Behaviour Profiling with Ambient and Wearable Sensing

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Abstract—**This paper investigates the combined use of ambient and wearable sensing for inferring changes in patient behaviour patterns. It has been demonstrated that with the use of wearable and blob based ambient sensors, it is possible to develop an effective visualization framework allowing the observation of daily activities in a homecare environment. An effective behaviour modelling method based on Hidden Markov Models (HMMs) has been proposed for highlighting changes in activity patterns. This allows for the representation of sequences in a similarity space that can be used for clustering or data-exploration.**

Keywords—**body sensor networks, similarity based clustering, blob sensors, behaviour profiling.**

I. INTRODUCTION

Over the next fifty years, the proportion of people aged beyond 60 is expected to more than double. With demographic changes associated with the aging population and the increasing number of people living alone, the social and economic structure of our society is changing rapidly. In almost all countries, longevity has given rise to expensive age-related disabilities and diseases. With the steady decline of the ratio of workers to retirees, a fundamental change of the way that we care for the aging population is required.

Recent advances in the semiconductor industry have led to miniaturisation and cost reduction of both sensor and computing technologies, thus making truly pervasive monitoring of patients with chronic disease and those living alone a reality. For the elderly, home-based healthcare encourages the maintenance of physical fitness, social activity and cognitive engagement to function independently in their own homes. For care professionals, it also provides a more accurate measure of how well the elderly person is managing with his/her daily activities, thus better targeting limited human carer resources to those who need the most.

Research in pervasive healthcare has recently transcended from the traditional telecare systems and several groups have investigated 'smart homes' that can provide intelligent pervasive home monitoring. Examples include MIT's PlaceLab [1], BT's work on smart homes [2] and the Welfare Techno house in Japan [3]. Most of these projects employ a large number of sensors that are ubiquitously placed around the house. These sensors include temperature sensors, water flow and utility usage sensors, pressure sensors on furniture, as well as vital signs monitoring devices. These sensors provide data that can be analysed to observe patient behaviour or detect the occurrence of critical events such as falls.

One of the limitations of ambient sensing based on simple sensors is that it is difficult to infer detailed changes in activity and physiological changes related to the progression of disease. In fact, even for the detection of simple activities such as leaving and returning home, the analysis steps involved can be complex even by the explicit use of certain constraints. It is well known that subtle changes in behaviour of the elderly or patients with chronic disorders can provide telltale signs of the onset or progression of the disease. For example, research has shown that changes in gait can be associated with early signs of neurologic abnormalities linked to several types of non-Alzheimer's dementias. Subjects with neurologic gait abnormalities had a greater risk of developing dementia.

Another challenge associated with the current ambient sensing framework is the availability of the training data. In many scenarios, the requirement for the patient to perform specific activities in order to obtain a 'labelled training' set is not realistic. The large number of sensors involved also makes a wide-spread practical deployment difficult. The purpose of this work is twofold. First, we aim to provide a simple hardware architecture with an integrated use of e-AR (ear-worn activity recognition) sensor and blob based ambient sensors. We demonstrate that by the use of these two types of sensors, it is possible to provide rich information that can be used for analysing most types of daily activities. Second, we propose an effective visualisation framework and behaviour modelling method based on Hidden Markov Models (HMMs) for highlighting changes in activity patterns without the use of explicit labelling of data into activity categories. These two unique features of the system make it easily deployable to a range of homecare settings.

II. COMBINING AMBIENT AND WEARABLE SENSING

Ambient sensing refers to the use of environment sensors for the monitoring of daily activities. In this work, blob sensors based on the concept of using abstracted image blobs to derive personal metrics and perform behaviour profiling are used [4]. With these sensors, the captured image is immediately turned into blobs that encapsulate shape outline and motion vectors of the body at the device level. No appearance data is stored or transmitted at any stage of the processing and it is not possible to reconstruct this abstracted information back to images. This ensures the privacy of the patients and also makes the device usable to all areas of a home environment. The shape of a blob (or outline) detected by the sensor depends on the relative position of the subject and the sensor. A view-independent model can be generated by fusing a set of blobs captured by respective sensors at different known positions, which can be used to generate a more detailed activity signature. Figure 1 shows several example outputs of the blob sensor. The main information derived from the blob sensors in this work is room occupancy and the number of people in the room. More elaborated analysis of blobs for posture and gait recognition is performed in a separate study [4]. The focus of this paper is directed towards overall activity patterns within the house. For N rooms, at time t, the blob sensors provide a vector of room occupancy $L_t(N)$ of size N.

