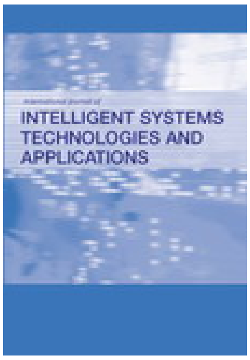

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Daily activity monitoring system designed for elderly people using hidden Markov models based on real world datasets

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Daily activity monitoring system designed for elderly people using hidden Markov models based on real world datasets

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Abstract: This work describes how our abnormal behaviour detection system functions for seniors in their home. Our research is based on the data gathered by a domotic box that is available for purchase. The box was initially intended to continuously detect the owners' daily actions using non-intrusive home automation sensors. The enhancement of the detection of the health changes, deducted by the abnormal behaviour of the user, is closely related to the evolution of the activity recognition of the box. Our system aims to report a relevant context-aware alert to health care service experts. By refining the detection of the activity level of the occupants, we could identify warning manifestations for early intervention. In this paper, we will describe the process of pointing out irregularity in the daily activity pattern of a user or the detection of a malfunction of the box to maintain the accuracy of the service it offers.

Keywords: activity monitoring; ambient assisted living; AAL; data processing; smart homes; elderly; assisted living; sensors; statistical approach.

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1 Introduction

Smart homes are no longer merely considered to be a luxury option, but rather a technology that may improve our family's security, health, and general well-being (Kaye et al., 2011).

In fact, smart home services, including domotic boxes, offer quite a few benefits to seniors. One of the prominent uses of smart homes is enabling older individuals to live independently. Which leads to the objective of our work; offering a convenient and fully assisted living platform that permits elderly people to remain at their home independently for as long as possible (Ni et al., 2015).

The world's elderly population has considerably increased in previous years and is on course to reach about 2 billion in 2050 (Ageing and Health, 2022). Ambient assisted living (AAL) aims to cope with the growing need for seniors' health care services. It has been determined that anomaly detection, in activity of daily living (ADL), is a crucial feature of senior assistive technologies (Li et al., 2015; Ruano et al., 2019).

At a certain age, every person is subject to developing specific health complications (Sakellarides, 2019). One of the significant aspects of assistive technologies is the activities of daily living (ADL) recognition and its level of accuracy. This is where the domotic box developed by our partner company NOVIATEK comes in. Using unobtrusive sensors, the box provides us a rich ground truth, which enables us to extract the daily activity patterns of the user and apply it as a baseline. The data acquired is the succession of different daily life activities (bathing, toileting, transferring, continence, and feeding) from which we extract the key actions. In this paper, we have improved the potency of the anomaly detection system by extending and digging deeper into the level of the recognised daily activities. In order to establish a baseline, we model the ADL data, which represents the individual's daily activity routine.

After conducting an investigation on current literature on the approaches dedicated to anomaly detection, we chose hidden Markov models (HMMs) to construct our model so we can obtain an adaptive and historical-based system. HMMs are efficient when it comes to learning sequential data.

We compare the subsequent sequences to the baseline model (HMM initial model) in order to detect deviation from normal program behaviour. We first validated the model by analysing different user profiles and their life routine. In this work, we will focus on one specific user case that represents clearly the objective of our system by taking into account a number of daily activities and an alerting behaviour change.

1.1 Motivations and challenges

The main aim of our research work is to provide an unobtrusive assistive system for elderly people who live by themselves. Regarding the user case, the major motivations of the system are stated as follows:

- Analyse the data collected by the box and effectively select the key activities.
- Build a solid baseline corresponding to the routine behaviour of the user.
- Detect any deviation from 'normal' program behaviour that reflects a health deterioration sign.

Human behavioural routine is complex and subject to change due to many factors. In our work, the abnormality will be primarily based on the absence of certain crucial activities which help to automatically intercept an alerting sign. Providing a highly precise alert involves many challenges.

- The chosen sensors should be adapted to the existing living environment.
- An efficient reasoning over the routine behaviour pattern of every specific user.
- Establishing a dynamically adjusted threshold to incorporate changes in the individual's routine.

