Human behaviour modelling for welfare technology using hidden Markov models

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ABSTRACT

Human behaviour modelling for welfare technology is the task of recognizing a person's behaviour patterns in order to construct a safe environment for that person. It is useful in building environments for older adults or to help any person in his or her daily life. The aim of this study is to model the behaviour of a person living in a smart house environment in order to detect abnormal behaviour and assist the person if help is needed. Hidden Markov models, location of the person in the house, posture of the person, and time frame rules are implemented using a real-world, open-source dataset for training and testing. The proposed model presented in this study models the normal behaviour of a person and detects anomalies in the usual pattern. The model shows good results in the identification of abnormal behaviour when tested.

1. Introduction

The older population in Nordic and other European countries has substantially increased. In the European Union, 5.5% of the population is aged 80 or above as of 2017. This number will almost double to 12.7% by 2080 [1]. In Norway, 38.5% of households with people aged 65 and over live alone [2].

In Nordic countries, the term *welfare technology* refers to “technology used for environmental control, safety and well-being in particular for elderly and disabled people” [3]. Welfare technology is more often referred to as *ambient assisted living* outside of Scandinavia.

In this work, human behaviour modelling (HBM) is proposed as a type of welfare technology that can recognize an individual’s behaviour patterns in a smart house, thereby helping to construct a safe environment. Smart house development is important for those who prefer to live in their own homes as long as they can care for

The work presented here is based on the theory that people generate patterns in their daily activities and behaviour [6,7]. Therefore, a repetitive pattern in the person's behaviour helps to recognize, model, and predict future events.

In order to recognize the behaviour of a person, Hidden Markov models (HMM) were used. Posture checking and time frame logic were added as an extra layer of recognition to model the behaviour of the person as normal or abnormal.

HMM was used because it is a statistical method that assumes a Markov process with missing or unobserved states. Moreover, the Markov assumption is a sequence of events in which the probability of each event depends only on the previous event.

For the modelling, a real world, open-source dataset was used. The dataset comprised a finite number of days, in which half the days were used for training and the other half for testing. Once the HMM model was trained, the Viterbi algorithm was used to test the validity of the model for the remaining days in the dataset. The Viterbi algorithm enables detecting whether the input sequence for themselves, and are defined as living environments designed to assist residents with their daily activities and to promote independent lifestyles [4].

Therefore, HBM is developed to detect abnormal behaviour (anomalies) in a person's behaviour patterns and provide assistance if needed. “Anomaly detection refers to the problem of finding patterns in data that do not conform to expected behaviour”[5]. Examples of abnormal behaviour could be falls and early signs of dementia.

In the present study, the term *behaviour* refers to the activity, duration of activity, location, and posture of a person. Recognizing a person's behaviour patterns helps in constructing a safer environment for older adults, people with disabilities, and a more comfortable lifestyle in general for any person.

testing (or a new input sequence) is classified as a normal or an abnormal behaviour.

1.1 Aim and Objectives

The aim of the present study is to model the behaviour of a person living in a smart house environment, to detect abnormal behaviour and alert family or a caretaker if assistance is needed.

The main objective of using HMM for human behaviour modelling is to predict whether the current activity is normal or abnormal. HMM is used because it is a statistical method that works well with a small dataset or insufficient training data [8,9].

1.2 Activity vs Behaviour

In the present study, the term *activity* refers to the actions of people in a specific room or area. These actions are known as activities of daily living (ADL) and include sleeping, personal hygiene, showering, dressing, undressing, eating, etc. ADLs are more formally defined as the actions that require "basic skills and focus on activities to take care of one's own body".

The term *behaviour* in the present study refers to the combination of activity, duration, location and posture of the person.

- **Activity**: ADL.
- **Location**: place in the house where the person is doing the activity (bedroom, bathroom, kitchen, etc.).
- **Posture**: position of the person (lying, sitting, standing).
- **Duration**: The time span from the start to the end of an activity, given in hours, minutes and seconds (hh:mm:ss).

An example of a behaviour can be having breakfast. The breakfast behaviour comprises eating (activity), being in the kitchen (location), sitting (posture) and within a time span (duration). Behaviour can also be a sequence of activities.

The rest of this paper is organized as follows. In section 2, presents the background. Section 3 discusses the methods. Section 4 describes the experiments. Section 5 presents the results and section 6 discusses the results. Finally, the conclusion is provided in section 7.

2. Background

Improving the lives and safety of older adults has been an important area of research with regard to smart house welfare technology [10–12]. This generally includes detecting falls, among other issues, and warning family or caretakers of any potential dangerous or abnormal situation [13–15].

Ideally, a smart house designed to help people should search for patterns in the user's activity or behaviour and detect any deviation from this pattern. Other projects aim to ease a person's daily life regardless of age, while increasing comfort and security [16].

The general technique used to achieve the aforementioned goals is Human Activity Recognition (HAR), which is the task of recognizing the activities of a person. There are several analysis methods used for HAR[17]. However, studies involving human behaviour modelling have not received the same kind of attention.

One study involving HAR modelling used decision trees with promising results of 88.02% for the activity recognition task. However, they study concluded that for modelling human activities, decision trees did not meet the expectations [18].

Therefore, in this section, we use the knowledge derived from the state-of-the-art techniques in HAR as a foundation for the present work in human behaviour modelling. Among the most popular analysis methods used for HAR are machine learning techniques and statistical methods.