Fig. 1 Outputs of the blob sensor, showing 3 different activities.

In this work, we use a combined wearable-ambient sensor framework to determine the location of the person being monitored. To allow the identification of the patient(s) being monitored in a multi-dwelling environment, the patient wears an e-AR sensor (ear worn activity recognition sensor). The e-AR is presented in more details in [5], and is based on the BSN platform that consists of a Texas Instrument MSP430 processor, a Chipcon CC2420 radio transceiver and an Atmel 512KB EEPROM [6, 7]. The e-AR sensor contains a 3-axis accelerometer and a MCC ChipOX SpO_2 that can be used to monitor the change of the physiological parameters of the patient (as investigated in [8]). However, its primary function in this work is to locate the patient being observed. Thus, at each time stamp, the signal strength transmitted from the wearable sensor to the receivers (typically co-located with the blob sensor) is recorded. For M receivers, the wearable sensors provide a vector $X_t(M)$ of signal strength of size M.

III. A BAYESIAN CLASSIFIER TO IDENTIFY PATIENT LOCATION

A Bayesian classifier is used to model the relationships between the signal strengths and the room occupancies. For each vector of signal strengths X_t at a time t, the classifier provides a likelihood of room occupancy. Training data is obtained by recording both occupancies and signal strengths of a person while being alone in the house. In this case, a simple Naïve Bayes classifier was used due to its simplicity, but Gaussian Mixture Models could also be used to model these relationships. Thus at each time stamp, the classifier provides a probability of being in a certain room (an occupancy vector), given a vector of signal strengths:

$$P\left(L(j)/X_t\right) = \frac{\prod_{i=1}^{N} P\left(X_t(i)/L(j)\right) P\left(L(j)\right)}{L(j)} \qquad (1)$$

The classifier is used whenever there is an ambiguity over the number of people in a certain room. However, it is not used if the ambient sensors determine that there is only one person in the house and there is no uncertainty in the number of occupants. The training data-set (of signal strengths) was obtained over 10 minutes from a single person moving in a lab-based environment. The training labels for the classifier are the values of the occupancy vector $L_t(N)$. Table 1 shows the 5-fold cross validation averaged results of this classifier on the training dataset.

Table 1 Results of correct classification using the Bayesian classifier

Classifier results\Room number	**1**	**2**	**3**	**4**	**5**
Success rates (percent)	70	94	100	66	79

IV. A REALTIME ACTIVITY GRID

Given the data from both the blob and e-AR sensors, the Bayesian classifier can be used at each time step to enhance the certainty of the location of the patient. This can be used by the observers as a real-time activity grid. Figure 2 illustrates an example of two patients (colour-coded green and red) who are being observed moving around a house that has five rooms. A combined use of wearable and ambient sensors is employed to determine the position of the patient being observed. This framework is scalable for monitoring multiple patients cohabiting with normal individuals. In this case, the identities of the normal individuals are recognised and they are simply shown as grey bullets on the activity grid. This activity grid provides a novel framework that is easy to use by healthcare professionals without intruding on the privacy of the patients because of the relative abstractness of the display used. Several behaviour patterns can be observed, including the patient's interaction with other people, and the general habits of the patient. Thus, the system can also be used for examining social interaction of the patient in terms of the frequency and pattern of receiving visitors.

It is worth noting that comparing activity grids over different periods can become a cumbersome task for an observer. In this work, a method for representing the behaviour pattern of the patient and its temporal variation is developed based on an HMM framework.