1.2 NOVIAcare

The NOVIAcare pack is sold in French pharmacies and includes the domotic box, six sensors (possibility of getting more sensors for more personalised supervision) and a medallion bracelet (Figure 1). Through a dedicated mobile application available on Google Play and AppStore, Noviatek is maintaining the link between the users and their relatives by presenting daily monitoring reports. The daily reports are equally displayed on the box, for the user's personal use. It also provides services to the user, such as medication reminders and sudden change of the home temperature. The box aims to alert the relatives or the emergency health services if an alerting situation occurs and requires urgent intervention. The three main qualities of NOVIAcare are intuitiveness, practicality and discreetness.

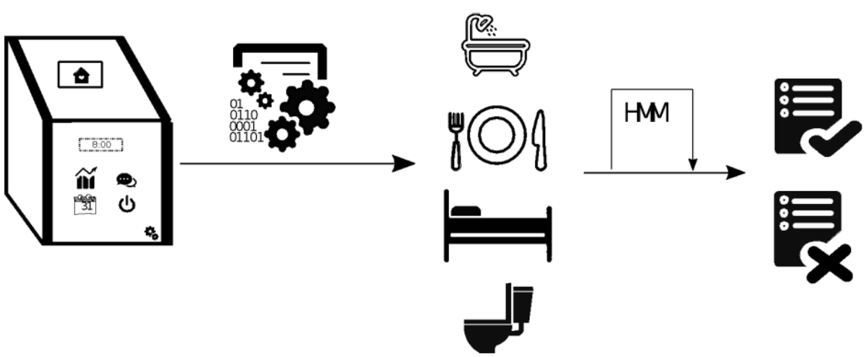
Figure 1 The pack of the box NOVIAcare (2022) (see online version for colours)

2 Methodology

2.1 Data processing

In this section, we will present the monitoring system in more detail. Figure 2 illustrates the overall data process. The starting point is the data collected from the box from which we construct the baseline routine behaviour and the final output remains the analysis of the subsequent sequences (Figure 2).

