Hybrid Learning Architecture for Unobtrusive Infrared Tracking Support

K. K. Kiran Bhagat, Stefan Wermter, and Kevin Burn

Abstract—**The system architecture presented in this paper is designed for helping an aged person to live longer independently in their own home by detecting unusual and potentially hazardous behaviours. The system consists of two major components. The first component is the tracking part which is responsible for monitoring the movements of the person within the home, while the second part is a learning agent which is responsible for learning the behavioural patterns of the person. For the tracking part of the system a simulation portraying a virtual room with passive infrared sensors has been designed, while for the learning agent a hybrid architecture has been implemented. The hybrid architecture consists of a Markov Chain Model, Template Matching, Fuzzy Logic and Memory-Based reasoning techniques. The hybrid structure was selected because it combined the strengths of the constituent algorithms and because it supports the learning with limited training data. The resultant system was able to not only classify between the normal and the abnormal paths but was also able to distinguish between different normal routes. We claim that passive infrared tracking combined with a hybrid learning architecture has potential for adaptive unobtrusive tracking support.**

I. INTRODUCTION

Present world statistics predict that the ratio of the number of people over the age of 65 to those aged 16-65 is going to increase considerably by the year 2040. This sharp rise could cause serious shortage in facilities and personnel required to take care of the elderly [7]. However, most of the elderly would like to stay in their own homes as long as possible and this motivates our attempt to offer support e.g. by a monitoring system which could alert distant carers.

There have been several approaches to develop human indoor tracking systems. For instance, Nait-Charif and Mc Kennan [1] describe a head tracking system within a supportive environment using a camera. Their system was capable of performing high level activity summarisation and thereby determining unusual activities. Haigh et al [2] describe the essential features of an independent lifestyle assistant. The proposed system would combine various home sensing and automation technologies based on a control system incorporating knowledge-based situation awareness and an intelligent decision support and response system, customized to the need of the elderly people. Nair and Clark [3] describe an automated indoor surveillance system that uses HMM models to monitor the movements of people within corridors.

Although the above systems have excellent performances, the major reason why these technologies have not yet become widely used within homes is that these methods involve the use of cameras and other obtrusive technologies to monitor the person, and this is considered by many as a breach of their privacy [4].

Apart from these, there are a few simpler home supportive technologies such as pressure pads and worn fall detectors which are currently being used. The problem with these is that they have relatively lower functionality and are prone to cause false alarms [14].

In order to overcome this issue, the present system is based on using only unobtrusive passive infrared (PIR) sensors for tracking purposes. In order to compensate for the occasional lack of visibility of PIR sensors, provisions have been made to accommodate subject-location inputs from other tracking methodologies based on RFID and Wi-Fi systems, as described by Corchado et al [15]. A learning agent using a hybrid architecture is used for learning the normal paths of a resident and to flag if abnormal path activity is detected. We claim that PIR tracking combined with hybrid learning has potential for adaptive unobtrusive tracking support.

The following section describes the methodology used for both the tracking and the learning agent, followed by a description of the system architecture. Section 3 describes the experiments carried out and an analysis of the results. Finally, the entire system is analyzed and the results are shown and discussed.

II. APPROACH

A. Methodology

The tracking part of the system is designed to collect data which will be given to the learning agent. The data required by the learning agent consists of the location of the person and the time spent at that location. In order to collect this data, first a virtual room was designed, with PIR sensor clusters placed in different locations so that the entire area of the house was covered.

These PIR sensor clusters were fitted with Fresnel lenses which helped not only to improve the visibility but also to

Manuscript received December 15, 2007.

K. K. Kiran Bhagat, Stefan Wermter, and Kevin Burn are with the Hybrid Intelligent Systems group, School of Computing and Technology, University of Sunderland, UK, www.his.sunderland.ac.uk. (e-mail: Kiran.bhagat@sunderland.ac.uk, Stefan.wermter@sunderland.ac.uk, Kevin.burn@sunderland.ac.uk).