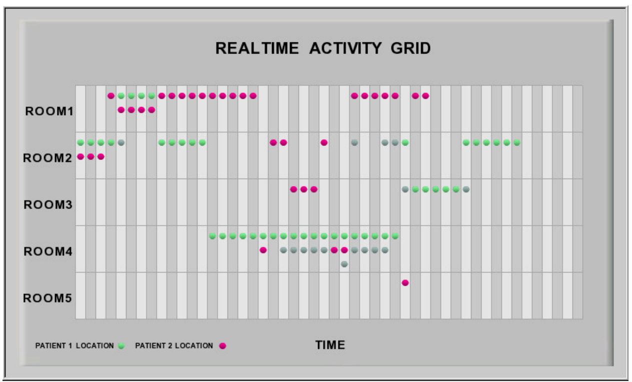

Fig. 2 A real time activity grid showing 2 people being observed as they move between 5 rooms. They are shown as the green and red dots. Other people are represented as grey dots.

V. SIMILARITY-BASED BEHAVIOUR CLUSTERING USING HMM

Some of the relevant research to behaviour and activity monitoring includes work by Oliver *et al.* [9] who look at identifying human activities from multimodal sensor information. In [9], they use Hidden Markov Models (HMMs) and Dynamic Bayesian Networks for recognising office activities. Whereas in [10], they investigate a Bayesian framework using HMMs and Coupled Hidden Markov Models (CHMM) for recognising different human behaviours and interactions. However, their work is focused on recognition of activity rather than clustering or developing a similarity measure. In addition to that, the method is not applied to home environments. Relevant work which examines traces of activities includes the work on location based activity recognition by Liao *et al.* [11]. Although they provide methods of recognising activities from location sequences, the method requires labelling of activities, which could prove to be difficult in the case of elderly patients.

In this work, we will investigate a method of clustering behaviour sequences based on behavioural modelling using HMMs based on both wearable and ambient sensors but without explicitly defining activities, thus respecting the patients' privacy. The HMM analysis framework is based on that of Bicego *et al.* [12, 13], who introduce a similarity based clustering of sequences using HMMs.

A. Hidden Markov Models

HMMs are finite state stochastic machines that allow dynamic time warping for modelling sequential data. An HMM can be defined by the following [14]:

- $S = \{S_1, S_2, S_3, ..., S_N\}$, a finite set of hidden states.
- The transition matrix A, where each element a_{ij} represents the probability of moving from one hidden state S_j to another hidden state a_i.
- The emission matrix B where each element indicates the probability of emission of an observable symbol O.
- $\pi = \{\pi_i\}$, the initial state probability distribution.

Therefore, an HMM can be represented by the triplet $\lambda = (A, B, \pi)$. The Baum-Welsh algorithm can be used to learn the parameters of an HMM, where the likelihood of a sequence of observable states given the model is maximised.

B. Similarity Based Clustering of Sequences

Standard approaches to clustering with HMM include the training of an HMM with a sequence, then using pair-wise distance based methods to perform the clustering. However, Bicego *et al.* [12, 13] introduce a clustering approach for sequences in a feature space that is generated using HMMs. The features describing a sequence O are calculated as similarity measures $D(O, O_i)$ between a sequence O and other reference sequences O_i. The reference sequences can be selected sequences from the whole set as chosen by experts, or the whole dataset can be used. The algorithm to represent the sequences in a new feature space is as follows:

- Select a set of reference sequences $\{P_1, ..., P_R\}$.
- Train an HMM λ_r for each sequence P_r.

- Represent each sequence in the data by a vector of similarities to the elements of the reference set. Each element of the similarities vector $D_R(O_i)$ is the log likelihood of the HMM λ_r predicting sequence O_i normalised by the length T_i of the sequence O_i:

$$D(O_i, P_r) = \frac{1}{T_i} \log P(O_i / \lambda_r) \qquad (2)$$

For patient behaviour profiling, one is interested in observing the clustering of sequences in the new feature space, as well as observing the Similarity matrix D in a lower dimensional space. This allows the observation of similarities and differences between labelled behavioural sequences.

Table 2 Sequences of different lengths showing a person with different behavioural patterns between 5 rooms.