Figure 2 Data process

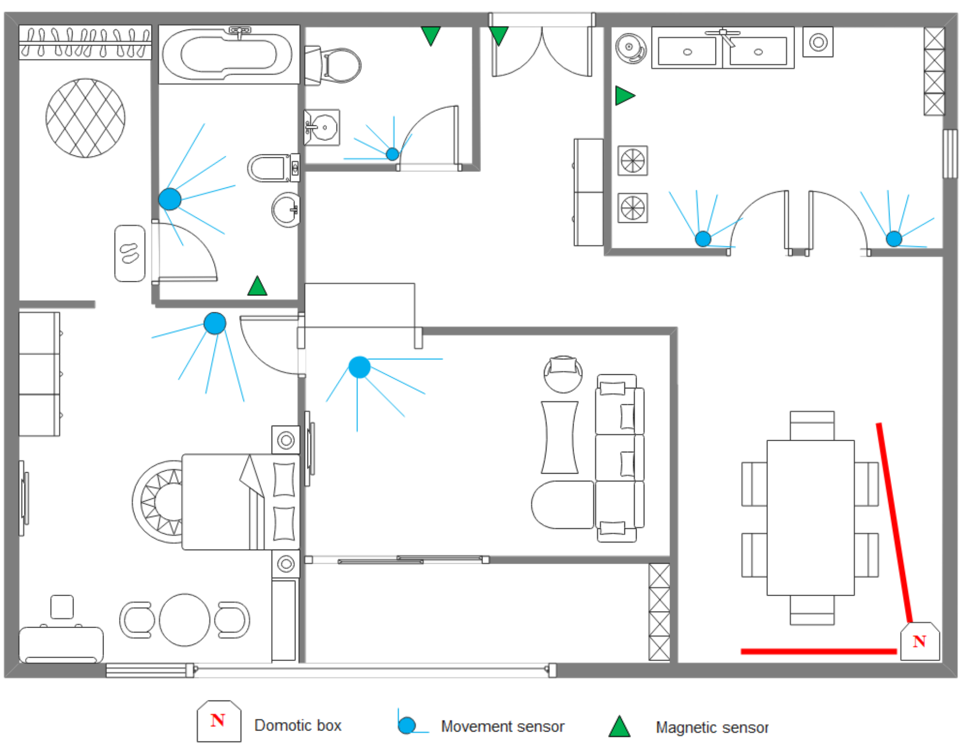


Using different non-intrusive sensors such as humidity sensors, bed and chair sensors, the box collects data that permit the detection of the user's daily life activities (Figure 2). The aim is to prevent the user from wearing a device on their person, this could lead to a cognitive load that some elderly people cannot tolerate. Among the different activities detected, we take 'significant activities' into account for our study. Indeed, all the activities of daily life are significant and important; however, the absence of some (food related activities for example) is automatically an alerting sign. In the future, as an extension of our system, it is possible to gradually integrate more activities to the development. That being the case in this paper regarding the first version of our system. Every sensor can be configured with the minimum time for which a change occurs on the sensor and before the events 'start of use' and 'end of use' are registered. As presented in Figure 2, the output of the data process is the behaviour analysis based on the daily activities using the statistical model we chose to work with.

- *Motion sensors:* The most present type of sensor is the motion sensor, and more precisely the passive infrared sensor (PIR) that detects body heat (infrared energy) by checking alterations in temperatures. When the sensor heats up, it might detect heat and movement in the perimeter.
- *Contact sensors:* To detect motion on a door or window, contact sensors employ a magnet. As the door or window opens, the sensor detects the separation of the associated magnet from the sensor, which sets off an alarm.
- *Wireless motion sensors:* Most motion sensors on the market right now are wireless. Setting up wireless sensors is quite simple. They connect wirelessly with the other parts of the security system without the need for training.

In the users' residence, the areas we take into consideration are the bedroom, toilet, bathroom, kitchen and entrance of the house (Figure 3).

Figure 3 Floor plan of the user's home and the location of different sensors and the box (see online version for colours)



The context domain we will focus on in this paper, in order to build our context-aware model, is user activity. To move on to the description of the model design for activity patterns, we will first present the different activities related to every location (Table 1).

Table 1 Different activities to present the daily activity patterns

Bedroom	*Kitchen*	*Bathroom*	*Restroom*	*Entrance*
• Long sleep (A_1) • Short sleep (A_2) • Short passage (A_3)	• Breakfast (A_4) • Lunch (A_5) • Morning snack (A_6) • Dinner (A_7) • Evening snack (A_8)	• Wash hands (A_9) • Toileting (A_{10}) • Taking a shower (A_{11})	• Short passage (A_{12}) • Long passage (A_{13})	• Going in (A_{14}) • Going out (A_{15})

These selected activities are what we will focus on for our study. The objective is to start with basic yet high level activities that do not require the use of video monitoring for privacy concerns.

The dataset log collected is date-wise to isolate a sequence of ADLs and distinguish the different levels of activities. This enables us to construct the dataset of training samples.

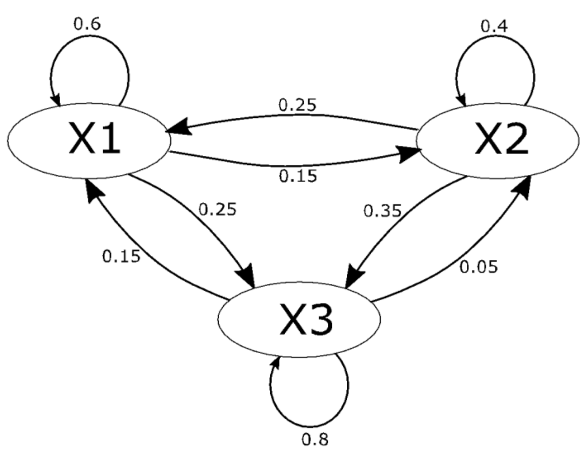
2.2 *Statistical approach*

2.2.1 *Markov model*

Markov model has been successfully used to model many real-world processes in a wide range of fields and is considered a reliable tool for making predictions for future values (Rabiner, 1989). Markov model assumes that the probability of being in a state t solely depends on the state at the time $(t - 1)$. It is brought out to deal with sequential data indexed at time t $\{1, 2, 3, \ldots, k\}$.