Machine learning techniques require a large amount of data for training. In contrast, classic statistical methods are more effective than machine learning techniques when a smaller dataset is used [19]. Therefore, for pattern recognition within smart houses, a statistical approach tends to perform better since the datasets are usually small.

Useful statistical algorithms include HMM and Hidden Semi-Markov Models (HSMM). HMM have been used for several other tasks with excellent results, such as speech recognition, pattern recognition and artificial intelligence [20]. combination with other methods such as neural network and intelligent agents [22,23]. The center for advanced studies in adaptive systems (CASAS), from Washington State University, implemented HMM with promising results with several residences in a smart house [24]. Another study on HAR for diabetes patients in a smart house was developed using HMM with 98% accuracy [25].

Several other studies are not traditionally called HAR but ADL recognition or detection. Both HAR and ADL recognition works have the same aim. A two-stage, multi-Markov model for ADL detection was used by Kalra et al. [26]. Another study used the dataset from CASAS to recognize ADL [27] and compared support vector machines (SVM), HMM, Fishe kernel learning (FKL) and random forests (RF). Gayathri et al. [28] also used the dataset from CASAS to detect ADL using Markov logic networks.

In addition, ADL recognition has been studied with HSMM. One of the first research on modelling ADL is the work of Duong et al. [10], who used a Switching Hidden Semi-Markov model (S-HSMM) for activity recognition and abnormal detection in a pervasive environment. Duong created a double-layered extension of HSMM. That model focused on distinguishing a person's major routines (making breakfast, eating breakfast, etc.). Another very important work on HSMM for HAR using on real world activity recognition data is the work of Van Kasteren et al. [29].

The studies mentioned so far focus on HAR/ADL recognition using HMM. There are, however, other studies that use other techniques for HAR recognition, such as machine learning techniques.

One machine learning technique for anomaly detection is Hierarchical Temporal Memory (HTM). Some studies have used HTM for anomaly detection in streaming data, online sequence learning and short-term forecasting of electrical load time series [30–32]. However, there are very few works using HTM for abnormal behaviour detection for welfare technology.

Although machine learning techniques could be useful for HBM, they require large amounts of data [19]. This is particularly a problem in smart house environments, where it is difficult to obtain large relevant datasets. Finding a person who is willing to live in a smart house that is set up to collect data is challenging, especially if the final user in an older person, where many ethical challenges are involved [4]. Therefore, the data used in this study is an open-source small dataset.

In addition, anomalies in the behaviour of a person cannot as of yet be learned from the currently available dataset. The publicly available datasets comprise a person living alone for a few days or months and performing his or her daily activities. The datasets do not contain any abnormal behaviour in their patterns. Therefore, in the present study, we have created a fictional dataset with abnormal behaviour to test our model.

The studies described in this section show that HMM has been implemented with good results for HAR/ADL. Therefore, in the present study, HMM is implemented for the first step of human behaviour modelling.

3. Methods

3.1 Design

First, the HMM algorithm was implemented. The activities of the person can be modelled as Markov chains. Therefore, HMM was implemented in order to train the algorithm and recognize the activities. The person's activities were used as the hidden states, and the observable states were the person's location (obtained from

One of the first works on HMM for HAR is the work of Yamato et al. [21]. Later on, HMM has been used separately or in

the sensor data in the dataset). MATLAB was used to implement the HMM.

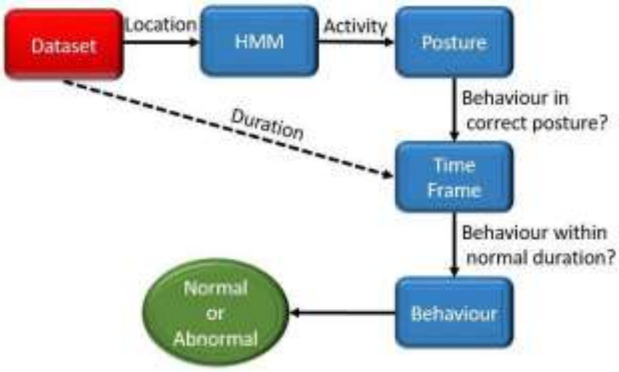

Fig. 1 Flow diagram of proposed methodology for HBM

The HMM was trained using the Baum-Welch algorithm. Later, the Viterbi algorithm was used to find the most probable activity given the input sequence.

The HMM module outputted the activity of the person. The person's posture was then checked using a Boolean method to detect abnormal behaviour such as falls (section 4.2). Afterwards, time rules were applied, considering the duration for each activity. The time frame rules enable more accurate detection of any abnormal behaviour in the person (section 4.3). Fig. 1 shows the proposed methodology used in the present work.

HSMM was also used in the present study as an alternative to HMM. HSMM was chosen because HSMM "can have any arbitrary duration distribution" [33] . The HSMM implementation was programmed with the *mhsmm* package for R [34]. The main reason for using HSMM was to compare the performance of HMM and HSMM with regard to HBM.

3.2 Data

The data used for this study come from an open dataset named *Activities of Daily Living (ADLs) Recognition Using Binary Sensors Data Set*, available for download [35]. The data collected comprise information about the ADLs gathered by two people, living on a daily basis in their own homes. The dataset is in a text file format.