Sequence Number	Description	Group
1	Walking in all 5 rooms	1
2	Walking in the corridor, spending almost equal times in rooms 3 and 5	2
3	Similar to 2 but doing more activities in room 3	2
4	Spending time in room 3 with a short period in room 4	2
5	Doing activities between rooms 2, 3 and 5	2
6	Doing activities in all five rooms, mostly walking in room 2.	3
7	Activities in all rooms, although spending more time in room2.	3
8	Activities in all five rooms.	3
9	Moving between rooms 2 and 4 and interacting with another person in room 4.	4
10	Moving between rooms 1, 2, 3 and 4 and interacting with another person in room 4.	4
11	Interacting with another person in room 1 for a long time, but also going to rooms 2, 3 and 5 briefly.	5
12	Interacting with someone in room 1 for a very short time, and then walking in rooms 2 and 5.	5
13	Walking in all 5 rooms	1

VI. Experimental Setup

A simulation study was performed in a lab based environment representing a house with five different rooms. Blob sensors were placed in the ceilings of each room as shown in Figure 3, and a BSN receiver was placed in each room. One person was asked to wear an e-AR node while performing a list of 13 activity sequences in these rooms. The person had no limitation on time or type of activity but had to follow the guidelines given in Table 2. During the experiment, there were also several other people moving around the rooms to simulate a cohabiting environment.

The behaviour patterns in Table 2 were categorised into 5 groups according to the type of behaviour done. For example, group 2 contains sequences that include activities done in room 3 (such as sequences 3 and 4) shown in Figure 4. Although other people are shown moving around in figure 4, the Bayesian Classifier explained in section 2 allows the exact location of the person being tracked (shown as a red dot).

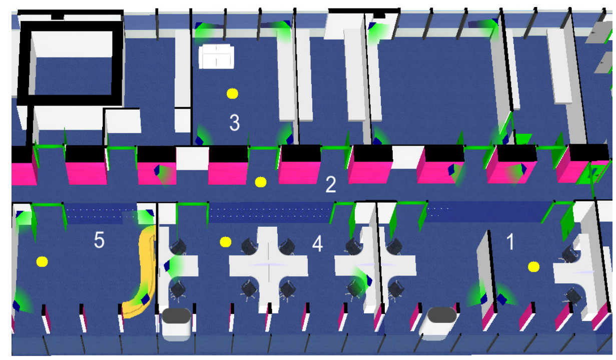

Fig. 3 A simulation environment showing the 5 rooms used (labeled 1-5). The blob sensors are shown in green and the BSN receivers are shown as yellow ellipses. Each room had 1 BSN receiver, but several blob sensors.

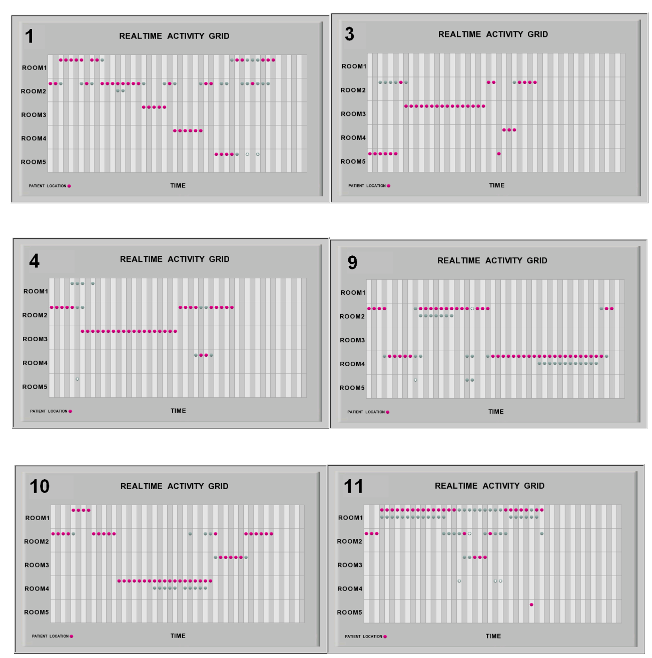

Fig. 4 Behaviour sequences from Table 2 showing different behaviour patterns. The numbers refer to the sequence number in Table 2. Activity sequences are normalized over time (although they are originally of different lengths) for display purposes.