To illustrate a Markov model, we consider a three-state Markov chain ($X1$, $X2$, $X3$) with transition probabilities derived from gathered data (Figure 4).

Figure 4 State transition graph



From each state, there are transitions to the two other states and a transition to the state itself. Therefore, for each state, the sum of transition probabilities must be equal to one. We can determine through this model the transition probability of a sequence model starting from an initial state. For example, the probability of the sequence $X3$, $X3$, $X1$ is the probability of the sequence $X3$, $X1$ knowing $X3$, i.e.,

$$P(X3, X1|X3) = P(X3|X3) \cdot P(X1|X3, X3)$$
$$= PP(X3|X3) \cdot P(X1|X3) = 0.8 * 0.15 = 0.12$$

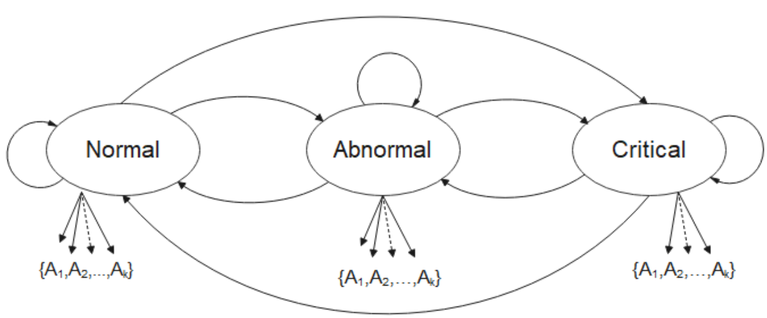
2.2.2 Hidden Markov models

A statistical learning attempts to model, understand and analyse complex datasets in general and sequential data in particular. Statistical methods focus mainly, in this context, on supervised and unsupervised modelling and prediction (Barbará et al., 2006). To build our system, we adopt an HMM-based approach (Forkan et al., 2015).

HMM is a tool for describing the development of observations related to internal factors, which are not observable at first hand. It permits forecasting a sequence of undetermined variables from a set of observable variables. HMM implies that the basic Markov model (Subsection 2.2.2) is unknown to the statistician. Precisely, only the observed data is known contrary to the information about the states that is unknown. In other words, the model producing the data is known but not the process behind it.

HMM is a basic method for modelling correlated time series (Chimienti et al., 2021). It consists of an observation sequence that is represented in our study by the activities sequence $\{A_1, A_2, \ldots, A_k\}$ and a hidden state sequence which in our case is the annotations qualifying the normality of the activities sequence $\{S_1$ = 'normal', S_2 = 'abnormal', S_3 = 'critical'$\}$ (Figure 5). The activity A_k operated at time k corresponds to quantities measured by the box sensors that permits, after analysis, the identification of the activity. The state variable S_k, where k in $\{1, 2\}$, represents the class label at time k that should be inferred (Rabiner, 1989).

Figure 5 Model of detection of the activities sequence abnormality



Inferred from sample data D, independent and identically distributed (IID) samples from a stationary probability distribution P are often assumed to be represented by normal data points. The goal is to determine if a new data point, z, may be assumed to have been produced by P or not and whether it is anomalous or not when compared to the sample data (Mohri and Rostamizadeh, 2007).

As a parametric model, HMM presupposes that the underlying distribution relates to a family of parameterised distributions, i.e., P_θ: $\theta \in \Theta$, where the parameters θ belong to a parameter space Θ and can be estimated from available sample data D. A common way to estimate the parameters θ of a distribution P_θ that best fits the data D is to use a maximum likelihood (ML) estimation (Biernacki et al., 2003).

Typically, the EM algorithm begins by randomly selecting the parameter initial values (Ling et al., 2003) after which iteratively evaluating the values that result in the sample data's highest likelihood:

$$\hat{\theta} = \arg\max_{\theta \in \Theta} (D|\theta).$$

This algorithm is also known as the Baum-Welch algorithm.

Moreover, in our context, we are more interested in achieving a trustworthy and accurate estimate of the predicted data distribution based on the sample data D than we are in the parameter values of the model.