The dataset properties are depicted in Table 1. The information in the dataset includes the date, time, location of the sensor, type of sensor, location (room) in the apartment and activities.

Table 1: Attributes of the *OrdonezA* dataset used [36]

Name	Value
Setting	Apartment
Number of locations	4 Rooms and hall/entrance
Number of labelled days	14 days
Labels (ADLs included)	Leaving, Toileting (Personal hygiene),Showering, Sleeping, Breakfast, Lunch, Dinner, Snack, Spare Time/TV, Grooming
Number of sensors	12 sensors
Sensors	PIR: Shower, Basin, Cooktop Magnetic: Maindoor, Fridge, Cabinet, Cupboard Flush: Toilet Pressure: Seat, Bed Electric: Microwave, Toaster

Note that in the present work, we used the same terms as they are used in the dataset. Therefore, the term *toileting* is used as it is instead of the more proper term *personal hygiene*.

There are two instances of data, one of 14 days (OrdonezA), and one of 21 days (OrdonezB), corresponding to each user, person A and person B, respectively. The activities were manually labelled by the users. Both dataset *OrdonezA* and dataset *OrdonezB* were used in this study.

An open-source dataset was chosen in order to obtain unbiased results. In addition, this dataset comprises real-world data and it has been used in other research [36]. The fourteen days' activity data for the first dataset is shown in Fig. 2.

3.2.1 Data Handling

The dataset is a text file that can be imported into MATLAB. Each day in the dataset represents a day sequence.

For *OrdonezA*, seven days were used as a training sequence, and another seven days were used as a testing sequence. For *OrdonezB*, fourteen days were used as a training sequence, and another seven days were used as a testing sequence.

The house room *location* was chosen as the main observed variable, and the *activities* were the hidden data. Table 2 depicts the first day from the dataset.

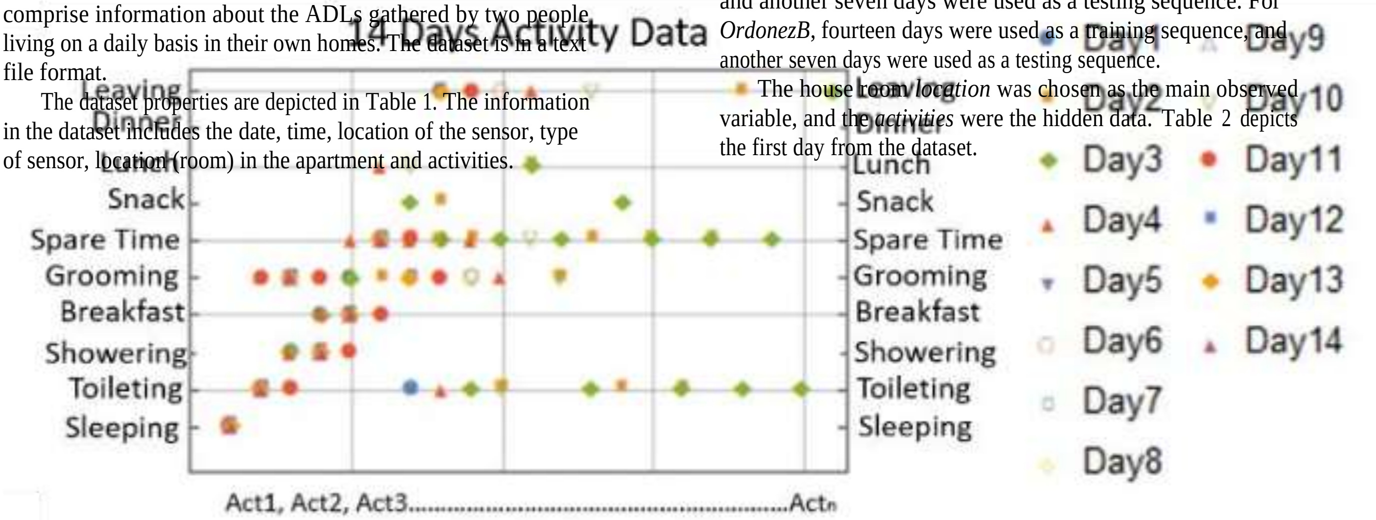

Fig. 2 Activity Data Graph. Each day is shown in a different colour, according to the legend at the right. The first activity is always *sleeping* and the last activity is *leaving*. The activities are shown in a sequence.

Table 2: Example of *Day 1* in the dataset. The dataset comprises the date, start time, end time, activity and location. To train the HMM, *location* was used as an observable variable and *activity* was used as the hidden variable.

Date	Start Time	End Time	Activity	Location
28-11-11	02:27:59	10:18:11	Sleeping	Bedroom
28-11-11	10:21:24	10:23:36	Toileting	Bathroom
28-11-11	10:25:44	10:33:00	Showering	Bathroom
28-11-11	10:34:23	10:43:00	Breakfast	Kitchen
28-11-11	10:49:48	10:51:13	Grooming	Bathroom
28-11-11	10:51:41	13:05:07	Spare_Time/TV	Living Room
28-11-11	13:06:04	13:06:31	Toileting	Bathroom
28-11-11	13:09:31	13:29:09	Leaving	Hall
28-11-11	13:38:40	14:21:40	Spare_Time/TV	Living Room
28-11-11	14:22:38	14:27:07	Toileting	Bathroom
28-11-11	14:27:11	15:04:00	Lunch	Kitchen
28-11-11	15:04:59	15:06:29	Grooming	Bathroom
28-11-11	15:07:01	20:20:00	Spare_Time/TV	Living Room
28- -	20:20:55	20:20:59	Snack	Kitchen
28- -	20:21:15	02:06:00	Spare_Time/TV	Living Room

An additional column for *posture* was added to the dataset. The values of the *posture* variable were *lying*, *sitting* and *standing*. The values were assigned according to each activity and coded to numbers in order to develop the MATLAB code. Table 3 shows the values allowed for each activity.