.

categorize different distance sectors. These sensor clusters were based on the work done by Shankar et al [5].
The virtual representations of these sensors were placed in different positions in the room and are shown in the figure 1.

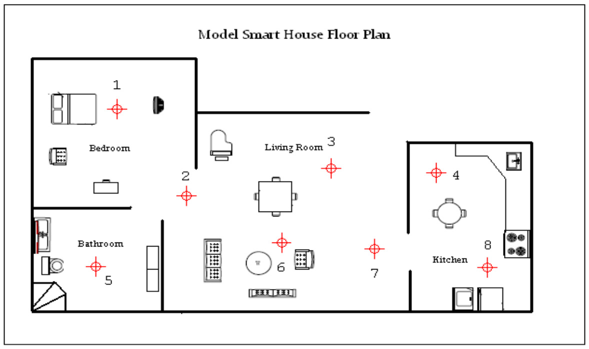

Fig 1: Layout of model smart house based on Russo et al [10]

The area covered by the sensors is shown in figure 2. The different shades represent the different types of signals generated, which depend on the person's proximity.

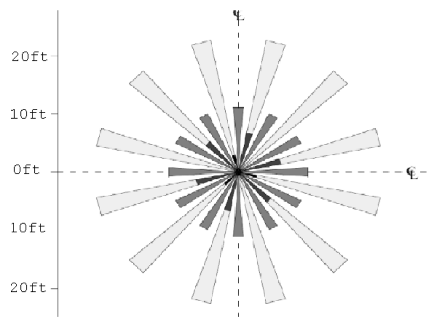

Fig 2: Top view of the sensor (CM0.77GIVX) from [11]

For simplicity in data collection and experimentation we are using a virtual room in our experiments using a mouse to mark the points in the path with delays proportional to the actual stopping times of a resident in the house. Figure 3 shows how the simulation generates the path. The tracking part generated representative pathways with the locations and time spent at each location.

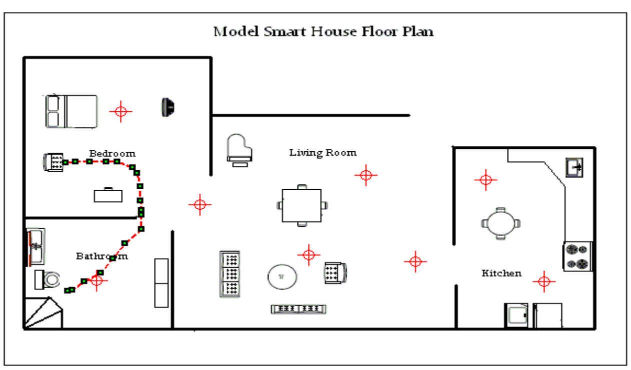

Fig 3: Route marked in the simulation

Then the learning part of the system learns the normal routes taken by a person including the time spent at each location. This is done by a hybrid learning agent which consists of techniques adapted from Markov chains, feature matching, fuzzy logic and memory based reasoning.

First, the path data is pre-processed into a form that would be suitable for learning. This involves dividing the path into different parts depending on the proximity to the sensors taking any obstructions into account. Due to the radial nature in which the sensors gather information, we convert the Cartesian coordinate location points into polar coordinate points, making each sensor the centre of its own region.
After this pre-processing, the route, now represented in terms of radial coordinates, was marked depending on the sector they were in. The region covered by each sensor was divided into angular and distance sectors and these sectors were marked in a systematic manner. This resulted in converting the data set which was in terms of polar coordinates and time spent at each location, into a data set of sector numbers and the time spent in that sector. Also, an input state table was generated based on the value of the delta threshold. This process involved dividing the table generated by the previous step into blocks of equal size depending on the value of the delta threshold. This threshold can be specified by the following equation:

If $T<\Delta$

Input_State_table (t) = input_vector (T)

Else if $T > \Delta$

Input_State_table (t *to* t + (T/Δ)) = input_vector (T)

