia.pdf. [Accessed: 03-Jan-2012].

[8] A. Burns and S. Iliffe, "Alzheimer's disease," BMJ, vol. 338, no. feb05 1, pp. b158–b158, Feb. 2009.

[9] J. Poole, "Poole's Algorithm: Nursing Management of Disturbed Behaviour in Aged Care Facilities," 2009.

[10] D. Barber, Bayesian Reasoning and Machine Learning. Cambridge University Press, 2012, p. 728.

[11] N. AlBeiruti and K. Al-Begain, "A Survey on Home-based Technologies for Detecting Behavioural Abnormalities and Cognitive Decline in Elderly People," in 2011 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT), 2011, pp. 366–369.

[12] L. Atallah and G.-Z. Yang, "The use of pervasive sensing for behaviour profiling -- a survey," Pervasive Mob. Comput., vol. 5, no. 5, pp. 447–464, 2009.

[13] L. Chen, J. Hoey, C. D. Nugent, D. J. Cook, and Z. Yu, "Sensor-Based Activity Recognition," IEEE Trans. Syst. Man, Cybern. Part C (Applications Rev., vol. 42, no. 6, pp. 790–808, Nov. 2012.

[14] M. Buettner, R. Prasad, M. Philipose, and D. Wetherall, "Recognizing daily activities with RFID-based sensors," in Proceedings of the 11th international conference on Ubiquitous computing - Ubicomp '09, 2009, p. 51.

[15] L. Atallah, M. ElHelw, J. Pansiot, D. Stoyanov, L. Wang, B. Lo, G. Z. Yang, and R. Magjarevic, "Behaviour Profiling with Ambient and Wearable Sensing," in 4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007), vol. 13, S. Leonhardt, T. Falck, and P. Mähönen, Eds. Springer Berlin Heidelberg, 2007, pp. 133–138.

[16] M. ElHelw, J. Pansiot, D. McIlwraith, R. Ali, B. Lo, and L. Atallah, "An integrated multi-sensing framework for pervasive healthcare monitoring," in Pervasive Computing Technologies for Healthcare, 2009. PervasiveHealth 2009. 3rd International Conference on, 2009, pp. 1–7.

[17] D. McIlwraith, J. Pansiot, and Y. Guang-Zhong, "Wearable and ambient sensor fusion for the characterisation of human motion," in Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on, 2010, pp. 5505–5510.

[18] D. J. Cook and L. B. Holder, "Sensor Selection to Support Practical Use of Health-Monitoring Smart Environments.," Data Min. Knowl. Discov., vol. 1, no. 4, pp. 339–351, 2011.

[19] D. N. Monekosso and P. Remagnino, "Behavior Analysis for Assisted Living," IEEE Trans. Autom. Sci. Eng., vol. 7, no. 4, pp. 879–886, Oct. 2010.

[20] P. Rashidi, D. J. Cook, L. B. Holder, and M. Schmitter-Edgecombe, "Discovering Activities to Recognize and Track in a Smart Environment.," IEEE Trans. Knowl. Data Eng., vol. 23, no. 4, pp. 527–539, Jan. 2011.

[21] T. L. M. van Kasteren, G. Englebienne, and B. J. A. Kröse, "Activity recognition using semi-Markov models on real world smart home datasets," J. Ambient Intell. Smart Environ., vol. 2, no. 3, pp. 311–325, Aug. 2010.

[22] P. Natarajan and R. Nevatia, "Coupled Hidden Semi Markov Models for Activity Recognition," in 2007 IEEE Workshop on Motion and Video Computing (WMVC'07), 2007, pp. 10–10.

[23] T. L. M. van Kasteren, A. K. Noulas, and B. J. A. Kröse, "Conditional Random Fields versus Hidden Markov Models for activity recognition in temporal sensor data," in Proceedings of the 14th Annual Conference of the Advanced School for Computing and Imaging, 2008.

[24] D. J. Cook, N. C. Krishnan, and P. Rashidi, "Activity discovery and activity recognition: a new partnership.," IEEE Trans. Cybern., vol. 43, no. 3, pp. 820–8, Jun. 2013.