VII. Results

A. Observing behaviour by using Transition matrices

Several observations can be made by examining the Markov state transition matrices (given in Figure 5) from the sequences in Table 2. Although sequences 3 and 4 show some similarity, it is difficult by using these traditional transition matrices alone to judge their similarity to other sequences in Table 2. Sequence 11, on the other hand, is quite different from the others as it involves the observed subject spending a long time in Room 1 interacting with another person (as can be seen in the last activity grid in Figure 4). However, it is difficult for a user to deduce that from the transition matrices in Figure 5. The HMM similarity framework proposed, however, provides easy abstraction of this information for comparing behaviour sequences of different lengths.

0.9	0.06	0	0	0.03
0.057	0.87	0.019	0.019	0.038
0	0.077	0.92	0	0
0	0.067	0	0.94	0
0.056	0.117	0	0	0.83

1

0	0	0	0	0
0	0.85	0	0	0.15
0	0.032	0.97	0	0
0	0.17	0	0.83	0
0	0.07	0.07	0.07	0.8

3

0	0	0	0	0
0	0.92	0	0.038	0.038
0	0.027	0.97	0	0
0	0.167	0	0.83	0
0	0	0.33	0	0.67

4

0	0	0	0	0
0	0.91	0	0.057	0.029
0	0	0	0	0
0	0.018	0	0.96	0.018
0	0.4	0	0	0.6

9

0.86	0.14	0	0	0
0.033	0.9	0.033	0.033	0
0	0.083	0.917	0	0
0	0.026	0	0.97	0
0	0	0	0	0

10

0.97	0	0	0.015	0.015
0.071	0.79	0.071	0.0714	0
0	0.09	0.90	0	0
0.09	0.09	0	0.82	0
0.33	0	0	0	0.67

11

Fig. 5 Transition matrices of the activities in Table 2 of dimension 5x5 showing the probability of transition of a person from a room (vertical row) to another (horizontal row).

B. Results of the HMM Similarity Framework

The HMM framework described above was used to obtain a feature matrix to describe each sequence. The dimensionality of each feature is 13 since we have 13 different behaviour sequences. PCA was used to reduce the dimensionality of the matrix and observe similarities between different behavioural sequences. The results are shown in Figure 5 where each group is colour-coded. It is evident that the following observations can be deduced from Figure 5:

- Sequences 2, 3, 4 and 5 cluster together. These sequences mainly involve activities in Room 3. Although the movement between rooms and the types of activities done are quite varied (as shown for sequences 3 and 4 in Figure 4), they are grouped together since they describe a certain common behavioural pattern that is not present in other sequences.
- Sequences 13 and 1 are similar and describe a general motion between all 5 rooms. Sequence 8 is also quite similar.
- Sequence 10 is closer to sequence 1 than sequence 9. Figure 5 shows that in general, sequence 10 resembles 1 more, as it involves more rooms, whereas sequence 9 involves a long time in room 4 interacting with another person.
- Sequence 11 is significantly different from the others, as it involves the person spending a long time interacting with someone in room 1. This behaviour is shown to be quite different from all other sequences.

By comparing the results with the initial labelling of behaviour sequences given in Table 2, intrinsic similarities of the patterns can be observed. By assuming that certain clusters of behaviour sequences represent a normal activity of a patient over a period of time, the graph provides an effective means of observing deviations from normal behaviour patterns. If this deviation is large, such as that shown by sequence 11, further data analysis can be performed to establish why the class deviates from the 'normal behaviour' cluster. This can then trigger a scheduled home visit by the carer.