Where 'T' is the time spent by the person in the location,
't' represents the entry in the Input state table and
Δ represents the delta threshold value

Once the path was marked into various sectors per sensor and after generating the input state table, it was represented as a Markov chain and then a corresponding transition matrix was generated. The generation of a transition matrix is described by the following example.
Consider the case where the person enters sector 3 at time 't' and exits in sector 4 at time t+2. This would result in a Markov chain represented as

3 →3→4

This implies that the person has entered state 3 and left state 3 after the first Δ and then entered state 3 again and left state 4 after the second **Δ.** Therefore, the elements of the (third row, third column) and the (third row, fourth column) in the transition matrix would be assigned a "dot" each. The overall value is then calculated by the equation:

Cell_Value = (number of dots in cell) / (total number of dots in that row) (1)

A sample of the transition matrix used by the system is shown in the figure 4. The transition matrix in the figure can be interpreted as the probability of the person entering the region in sector 2 and remaining in sector 2 is 0.125 while the probability of the person entering the region in sector 2 and going to sector 3 is 0.725.

0	0	0	0	0	0	0	0
0	0.125	0.725	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0.5	0	0.5	0	0	0
0	0	0	0.33	0	0.33	0.33	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Fig 4: Sample Transition Matrix

The transition matrix was then used as a template and depending on the training or the testing stage this template was matched with the previous templates in the 'Knowledge Base'. The *knowledge base* is the region wherein all the previous paths are stored and categorised systematically according to their zones. The similarity coefficient produced by template matching is known as the Normalized correlation coefficient [12]:

$$\gamma(u,v) = \frac{\sum_{x,y}[f(x,y) - \bar{f}_{u,v}][t(x-u,y-v) - \bar{t}]}{\left\{\sum_{x,y}[f(x,y) - \bar{f}_{u,v}]^2 \sum_{x,y}[t(x-u,y-v) - \bar{t}]^2\right\}^{0.5}} \quad (2)$$

Here *f(x, y)* represents the current sample while *f(u, v)* represents the stored template in the knowledge base. This approach was chosen instead of the normal cross correlation because a simple correlation between a pattern and a high intensity region in the transition matrix may be more than the correlation between the pattern and an exact match. NCC overcomes this drawback by normalizing the pattern and feature vectors to unit length, giving rise to a cosine-like correlation coefficient [12]. Similar template matching was done for all the parts of the routes in different sensor regions. This step thus resulted in a set of similarity coefficients.

When the system is being trained, the templates in the knowledge base are updated by taking the weighted average between the new sample and the product of the old transition matrix and a *forgetting factor*. The forgetting factor was introduced into the calculation because of two major reasons. The first is that without a forgetting factor there exists a risk of the system being saturated after being trained by a large dataset, as all the values of all the entries in the transition matrix would continuously be increased. The second is that human behaviour changes with time and the inclusion of a forgetting factor would enable the system to forget the older patterns and base its judgement mainly on the newer patterns that it has observed.

In order to incorporate specific prior knowledge into the system, *fuzzy rules* are used. These rules were fuzzified and converted into a set of membership values that were assigned to various sensors. Depending on these membership values, the overall path's similarity coefficient was calculated by taking into account the weighted average of the membership values and the corresponding individual sensors' similarity coefficients.

This can be explained formally as follows: Let the correlation coefficients of the zones be c1, c2, c3...c8 and the weights for each of the zones be w1, w2, w3...w8, then the overall similarity coefficient is calculated as

Overall Similarity coefficient = ((c1*w1) + (c2*w2) +...+ (c8*w8))/ (w1+w2+...+w8) (3)

After the system was able to distinguish between a normal and an abnormal path, it was updated to distinguish between different known pathways. This was done by repeating the entire process described and finally comparing the overall similarity coefficients of the known pathways. The present route was labelled after the pathway with the highest overall similarity coefficient.