A total of 10 *activities*, 5 *locations* and 3 *postures* were used.

Number	Posture	*Allowed activity*
1	Lying	Sleeping, Spare Time
2	Sitting	Personal Hygiene, Breakfast, Spare Time, Snack, Lunch, Dinner
3	Standing	Showering, Grooming, Leaving

Table 3: Assigned number and posture of the person according to the activities

3.3 *Hidden Markov Model*

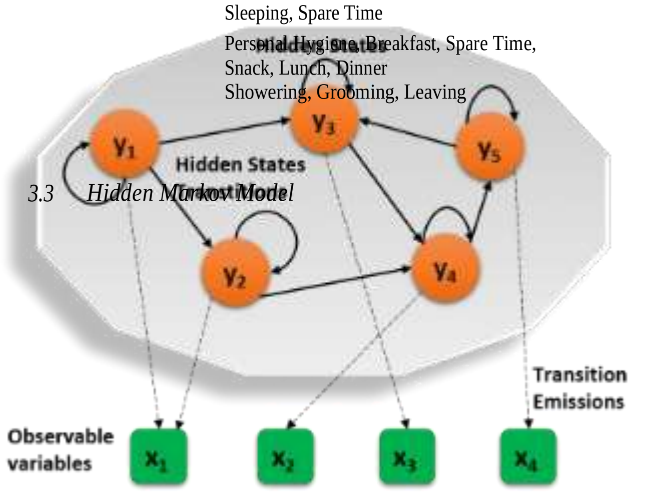

Fig. 3: Schematics of HMM representation

The idea of Hidden Markov Models (HMM) was first introduced in the late 1960s [9]. HMMs are a "subclass of Bayesian networks known as dynamic Bayesian networks" [20]. HMM is a generative probabilistic model that is used for generating hidden states from observable data.

HMMs utilize Bayesian rules such that a separate model $p(x|y)$ is learned for each class. Therefore, the posterior probability $p(y|x)$ can be calculated.

variable (sometimes called the *event*) occurs at each instant of time. The hidden variables, *Ys*, can be observed by another set of stochastic processes that produce the sequence of observations *Xs* [9]. Each hidden state *y* can emit one and only one possible observed variable *x*.

The HMM is fully determined by three probabilities:

1. The transition probability (A)
   - $p(y_{t+1}|y_t)$
2. The emission probability (B)
   - $p(x_t|y_t)$
3. The initial state distribution (π)
   - $\pi(y_0)$

The aim of the HMM is to solve the following three problems:

1. **Evaluation**: Inferring the probability of an observation sequence given the fully characterized model.
2. **Decoding**: Finding the path of hidden states that most probably generated the observed output.
3. **Learning**: Optimizing the model that best describes how a given sequence of observations (also known as a *training sequence*) occurs.

In the present study, the focus is on learning and decoding to recognize the behaviour of the person.

3.3.1 *Hidden Semi-Markov Model*

HMM does not take into account the duration parameter of the current activity. Therefore, to model the behaviour of the person, an additional layer is needed to consider the duration.

To overcome this additional layer, HSMM were also studied as an alternative solution for behaviour modelling.

HSMM is an extension of HMM. HSMM allows "the underlying process to be a semi-Markov chain with a variable duration or sojourn time for each state" [37].

The HSMM can produce a sequence of observations. The number of observations that are emitted during state ***i*** is constrained by the length of time spent (duration) in state ***i***, usually represented as *d*. Thus, for each state ***i***, there is a specified duration distribution D_i, which can be parametric or non-parametric.

As a result, the HSMM parameters are the same as the HMM, plus the sojourn time for each state. $\lambda = (A,B,D,\pi)$.

Fig. 4 shows a representation of the HSMM. The HSMM runs from 1 to *T* times, where *x* is the current observation, *y* is the current state and *d* is the duration variable of the current state. Thus at each step, the variable comprises $V_t=\{y_t,d,x_t\}$. Each state duration can be modelled by any distribution in the exponential family.