Time series data can be used to characterise different behavioural states using HMMs. Covariate effects on behavioural transitions and behavioural state-dependent probability distribution parameters can both be taken into account by the highly adaptable HMM architecture.

3 Experimental results

3.1 Samples

Our study has been conducted on the data provided by a box commercialised in French pharmacies. Hence, our work is based on real-world datasets. The first 70 days' of data are used to train the model while the remaining 50 days' of data are used for testing. Real-world users are not the same as clinical trial users. Regardless of how good the conditions of a clinical trial might be, the issues remain related to how the results will extend to more diverse user profiles or what the long-term outcomes will be.

However, using real-world datasets is just as useful as much as it is challenging in the sense that they require eggshell treatment compared to working with ready to use datasets. On another note, it is necessary to ensure the consent of individuals in the use of their personal data.

An activity sequence example of a user during a day is shown in Table 2. The activity is usually saved in the database when it ends. Consequently, long sleep is often the first activity of the day within the database (normal sequences). In the database acquired, many tables exist. The most important three tables correspond to three hierarchical layers:

- *Low layer:* The table includes raw data collected from the sensors and includes the beginning and the end of each action.
- *Mid layer:* The conversion of the raw data into times/short passages.
- *High layer:* The passages are transformed into significant life events.

Table 2 Activity sequence of a day

Date format	*Activity*
Fri Jun 5 2020; 09:53:19	Long sleep
Fri Jun 5 2020; 10:01:43	Bedroom – short passage
Fri Jun 5 2020; 10:32:20	Breakfast
Fri Jun 5 2020; 10:37:25	Wash hands
Fri Jun 5 2020; 11:46:43	Toileting
Fri Jun 5 2020; 12:02:31	Lunch
Fri Jun 5 2020; 13:48:13	Morning snack
Fri Jun 5 2020; 14:04:06	Wash hands
Fri Jun 5 2020; 14:32:07	Restroom – short passage
Fri Jun 5 2020; 14:43:08	Taking a shower
Fri Jun 5 2020; 15:10:55	Resting
Fri Jun 5 2020; 17:33:19	Going out
Fri Jun 5 2020; 19:00:07	Going in
Fri Jun 5 2020; 19:05:25	Wash hands
Fri Jun 5 2020; 19:11:32	Restroom – long passage
Fri Jun 5 2020; 19:19:26	Bedroom – short passage
Fri Jun 5 2020; 19:45:47	Dinner
Fri Jun 5 2020; 19:59:44	Restroom – short passage
Fri Jun 5 2020; 20:07:08	Wash hands
Fri Jun 5 2020; 21:35:01	Evening snack
Fri Jun 5 2020; 22:16:13	Toileting
Fri Jun 5 2020; 23:19:25	Restroom – short passage

3.2 Case study

The main aim of this work is to present the process of detecting abnormal behaviour in the routine of a user of the box. The user has been having a stable lifestyle for three months starting from the day of the installation of the box. Besides the activity monitoring, the system can detect a malfunction of the sensors and subsequently alert a technician in order to intervene.

The first set of experiments we conducted were destined to evaluate/validate the model in order to move on to more realistic scenarios. The company provided us with different datasets of different users. Among the users of the box, we will present in this paper an illustrative user case where different abnormalities occur.

We purposely chose this user because it happens to identify both behavioural and sensor anomalies.

3.2.1 User profile

The user is a female and has been living alone for five years. She recently installed the box to monitor her activity to prevent health problems that the lack of exercise usually engenders. When she started using the box, she had no severe health issues.