Although this process was efficient, it had some deficits in recognizing paths which were similar to two ambiguous pathways. In order to resolve these ambiguous pathways, a memory based reasoning (MBR) approach was chosen. This part of the system was called only when there was a dispute between two known pathways. The MBR approach considers the individual similarity coefficients of the individual sensors. It then compares the individual similarity coefficients of the disputed paths. The path with the maximum number of sensors having the highest individual similarity coefficients was declared as the winner. This was later compared with knowledge of the normal winning sensors of each known path. In the case where the current path does not resemble any known path, it is marked as an unusual path.

B. Architecture

This section describes the architecture which was developed based on the methodology described in the previous section (Figure 5). First, the 'Data Generator' collects data which can be used by the learning agent. It can acquire data either from a virtual room simulation or from an external sensor grid.

The 'Data Pre-Processor' stage converts the data into a format that can be used by the learning agent. It divides the path into different segments based on the proximity to the different sensors. It is also responsible for converting the Cartesian coordinates into polar coordinates and assigning sector numbers to different locations.

The 'Transition Matrix Generator' is responsible for converting the input state table into a transition matrix template, according to the defined system parameters.

It then provides the transition matrix to the 'Learning Agent' which performs the template matching with the templates in the knowledge base and updates them if necessary.

The 'Knowledge Base' contains all the pathways learned by the system. It is organised systematically according to the sequence and zone.

In the 'Zone Prioritizer' the external fuzzy rules are applied to the similarity coefficients obtained from the previous stage.

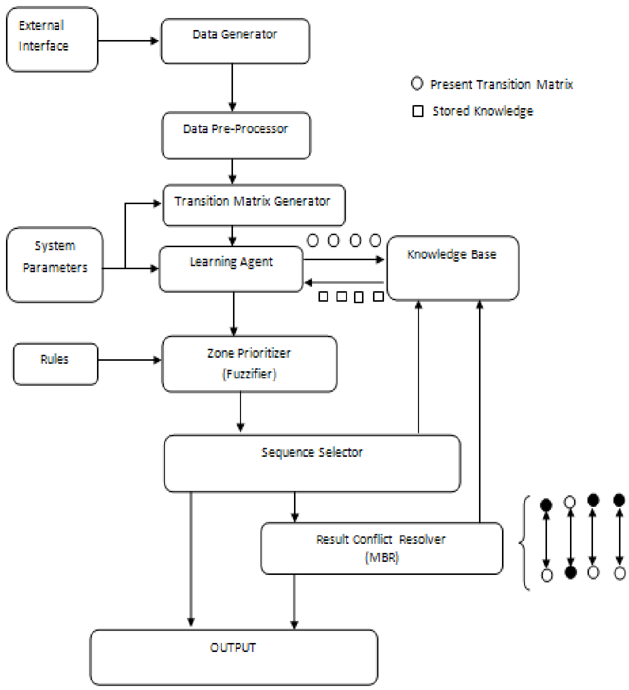

Fig 5: System Architecture

The 'Sequence Selector' selects the sequence with the highest overall similarity factor as the winner and the present path is labelled after it. The knowledge base is also updated if the sample has a very high similarity factor.

The 'Result Conflict Resolver' is a memory-based reasoning tool, which classifies the present path based on specific cases within the system [8].

The 'Rules' section contains rules that are derived from prior knowledge of the system and provisions have been made to include new rules, depending on the circumstances. The rules may also consist of precautionary clauses. For instance, if the resident is restricted or requires supervision in certain locations in certain times of the day, a relevant rule can be included which would notify the caregivers to take necessary steps when such a situation arises.

The 'System Parameters' provides the system with information regarding the position of the sensors, type of task to be carried out i.e. training or testing, forgetting factor values and the resolution of the sensors.

III. Experiments and Results

The working of the system, after it was built as described, is shown in the figures 6 to 9 below. The Similarity Factor displayed under every path represents the degree of similarity between the present path and the paths learned by the system, which are stored in the 'Knowledge base'.