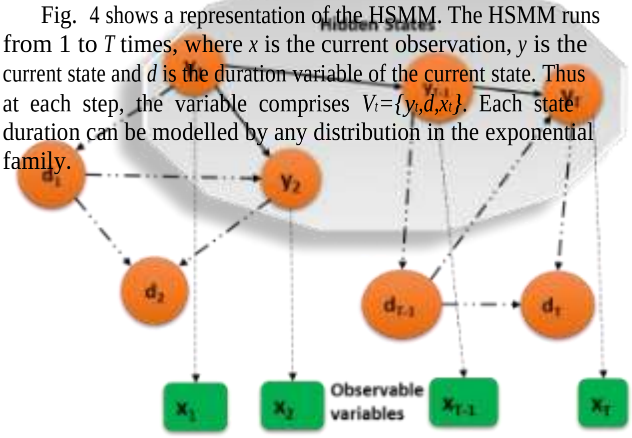

Fig. 4: Schematics of HSMM representation

Fig. 3 shows a schematic of HMM. The *Xs* are the observable variables and the *Ys* are the hidden variables. The observed

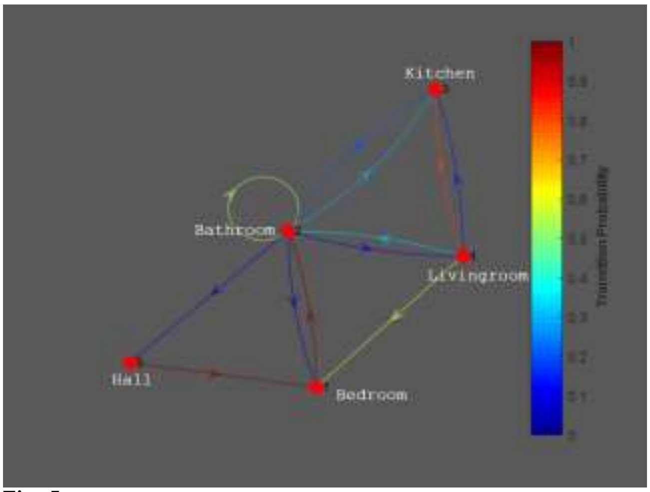

Fig. 5: Location transition with heat transition scale probability on the right side. The transitions were estimated using the Baum-Welch algorithm.

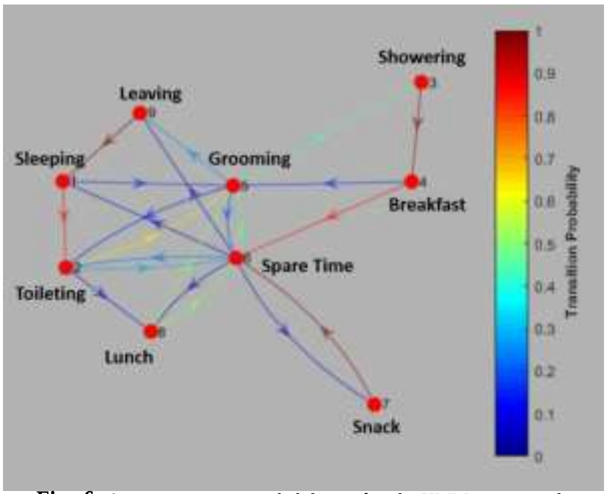

Fig. 6: Activity transition probabilities after the HMM was trained using the Baum-Welch algorithm

4. Experiments

The experiments were performed for both available datasets, *OrdonezA* and *OrdonezB*. However, in this section, the figures and explanations are only provided for the first dataset *OdonezA* in order to keep the text as clear as possible. Section 5 provides the results for both datasets. The experiments with the *OrdonezB* dataset follow the same procedure as described here for the *OrdonezA* dataset.

4.1 HMM and HSMM

The HMM was built by initializing the transition and emission probabilities (A and B). The *activities* data corresponded to the hidden state, and the *location* data corresponded to the observed data (traning sequence). The HSMM was built with the sojourn time *D*.

4.1.1 The Learning Task

The learning process deals with how to adjust the model parameters λ= (A,B,π) to maximize the probability of the observation sequence $p(X|\lambda)$, where X represents the observed sequence, $X=x_1,x_2,x_3...x_n$. The idea is to optimize the model parameters that best describe how a given observation sequence is produced [9]. The Baum-Welch algorithm is used for this.

For the *OrdonezA* dataset, the first seven days were used to train the model; this is known as the training data. The last seven days were used for testing. For the *OrdonezB* dataset, the first fourteen days were used to train the model and the last seven days were used for testing.

The training sequence uses the *location* data as the observable sequence. The dataset comprises five room locations, as depicted in Table 1.

Fig. shows the transition between the *locations*, estimated with the Baum-Welch algorithm. That is, $A(i,j)$, the probability of transition from state i to state j, given the training input sequence sequence of hidden states that produced that observable sequence. The Viterbi algorithm was used to achieve th is decoding task.

The observation sequence was the *location* data of a day. A total of seven days was used for testing, comprising the last seven days of each dataset.

The prediction accuracy was found by computing the percentage of the real or actual sequence state that agreed with the predicted sequence. Hence, the formula:

$$Accuracy = \sum \frac{predictedState}{\sum actualState} = totalState$$

4.1.3 HSMM

The HSMM was trained using the *mhsmm* package for R. The same parameters and training data as in the HMM were used. Only the duration parameter *D* was added to model the HSMM.

For the parameter *D*, the Gamma distribution was first used to model the duration of each activity. Second, a Poisson distribution was also used to model the duration of each activity.

4.2 Checking posture to detect possible fall

The *posture* of the person was checked using a Boolean logic method. The *posture* variable can have only three values: *lying*, *sitting* and *standing*. The primary check was applied to the posture *lying* because it could indicate a fall.