Figure 6 Our HMM-based classifier for two classes: normal and abnormal

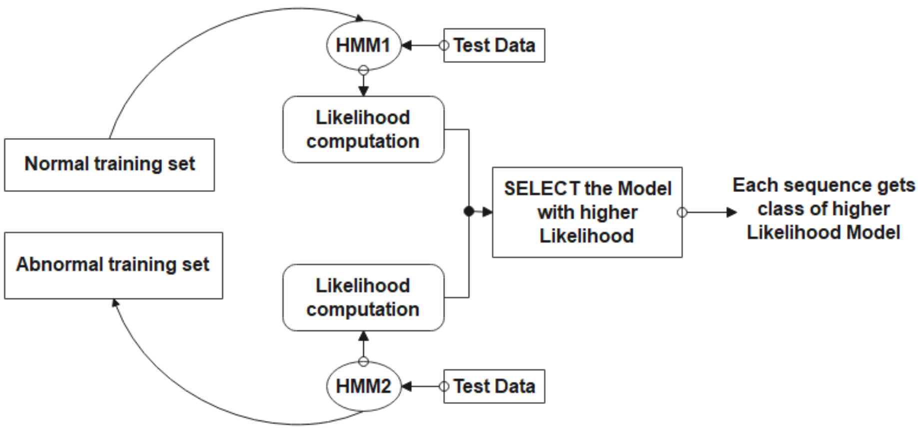
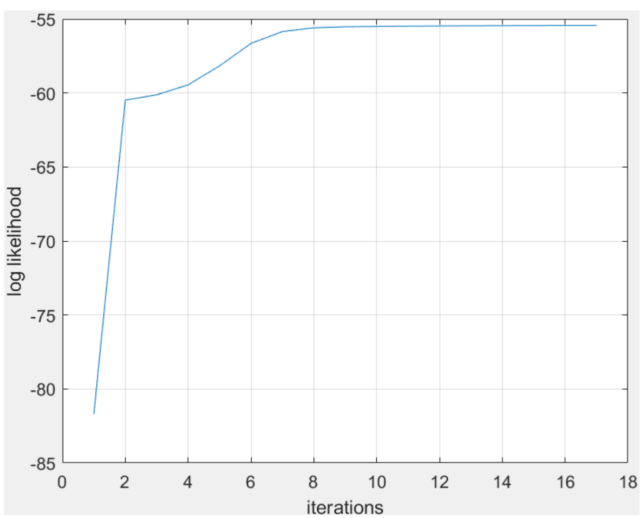


Figure 7 Learning curve of HMM1 (see online version for colours)



The anomaly may occur frequently across a series of activities. The influence of such frequency during categorisation will be negligible because the HMM models are constructed using long-term observations of normal and abnormal patterns. The situation in other contextual domains will also eliminate the seeming irregularity in the context of an action. Additionally, the model will be adapted to account for any sudden changes in activity patterns.

In our case, we have two classes:

$$Class\ 1 = Normal\ behaviour / Class\ 2 = Abnormal\ behaviour$$

For each class we will go through the four steps presented below in order to compute the log-likelihood of a sequence X using each model and then we pick the class that gave the highest probability. This is the class prediction.

Figure 8 Learning curve of HMM2 (see online version for colours)

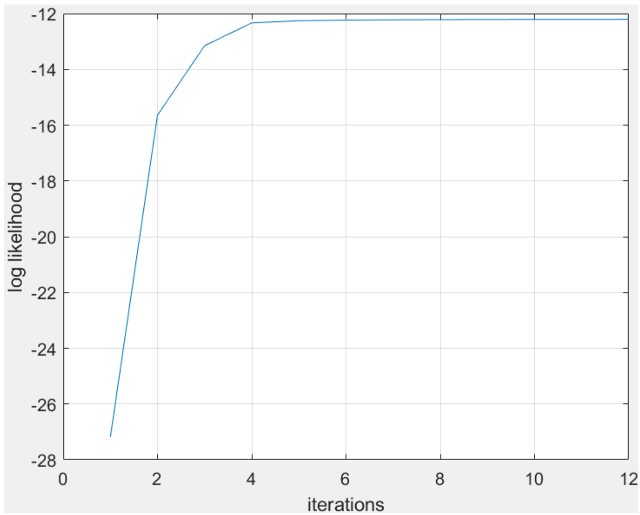
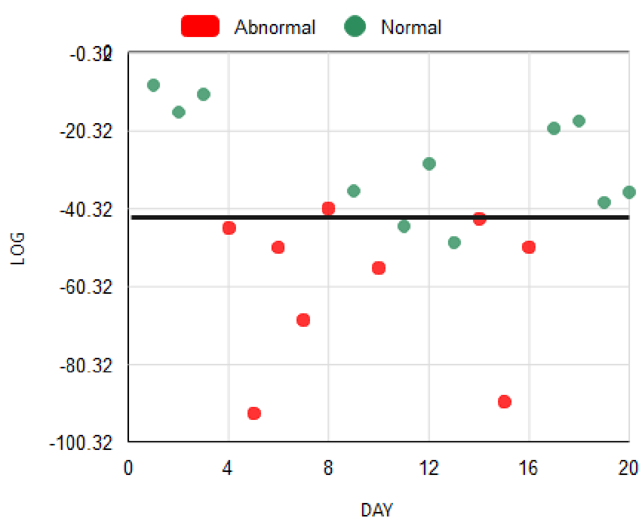