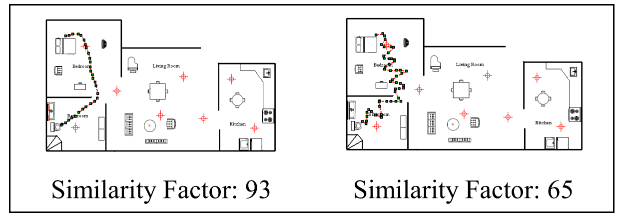

Fig 6: Bedroom to Bathroom

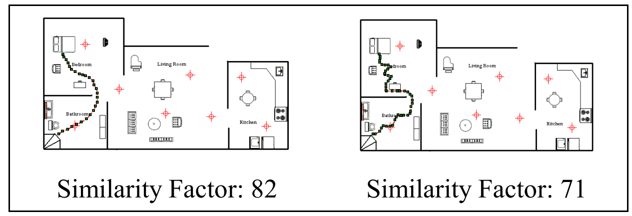

Fig 7: Bathroom to Bedroom

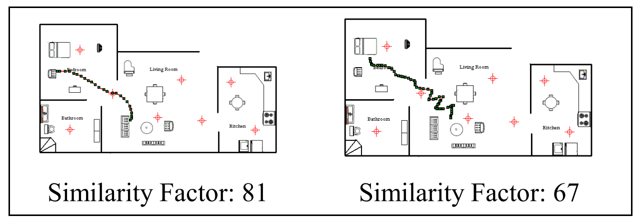

Fig 8: Bedroom to Livingroom

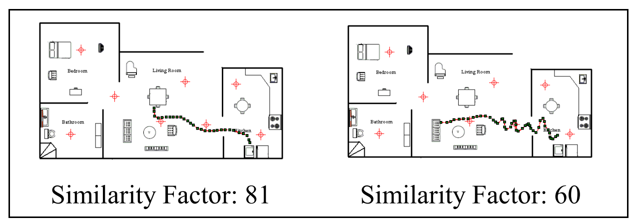

Fig 9: Livingroom to Kitchen

As is visible from the above figures, known paths have a considerably higher similarity factors when compared to paths with random movements and these were therefore classified as abnormal paths.

Several experiments were carried out to further observe the influence various parameters had on the overall efficiency of the system. In order to carry out the tests, a data base consisting of 100 training samples and 194 test samples was used.

TABLE I
Dataset Distribution

Sequence Name	Samples for training	Samples for testing
Bedroom to Bathroom (1)	25	27
Bathroom to Bedroom (2)	25	42
Bedroom to Livingroom (3)	25	31
Livingroom to Kitchen (4)	25	40
Abnormal (5)	-	24

The paths used for training and testing were based on the Activity of Daily Log (ADL) described by the US department of health and human services [9]. The distributions of the various samples are shown in the table 1. The system was not trained on any unusual paths, because it is an open set. In order to identify the abnormal paths, a path that did not match known sequences was considered to be abnormal. Also during the training stage the system was systematically trained with different possible paths. For instance, for the path between the living room and the kitchen, the system was trained with all possible paths from various starting points to different end points, until the paths in the knowledge base had a high similarity coefficient.

A. *Impact of the number of zones on system efficiency*

The effect of the number of zones on the system's efficiency was observed by changing the number of zones seen by each sensor. This was done by altering the number of angular and distance regions observed by the sensor (see table 2). From the results shown in table 2, we see that the efficiency of the system increases as the number of zones decrease.

TABLE II
EFFECT OF CHANGING NUMBER OF SECTORS

Number of Angular sectors	Number of Distance Sectors	Total Number of Sectors	Overall System Accuracy
8	4	32	58.53
6	4	24	72.37
4	3	12	87.19

Although decreasing the number of zones would increase the efficiency of the system, it would contradict the purpose of closely monitoring the person's movements. Therefore a trade-off is needed between accuracy and required monitoring resolution.

B. *Impact of number of sensors on system efficiency*

The effect of the number of sensors and their positions on the overall efficiency of the system was analysed. The results are shown in table 3.