A priori knowledge was applied for this step. Therefore, the *lying posture* was only allowed in the *sleeping* and *spare time* activities, as shown in table Table 3. There should not have been any *lying* in any activity performed in the *locations: bathroom, kitchen* and *entrance*. If the posture *lying* was found in any of the aforementioned locations, then a fall was detected.

4.3 Time frame rules

Time frame rules were used to determine whether the current *activity* had a reasonable *duration*. The seven days that were used of *location*.

The hidden variables were the *activities*. A total of ten activities were trained. However, there was no data for the *activity dinner* in the training dataset *OrdonezA*. Fig. shows the trained HMM corresponding to the transition between the *activities*. In addition, a probability transition heat map of the *activities* is given in supplementary material (Fig. A.1).

4.1.2 The Decoding: Viterbi Algorithm

Once the model was trained and given a new observation sequence, it was possible to determine the best, most likely

for training the HMM were also used for training the *duration* of each activity.

First, the *duration* of each *activity* was extracted from the dataset. Then, the minimum and maximum *duration* for each activity in the training dataset was computed. Finally, to calculate the *duration* range for each *activity*, a ±20% threshold was used. Therefore, 20% was added to the maximum *duration* of each *activity*, and 20% was deducted from the minimum *duration* of each *activity*.

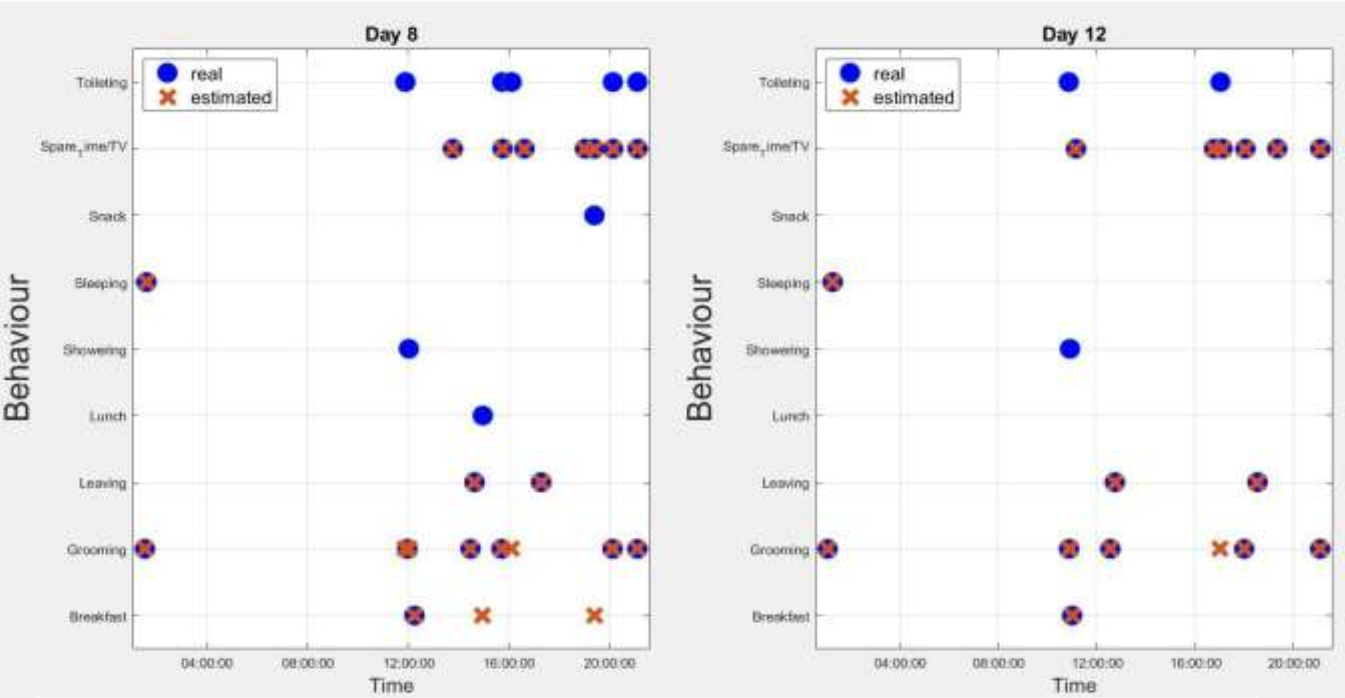

Fig. 7: Results for the OrdonezA dataset for Day 8 and Day 12: Blue circles show the real data. Red crosses show the estimated results

- Maximum Duration Allowed = MaximumDuration + 20%
- Minimum Duration Allowed = MinimumDuration − 20%

If the person spent more than the maximum or less than the minimum duration allowed for any *activity*, an abnormal behaviour alert was triggered.

information about abnormal behaviour in its patterns.

4.4 Fictional dataset test

The dataset used in the present study did not contain As mentioned in section 2, we were unable to find a relevant dataset containing both normal and abnormal behaviour for a person living in a smart house. Therefore, it was not possible to learn abnormal behaviour from the dataset used in the present project.

To overcome this challenge, we manually created a small fictional dataset containing some abnormal behaviour comprising of three days. The data in the dataset contained some changes in the duration, posture, and sequence of activities. These three fictional days were created to test whether the model presented in this work could detect abnormal behaviour in the person's behaviour.

Therefore, the *duration* of some of the *activities* was exaggerated. In addition, on the first fictional day, the *posture* for the activity *leaving* at the *Entrance* was changed to *lying*, to simulate a fall. Finally, the sequence of *activities* on the third day was changed.