Figure 9 20 values of log-likelihood of normal and abnormal activity sequences (see online version for colours)



Note: The line represents the cluster boundary between the class 'normal' and the class 'abnormal'.

We first construct an HMM1 for user 1 using training data from typical activity patterns (where each sample is a sequence of a day). Any new activity sequence after that which cannot be explained by the HMM1, is deemed abnormal. Similar to the deduction established for HMM1, our HMM2 is constructed using abnormal activity sequences, and any new activity sequence that is unlikely to HMM2 is regarded as normal (Figure 6).

The curve in Figure 7 is the learning curve of HMM1 (built using normal activity sequences), it indicates that the training stops when the log-probability is stabilised and no additional learning is needed. As shown in the figure, in about eight iterations, the learning curve has flattened.

Figure 8 presents the learning curve of the HMM2 (built using abnormal activity sequences). It shows that in four iterations, the learning curve has flattened.

Then, using the HMM Library of MATLAB and Simulink tool, an HMM λ is constructed with a random stochastic transition and emission matrix. Using EM (BaumWelch), we compute the Log-likelihood of the trained model given sample data.

To highlight the anomaly detection in the daily activity of the user, we presented in Figure 9, the values of the log-likelihood of 20 days where suspicious days have been detected through the values. The abnormal sequences identified in Figure 9 correspond to some of the activity sequences presented later on in Table 3.

Table 3 Some identified abnormal activity sequences

Activity sequence	*Observed abnormality*
$A_1A_{12}A_9A_2A_{11}A_{14}A_{15}A_{12}A_8A_1A_{12}A_9$	• No food besides the evening snack
	• Sleeping too much
$A_{12}A_2A_{12}A_1A_{11}A_4A_{12}A_9A_5A_9A_{14}A_{15}A_{10}A_9A_7A_2A_{12}A_2A_{12}A_1A_2$	• Frequent restroom visit at night
$A_1A_{10}A_{12}A_2A_6A_3A_{12}A_9A_1A_{12}$	• Not enough food
$A_1A_9A_2A_4A_9A_{11}A_9A_{14}A_{15}A_7A_9A_{10}A_8A_1A_9$	• No restroom visit
$A_2A_4A_{11}A_9A_5A_6A_9A_{10}A_9A_7A_{11}A_8$	• No restroom visit
$A_2A_{12}A_1A_4A_{10}A_{12}A_2A_{13}A_9A_3A_2A_8A_9A_{12}A_2A_{12}$	• Too much sleeping

Table 4 A 2 × 2 confusion matrix

		Ground truth	
		Positive	*Negative*
Prediction	Positive	True positives	False positives
	Negative	False negatives	True negatives

The detected abnormalities could also point to the dysfunction of some devices/sensors. For instance, our anomaly detection system identified a succession of abnormal daily sequences where the user did not go to the restroom. After contacting the box developers and analysing the collected raw data, we concluded that the issue was related to the sensor's deterioration and it was not an alerting health problem.

To detect pertinent alerts and provide efficient personalised monitoring, it will be beneficial to have medical assistance regarding the behaviour of the user before and during the use of the system. For the moment, we are making use of the expertise of health professionals who surround us (family and friends).

3.2.2 Confusion matrix and performance parameters

For assessing the performance of any classification model, in the field of predictive analysis, a confusion matrix is the most appropriate tool. It is a table of two rows and two columns (as shown in Table 4). The different terms in the confusion matrix are explained in Table 5.