TABLE III
EFFECT OF NUMBER OF SENSORS

Number of sensors	Overall Efficiency
4	64.02
6	78.53
8	87.19

The basic criterion for positioning the sensors was to cover the entire floor space of the model house. From the above results it is evident that the number of sensors in the house plays a major role in the overall system efficiency. If there are too few sensors, the entire area would not be covered and if there are too many sensors, it might make the system too complex as more than one sensor would be covering every point in the house.

C. *Impact of Delta threshold on system efficiency*

The delta threshold plays a major role in defining the size of the input state table. It represents the time slot which when exceeded by a person, adds a new entry into the input state table. This is similar to the effect of resolution of how closely the resident is monitored.

In order to observe the influence of the delta threshold on the input state table and eventually the entire system efficiency, its value was varied. The results of the variations are shown in table4.

TABLE IV
EFFECT OF DELTA THRESHOLD

Delta Threshold value	Overall system efficiency
0.1	82.31%
0.01	87.19%
0.001	84.79%
0.0001	86.01%

From the results of the above experiment we see that as the

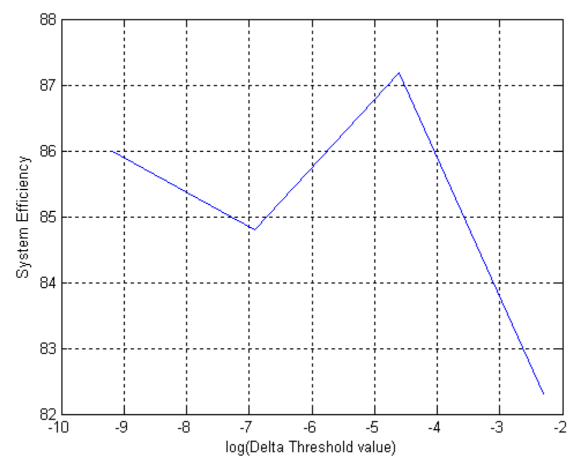

Fig 10: Plot between the log (Delta Threshold) and system efficiency

delta threshold value is decreased the time taken to process increases substantially. This is because the input state table would have many more instances to compute.

D. *Impact of Forgetting Factor on system efficiency*

The influence of the forgetting factor was observed on the system. The 12 sector system was chosen for this as it had the highest efficiency. The results of the experiment are as shown below:

TABLE V
EFFECT OF FORGETTING FACTOR

Forgetting Factor	Overall Efficiency
0.2	85.27
0.4	86.32
0.6	85.12
0.8	78.34

We can observe that the forgetting factor plays an important role in the overall working of the system. The relationship between the forgetting factor and the system efficiency was not fully linear. If the forgetting factor is kept high, the system would forget the old routes very quickly and would compare the present route only with the relatively new routes. If the forgetting factor is low, it would not forget the older routes and this would cause a saturation of the system as the transition matrix would be filled. Therefore, a system with a 0 forgetting factor would not remember anything, while the system with 1 as a forgetting factor would not forget anything.

E. Impact of fuzzy rules on system efficiency

The significance of the sensors in the room was varied and the impact this had on the overall system was observed. This was done by changing the membership function of different sensors in the system. Instead of a dynamically varying membership function, a static value is defined for each sensor [6]. These values are assigned based on their positions in the room, with the motivation that in smaller places the movements are more predictable compared to free open areas. An experiment was conducted by varying the membership functions of different sensors.

The rule described in this example is as follows: "A person's movements in a restricted space are more quantifiable while compared to his movements in a relatively open space"

In order to understand the effect which different sensors have on the system's performance, under this rule, they were grouped into three different categories depending on their position in the room.

The categories are shown below:

1) Sensors 1, 4, 5 and 8 were categorized into group 1 as they were placed within rooms which had a moderate amount of space to move around.
2) Sensors 2 and 7 were categorized in group 2 as they were placed within corridors between rooms.
3) Sensors 3 and 6 were categorized into group 3 as they were placed in rooms with large amount of free space.