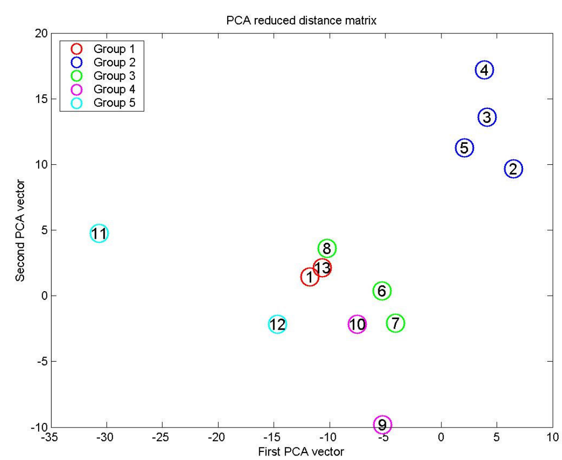

Fig.6 Each sequence described in Table 2 is represented a circle. The graph can be used to judge similarity between sequences.

VIII. Conclusions

This work presents a novel method of behaviour profiling based on ambient and wearable sensors. A behaviour modelling approach is considered since it is less intrusive to patient's privacy than identifying activities directly. A Bayesian classifier for extracting the intrinsic relationship between signal strengths from wearable sensors and room occupancy is used. The proposed method can be expanded to a more general home environment with minimal restrictions. Although a large amount of sensor data is obtained, most of the information can be abstracted immediately into high level information as the activity grid shown in this paper. The model can also deal with errors in the data resulting from data acquisition. Healthcare workers can use a reduced space grid to observe behaviour changes and social interaction. The HMM framework for behaviour clustering, could indicate an irregular event, as it would deviate from a cluster of normal behaviour. This can be used for more detailed analysis of the activity pattern or scheduling a home visit by the carers.

References

1. Intille, S.S., et al. *Using a live-in laboratory for ubiquitous computing research*. in *PERVASIVE 2006*. Berlin Heidelberg: Springer-Verlag.
2. Edwards, N., et al., *Life-Style Monitoring for Supported Independence.* BT Technology Journal, 2000. **18**(1): p. 64-65.
3. Tamura, T. *A Smart Home for Emergencies in the Elderly*. in *ICOST 2006*. 2006. Belfast: IOS Press.
4. Pansiot, J., et al. *Towards image-based modeling for ambient sensing*. in *BSN*. 2006.
5. Lo, B., et al., *Real-Time Pervasive Monitoring for Postoperative Care*, in *BSN 2007*. 2007: Aachen.
6. Yang, G.-Z., et al. *From Sensor Networks to Behaviour Profiling: A Homecare Perspective of Intelligent Building*. in *The IEE Seminar for Intelligent Buildings*. 2004: IEE.
7. Lo, B. and G.-Z. Yang. *Architecture for Body Sensor Networks*. in *The Perspective in Pervasive Computing*. 2005. IEE Savoy Place: IEE.
8. Aziz, O., B. Lo, and G.Z. Yang. *Pervasive Body Sensor Network: An Approach to Monitoring the Post-operative Surgical Patient*. in *BSN 2006*.
9. Oliver, N.M., et al. *A comparison of HMMs and dynamic bayesian networks for recognizing office activities*. in *UM 2005* 2005. Edinburgh: Springer, Berlin.
10. Oliver, N.M., B. Rosario, and A.P. Pentland, *A Bayesian computer vision system for modeling human interactions.* Pattern Analysis and Machine Intelligence, IEEE Transactions on, 2000. **22**(8): p. 831-843.
11. Liao, L., D. Fox, and H. Kautz, *Location-based activity recognition using relational Markov networks*, in *Proc. of the International Joint Conference on Artificial Intelligence*. 2005.
12. Bicego, M., V. Murino, and M.A.T. Figueiredo, *Similarity-based classification of sequences using hidden Markov models.* Pattern Recognition, 2004. **37**(12): p. 2281-2291.
13. Bicego, M., V. Murino, and M. Figuerido. *Similarity based clustering of sequences using Hidden Markov Models*. in *MLDM*. 2003: Springer-Verlag.
14. Rabiner, L. and B. Juang, *An introduction to hidden Markov models.* ASSP Magazine, IEEE [see also IEEE Signal Processing Magazine], 1986. **3**(1): p. 4-16.

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