5. Results

5.1 Results on first dataset OrdonezA

As described in section 4.1.2, the Viterbi algorithm estimates the *behaviour* of the person based on the observation sequence of the observable variable *location*. The last seven days were used for testing. The predicted *behaviours* were compared to the actual *behaviours* sequence in the dataset. The results for the *OrdonezA* dataset Day 8 and Day 10 are shown in Fig. . The supplementary material conta ins the results for all the test days in *OrdonezA* d a t a s e t (F i g . A . 2) . For the first day in the tes ting dataset, i t is possible t o see that the predicted *beh aviour* is *groomi ng* instead of *toil eting*. The same is true for most of the other days. One possible reas on for this estimation is that both of these *behaviours* are in the *bathroom location*.

In addition, the *behaviour breakfast* was predicted instead of the correct *lunch* and *snacking behaviours*. The same reason as before could be applied here, that the *behaviours breakfast*, *lunch* and *snacking* are all located in the kitchen. Therefore, the prediction accuracy was 72% using the HMM algorithm.

After the HMM results were obtained, the *posture* of the person was checked. There were no warnings when the *posture* was checked on any of the days assigned for testing because there was no abnormal behaviour in the testing dataset.

Finally, time rule was applied to the model to check the *duration*. Table 4 shows the warnings in the *behaviour* when the *duration* was checked. The results show that the model can detect whether the user has spent either too much or too little time performing a *behaviour*.

Most of the warnings are for the *behaviour breakfast*, because the *duration* of that *behaviour* varied a great deal. One reason for this is that the *behaviour breakfast* was predicted instead of the real *behaviour snack* or *lunch*, which usually take less time (snack) or more time (lunch).

Table 4: Warnings in behaviours when *duration* is checked for the OrdonezA dataset. The first column is the day in the testing data. The second column shows the predicted behaviour. The third column s hows the duration of the predicted behaviour.

Day	*Behaviour*	*Duration*	*MinTime*	*MaxTime*
Day 8	Grooming	00:00:05	00:00:09	00:11:16
Day 8	Sleeping	00:00:04	10:13:45	10:09:18
Day 8	Leaving	00:16:59	00:18:28	03:30:26
Day 8	Breakfast	00:43:08	00:03:40	00:12:44

Day 9		Grooming	00:13:38	00:00:09	00:11:16
Day 9		Breakfast	00:35:05	00:03:40	00:12:44
Day 10		Grooming	00:13:41	00:00:09	00:11:16
Day 10		Breakfast	00:35:56	00:03:40	00:12:44
Day 11		Leaving	03:49:40	00:18:28	03:30:26
Day 11		Grooming	00:00:02	00:00:09	00:11:16
Day 13		Leaving	04:03:00	00:18:28	03:30:26
Day 14		Grooming	00:15:46	00:00:09	00:11:16
Day 14		Breakfast	00:52:05	00:03:40	00:12:44

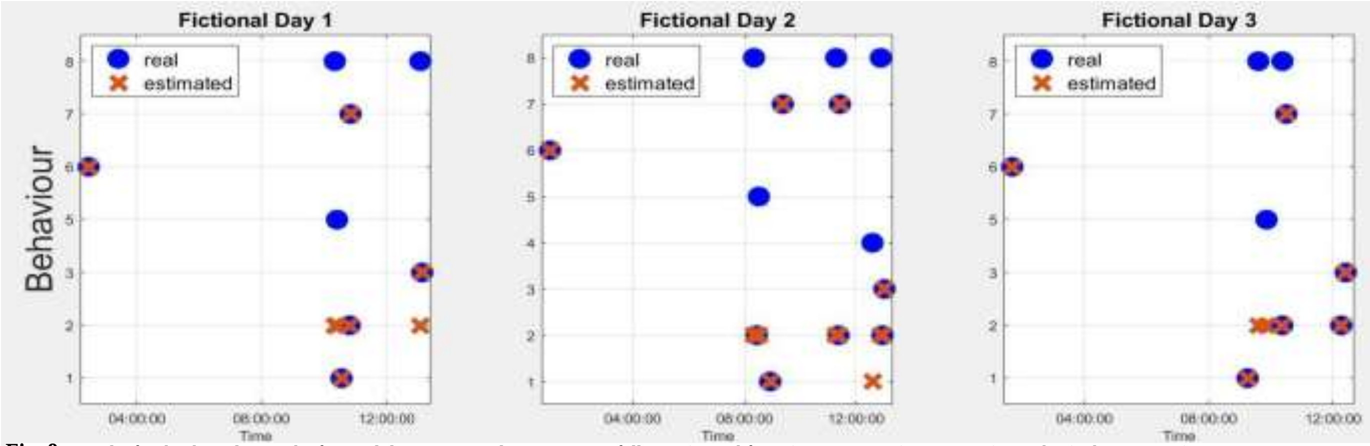

Fig. 8: Results for the three days in the fictional dataset. Legend in x axis is as follow: 1) Breakfast, 2) Grooming, 3) Leaving, 4) Lunch, 5) Showering, 6) Sleeping, 7) Spare Time/TV, 8) Toileting

Other warnings resulted for the *behaviour grooming* and *leaving*. Hence, the model detected that the person spent less time or more time than usual engaging in these *behaviours* and issued warnings.