The membership values of the sensors within each group were varied collectively. The results of the experiments are shown in table 6, from which it is evident that the above stated rule is valid and that some sensors have higher significance when compared to others.

TABLE VI
EFFECT OF VARYING THE MEMBERSHIP FUNCTION OF DIFFERENT CLASSES

Instance Number	Membership Functions			Overall System Efficiency
	Sensor class 1	Sensor Class 2	Sensor Class 3	
1	1.0	1.0	1.0	68.78
2	1.0	1.0	0.8	74.22
3	1.0	1.0	0.6	78.31
4	1.0	1.0	0.4	76.26
5	0.8	1.0	1.0	80.23
6	0.8	1.0	0.8	84.18
7	0.8	1.0	0.6	84.18
8	0.8	1.0	0.5	87.19
9	0.8	1.0	0.4	86.58

Analysing the results of this experiment, it can be concluded that if the sensors in pathways and restricted spaces are given more significance when compared to the sensors in relatively open areas the system has a better performance. Therefore the best result was achieved when sensors of class 2 were given the highest significance when compared to the class 1 sensors followed by the class 3 sensors.

Although for the present system there is a single rule that determines the membership values of the sensors, multiple rules can also be incorporated within the system to determine the effective membership function of each sensor.

A 3d representation of the room's layout based on the rule considered and the best values of the sensor's membership functions is shown in the Fig 11.

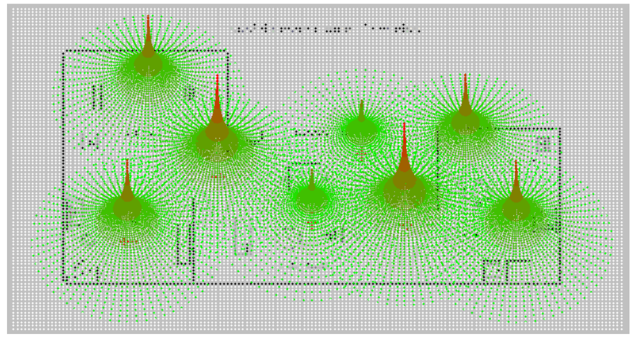

Fig 11: 3d representation of the membership functions of the sensors

As can be seen, the sensors in the corridors are given higher membership values than those placed within the rooms, while the ones in open spaces are given the smallest membership values. The height of the curve is directly proportional to the value of the sensor's membership function, to make the difference more visible.

F. Overall System Performance

The best overall efficiency attainable by varying the above parameters is 87.19%. The break up of these results in the form of a confusion matrix for the five types of pathways shown in table 1 is given in table 7.

TABLE VII
CONFUSION MATRIX SHOWING THE CLASSIFICATION OF THE SYSTEM

	Actual cases				
System Detected	15	1	1	0	0
	12	41	0	0	0
	0	0	27	0	1
	0	0	0	38	1
	0	0	3	2	22

The first four classes represented in the confusion matrix above show the four normal ADLs on which the system was trained while the fifth class represents the abnormal paths. The confusion matrix in the Table 7 shows the distribution of the performance. From the table the following observations can be made:

1. The main region of misclassification is between class 1 and class 2 because they both use the same pathways and only the direction is reversed. Also that region has a very high density of sensors per unit area.
2. The other class where the system produces some errors is the class of unusual pathways and the class 3 and

class 4. This most likely occurs because the density of sensors in the pathways of class 3 and class 4 is small and the region contains lots of open regions.

The confusion matrix represents the best result achieved by the system for the parameters against which it was tested. There is the possibility of achieving better results for a different set of parameters. However, we believe that this first result is promising and encourages further development.

IV. Analysis & Conclusion

The main reason for the design of this memory-based, learning and hybrid architecture was the size of the data set. The current selection of techniques enables the system to run with a minimum amount of training while delivering a promising performance. The present system is able to use the data of the first day to monitor the person on the second day.