[25] I. Fatima, M. Fahim, Y.-K. Lee, and S. Lee, "A unified framework for activity recognition-based behavior analysis and action prediction in smart homes.," Sensors (Basel)., vol. 13, no. 2, pp. 2682–99, Jan. 2013.

[26] S. Hagler, D. Austin, T. L. Hayes, J. Kaye, and M. Pavel, "Unobtrusive and Ubiquitous In-Home Monitoring: A Methodology for Continuous Assessment of Gait Velocity in Elders," Biomed. Eng. IEEE Trans., vol. 57, no. 4, pp. 813–820, 2010.

[27] T. L. Hayes, F. Abendroth, A. Adami, M. Pavel, T. A. Zitzelberger, and J. A. Kaye, "Unobtrusive assessment of activity patterns associated with mild cognitive impairment," Alzheimer's Dement., vol. 4, no. 6, pp. 395–405, 2008.

[28] W. D. Kearns, V. O. Nams, and J. L. Fozard, "Tortuosity in Movement Paths Is Related to Cognitive Impairment. Wireless Fractal Estimation in Assisted Living Facility Residents," Methods Inf. Med., vol. 49, pp. 592–598, 2010.

[29] T. Suzuki, S. Murase, T. Tanaka, and T. Okazawa, "New Approach for The Early Detection of Dementia by Recording In-House Activities," Telemed. e-Health, vol. 13, no. 1, pp. 41–44, 2007.

[30] G. Virone, "Assessing everyday life behavioral rhythms for the older generation," Pervasive Mob. Comput., vol. 5, no. 5, pp. 606–622, 2009.

[31] "Center for Advanced Studies in Adaptive Systems, Washington State University." [Online]. Available: http://ailab.wsu.edu/casas/. [Accessed: 16-Mar-2014].

[32] "House_n Research Group, Massachusetts Institute of Technology." [Online]. Available: http://architecture.mit.edu/house_n/index.html. [Accessed: 16-Mar-2014].

[33] "Aware Home Research Intitaive, Georgia Tech." [Online]. Available: http://www.awarehome.gatech.edu/. [Accessed: 16-Mar-2014].

[34] "Managing an Adaptive Verstile Home 'MavHome', Washington State University and the University of Texas at Arlington."[Online]. Available: http://ailab.wsu.edu/mavhome/index.html. [Accessed: 16-Mar-2014].

[35] A. Kawarada, T. Takagi, A. Tsukada, K. Sasaki, M. Ishijima, T. Tamura, T. Togawa, and K. Yamakoshi, "Evaluation of automated health monitoring system at the 'Welfare Techno House,'" in Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Vol.20 Biomedical Engineering Towards the Year 2000 and Beyond (Cat. No.98CH36286), 1998, vol. 4, pp. 1984–1987.

[36] "The Gator Tech Smart House (GTSH), Mobile and Pervasive Computing Research, the University of Florida." [Online]. Available: http://www.harris.cise.ufl.edu/gt.htm. [Accessed: 16-Mar-2014].

[37] "The ORCATECH Living Laboratory (OLL), Oregon Health & Sciences University." [Online]. Available: http://www.orcatech.org/resources/living-laboratory. [Accessed: 16-Mar-2014].

[38] "The Intelligent Dormitory (iSpace), Intelligent Environments Group, University of Essex." [Online]. Available: http://cswww.essex.ac.uk/iieg/idorm.htm. [Accessed: 16-Mar-2014].

[39] "BoxLab Wiki Page." [Online]. Available: http://boxlab.wikispaces.com/. [Accessed: 16-Mar-2014].

[40] S. Honda, K. Fukui, K. Moriyama, S. Kurihara, and M. Numao, "Extracting Human Behaviors with Infrared Sensor Network," in 2007 Fourth International Conference on Networked Sensing Systems, 2007, pp. 122–125.

[41] R. Dugad and U. B. Desai, "A Tutorial on Hidden Markov Models," Indian Inst. Technol., p. 16, 1996.

[42] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," Proceedings of the IEEE, vol. 77, no. 2. pp. 257–286, 1989.