Table 5 Meaning of different terms in the confusion matrix

Case: if sequence is normal or not	*What our model predicted*	*Conclusion 1*	*Conclusion 2*	*Conclusions combined*
Normal	Normal	*True* prediction	*Positive* prediction	True positive (*TP*), the sequence is normal and the model predicts its normality
Normal	Abnormal	*False* prediction	*Negative* prediction	False negative (*FN*), the sequence is normal and the model claims that it is abnormal
Abnormal	Normal	*False* prediction	*Positive* prediction	False positive (*FP*), the sequence is abnormal and the model claims that it is normal
Abnormal	Abnormal	*True* prediction	*Negative* prediction	True negative (*TN*), The sequence is abnormal and the model also predicts its abnormality

For user 1, in the case of:

$$Actual\_class = [1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2];$$

$$Predicted\_class = [1\ 1\ 1\ 1\ 2\ 1\ 1\ 1\ 1\ 1\ 2\ 2\ 2\ 2\ 2\ 1\ 1\ 2\ 2\ 2];$$

$$C = confusionmat(Actual\_class, Predicted\_class)$$

$$C = \begin{matrix} 9 & 1 \\ 2 & 8 \end{matrix}$$

- *Precision:* It is the proportion of positives identified correctly, and it gives the accuracy rate for the positives.

$$Precision = \frac{True\ positives}{Positive\ outputs}$$

$$Precision = 0.8535$$

- *Sensitivity:* It is the percentage of correctly classified positives among all positives. Sensitivity measures how to prevent false negatives.

$$Sensitivity = \frac{True\ positives}{Total\ no.\ of\ negatives}$$

$$Sensitivity = Recall = 0.8500$$

- *F-measure:* It evaluates how accurate a test is. It is derived from the test's recall and precision (sensitivity).

$$F\text{-}measure = \frac{2 \times Precision \times Sensitivity}{(Precision + Sensitivity) \times 100} = 85.1764\%$$

The idea behind the F-measure is that precision and recall are equally important and that a good F-measure can only be achieved when both measures are strong; which emerges in our situation. The categorisation of our model has a high degree of accuracy when taking the values of the three metrics into account.

4 Discussion

Our main claim in this work is that an intelligent environment that is completely unobtrusive is a solid starting point for gathering pertinent data for an ambient assisted living (AAL) system. Estimating the volume of data required to produce highly accurate alerts is challenging. The answer is to test the model's applicability on as many user datasets as you can with various profiles in order to refine it over time.

Many researches in the field of assistive technologies are based on data collected from cameras and adopt video monitoring approaches (Chung and Liu, 2008; Jansen and Deklerck, 2006) for the sake of accurate information and in order to cope with the dynamic state of the resident. This reasoning is undoubtedly correct but the rate of acceptance of surveillance-based approaches is extremely low for their intrusiveness. In general, the end user does not like the feeling of being watched (Alcalá et al., 2015; Chalmers et al., 2016); even less, elderly people are usually more sceptical about novel technologies (Chen and Chan, 2011). The use of non-intrusive sensors to build our AAL system grants the involvement of the user on a long-term basis and the continuity of the collection of the data.

5 Conclusions and perspectives

In this paper, we have presented a system for anomaly detection in the daily activity of seniors. In contrast to other solutions based on data collected in laboratory environments, we have used real datasets. After conducting a literature review on the available algorithms and solutions, we chose to adopt an approach based on HMM.

The aim of our work is to provide pertinent information that relies on an unobtrusive sensor system and to identify anomalies in future behaviours by using a statistical approach based on long-term context history.

For our ongoing work, augmentation and annotation of data is necessary for effective data analysis and elimination of irregularity and error for improved accuracy. We plan to implement more complex user profiles and use the expertise of a medical profile to build a solid baseline and pertinent personalised monitoring. We intend to work on including the routine behaviour analysis in order to identify changes that occur in the timetable. The aim is to detect the behavioural abnormalities that are related to the time of day, the duration and frequency. We could extend our abnormality detection approach to assess more complex human behaviour. We can also consider combining multiple models and evaluate their impact in terms of identifying alerting behaviours.

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