The other advantage for using a custom-made hybrid system is that its functioning is very transparent, unlike the traditional pattern learning methodologies. Also the modular nature of the system makes it easier to add additional features when compared to the usual black-box models. Other than this, the other nonlinear classification techniques have some problems with continuously monitoring a situation [13].

The system described in this paper was able to achieve a classification rate of up to 87.19%. It was able to correctly recognise 22 out of the 24 unknown pathways and 121 out of the 140 known pathways. Furthermore it was able to distinguish between known pathways within the four classes of pathways which were based on the activity of daily log (ADL) of aged people [9].

If the size of the training dataset would be increased by including many new pathways, there would be little scope for the occurrence of an unknown pathway, since all pathways would have been covered during the training stage. Our approach was also motivated by the fact that people have routine pathways which do not change significantly.

While the present system has a considerable degree of performance, future work could improve the system by further optimising the parameters values to make the system architecture as optimal as possible. Due to the number of parameters, an optimisation approach involving Particle Swarm Optimisation or Genetic Algorithms could be used. Furthermore, we plan to test this environment in a real home environment. However, in this paper we have demonstrated the overall system architecture and that passive infrared tracking combined with hybrid learning has potential for adaptive unobtrusive tracking support.

References

[1] Nait-Charif, H. and McKenna, S.J, "*Activity summarization and fall detection in a supportive home environment*" Pattern Recognition ICPR 2004 Proceedings of the 17th International Conference on Volume 4, Issue, 23-26 Page(s): 323 - 326 Vol.4 Aug. 2004

[2] Haigh K.Z, Yanco H.A "*Automation as caregiver: A survey of issues and Technologies*" AAAI Automation as Caregiver workshop, pages 39-53, 2002

[3] V. Nair and J. Clark "*Automated visual surveillance using hidden Markov models*" Centre for Intelligent Machines McGill University. In VI02, page 88, 2002

[4] Fran Marquis-Faulkes, Stephen J. McKenna, Alan F. Newell and Peter Gregor "*Gathering the requirements for a fall monitor using drama and video with older people*" Technology and Disability 17, Pg 227–236, 2005

[5] Shankar M, Burchett J.B, Hao Q, Guenther B.D, Brady D.J "*Human tracking systems using pyroelectric infrared detectors*" Optical Engineering 45(10), 106401, 2006

[6] Klir J.G and Yuan B "*Fuzzy sets and Fuzzy Logic: Theory and Application*" Prentice hall of India, 2005

[7] Doughty and Mills, Telecare Technologies To Manage Problems Of Rurally Isolated Older People In County Durham, Presented at "*Turned on to Technology – A Modern Vision for Person-Centred Care*", 2002

[8] Rachlin J, Kasif S, Salzberg S, Aha D.W, "*Towards a better understanding of memory based reasoning systems*" Dept of Computer Science, John Hopkins University, 2004

[9] Administration on Aging "*A Profile of old Americans*", US department of health and human services, 2006

[10] Russo J, Sukojo A, Helal A, Davenport R, and Mann W.C "*SmartWave: Intelligent Meal Preparation System to Help Older People live independently*" LG, 2004

[11] *CM0.77GIVX datasheet*, Fresnel Technologies Inc, 2000

[12] J. P. Lewis, "*Fast Template Matching*", Vision Interface, p. 120-123, 1995.

[13] Yang J, Xu Y and Chen C.S, "*Human Action Learning via Hidden Markov Model*"- IEEE transactions on Systems, man and Cybernetics – Part A: Systems and Humans, Vol. 27, No 1, January 1997

[14] SeniorWatch. "*Fall Detector*". Technical report case study of European IST Senior Watch Project IST – 1999 – 29086, 2001

[15] Corchado J, Bajo J, Abraham A, "*GERAmI: Improving the delivery of health care in geriatric residences*", IEEE Intelligent Systems, Special issue on Ambient Intelligence, IEEE Computer Society Press, 2008.