In order to test whether the model detected abnormal behaviour, a fictional dataset as described in section 4.4 was also used for testing.

The results for the fictional dataset are shown in Fig. 8. The results for the three fictional days show the *behaviour grooming* predicted instead of the *behaviour toileting* or *showering*. In addition, the second fictional day shows the prediction of the *behaviour breakfast* instead of *lunch*.

Regarding the check on the *posture* of the person, a warning was issued for the first fictional day: *"Warning: Person lying in Entrance, possible fall detected"*. Therefore, the model successfully checked the *posture* of the person and abnormal behaviour such as a fall was detected.

The model also issued another warning for the second fictional day as follows: "*Warning: Person is not lying while in bed"*. Thus, the model detected the abnormal behaviour in the *behaviour sleeping*.

Other warnings were issued by the model regarding the duration of some of the *behaviour*. The model detected that the person spent less time than usual engaging in the *behaviour leaving* for the second and third fictional days. Therefore, a warning was generated, stating that "*The person came back too early"*.

5.2 Results on the second dataset OrdonezB

The result graphs for the *OrdonezB* dataset are in the supplementary material (Fig. A.3). In short, fourteen days were used for training and seven days were used for testing.

The model predicted the *behaviour grooming* for several of the days in the testing dataset, instead of the real *behaviour toileting* or *showering*. As with the *OrdonezA* dataset results, this prediction was made because all three *behaviours* are performed in the *bathroom location*.

Similarly, the model predicted the behaviour *breakfast* instead of *lunch* or *snack* for several days in the testing dataset. The same reason as before applies here too: the *behaviours breakfast*, *lunch*

behaviours breakfast, lunch and *snack* all take place in the *location kitchen*.

To overcome this challenge in the prediction, the ideal dataset should state the *activity eating* instead of the *behaviour breakfast*. However, a limitation was that the dataset used in the present study is a combination of *activity* and *behaviour*. Therefore, *breakfast* is a *behaviour* that includes the *activity eating*. The difference between *behaviour* and *activity* is defined in section 1.2. This means that the model presented in the current study was able to detect that the person was *eating in the kitchen*, but it could not detect whether the person was having *breakfast, lunch* or *snacking*.

In addition, there should be enough training data to model a person's normal and abnormal behaviours. It is worth noting that the method used in the study is a probabilistic model. As a result, the *behaviour* predictions are based on the highest probable path given an input sequence. Hence, HMM has been shown to be a good method for HBM.

HSMM was also studied for modelling the behaviour because the duration is modelled explicitly. However, for the aim of this study, HSMM does not meet expectations. The main reason for the poor results obtained with the HSMM is that a person's *behaviour* must follow the exact same pattern all the time in order to model the duration.

Previous work in HSMM for activity recognition has effectively distinguished between having *breakfast*, *lunch* or *dinner* [33]. However, those experiments were constrained to the person following the same pattern of opening the fridge and then using the stove, sink, cupboard and table in the same sequence. Only the duration changed for the sequence.

and *snack* are all performed in the same *kitchen location*.

6. Discussion

In this study, a Hidden Markov model is used for predicting the behaviour of a person. The accuracy of the HMM is 72%. The results for both dataset *OrdonezA* and *OrdonezB* showed consistency in the predictions. Most of the mispredictions that occurred were for the *behaviour breakfast*, primarily because the

For modelling human behaviour in the present study, the constraint of following the same exact sequence is impractical, since people do not always follow the same strict pattern within each *behaviour*. Therefore, it was not possible to train the HSMM effectively as the dataset does not contain the same strict pattern for every day. Consequently, HMM was chosen as the best method for modelling a person's behaviour.

When the *posture* of the person was checked, the results showed that the model was able to detect a fall in the *entrance* in the dataset that was fictionally created. Hence, Boolean logic is a fast and effective method for the purpose of fall detection.

Lastly, the duration for each *behaviour* was checked using time frame rules. The current *duration* of each *behaviour* was extracted from the dataset. A ± 20% approach was implemented to determine whether the current *behaviour* was within the normal *duration*. The results showed that the model could effectively detect whether the person has spent too much or too little time in an .

The *posture* was checked before the *duration* because in our stimation, detecting a fall is more important than the duration of a .

Finally, the model in the present study is tested offline. However, in the future, the model should be run in real-time. This means there should be a period of learning. The results presented in this study show that our model was able to learn from seven days. In addition, the real-time model should be able to check the *behaviour* of the person at fixed time intervals in order to detect whether the *behaviour* is normal or abnormal, such as using a time event driven logic every sixty seconds.

7. Conclusions and Future Work

Human behaviour modelling (HBM) for welfare technology is proposed to detect abnormal behaviour. HBM allows detecting any deviation from the usual or normal pattern of the person. Hence, abnormal behaviours are possible to detect and alert a family member or caretaker if the person is in need of any assistance.

The behaviour of the person consists of the activity performed by the person, the duration, the location and posture of the person. Hidden Markov models (HMM), is used to model and predict the behaviour of the person. The experimental evaluation shows good results using an open source real world dataset.

Future work should focus on studying other algorithms, including statistical, machine learning and deep learning with the aim of developing HBM with possible improvements and compare them with the performance of the present study.

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