Modelling and simulation of activities of daily living representing an older adult's behaviour

Conference Paper · July 2015
DOI: 10.1145/2769493.2769544

CITATIONS
0

READS
17

4 authors, including:

Ahmad Lotfi
Nottingham Trent University
116 PUBLICATIONS 555 CITATIONS

Abubaker Elbayoudi
Nottingham Trent University
6 PUBLICATIONS 0 CITATIONS

Kofi Appiah
Nottingham Trent University
46 PUBLICATIONS 191 CITATIONS

Some of the authors of this publication are also working on these related projects:

Detect DoS attacks in MANETs View project

Intelligent Care Guidance and Learning Services Platform for Informal Carers of the Elderly (iCarer) View project
Modelling and Simulation of Activities of Daily Living
Representing an Older Adult’s Behaviour

Abubaker Elbayoudi ∗
School of Science and Technology
Nottingham Trent University
Clifton Lane, NG11 8NS,
Nottingham, United Kingdom

Ahmad Lotfi †
School of Science and Technology
Nottingham Trent University
Clifton Lane, NG11 8NS,
Nottingham, United Kingdom

Caroline Langensiepen
School of Science and Technology
Nottingham Trent University
Clifton Lane, NG11 8NS,
Nottingham, United Kingdom

Kofi Appiah
School of Science and Technology
Nottingham Trent University
Clifton Lane, NG11 8NS,
Nottingham, United Kingdom

ABSTRACT
The availability of datasets for monitoring the activities of daily living is limited by difficulties associated with the collection of such data. There have been many suggested software solutions to overcome this issue. In this paper, a new technique to generate realistic data is proposed. The new method provides virtual data to the researchers with the ability to rapidly generate a large simulated dataset with different factors that could be used to represent different behaviour of a user. This paper describes the use of Hidden Markov Model (HMM) and Direct Simulation Monte Carlo (DSMC) to generate data for Activities of Daily Living (ADL) representing an older adult’s behaviour. The combination of HMM and DSMC facilitates the generation of datasets capturing behaviour in terms of occupancy and movement activity performance in the environment. Simulated data is validated against data collected from a real environment.

Keywords
Activities of daily living, AAL, elderly, dementia, assistive technology, hidden Markov model, HMM, simulation, Monte Carlo.

∗Abubaker Elbayoudi is a PhD research student who has conducted the research as part of his thesis.
†Ahmad Lotfi is the corresponding author. The corresponding email address is: ahmad.lotfi@ntu.ac.uk

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

PETRA ’15, July 1-3 2015, Corfu Island, Greece.
©2015 ACM. ISBN 978-1-4503-3452-5/15/07 ...$15.00
DOI: http://dx.doi.org/10.1145/2769493.2769544.

1. INTRODUCTION
In the past few years, there has been an increase in the development of health monitoring systems. This increase is because of several factors such as development in technologies that are used in monitoring as well as increasing challenges of an ageing population. People aged 60 and above will be approximately 22% of the world population by 2050 [17]. If this trend continues, it would lead to a prospect of spiralling social security costs unless new ways of providing care are developed.

Homes equipped with appropriate sensors are referred to as “Smart Homes” or “Intelligent environments”. Analysis of the elderly people’s Activities of Daily Living (ADL) in an intelligent home environment can be used to help caregiver monitor and understand the older adult’s behaviour. Therefore, it is very important to identify the older adult’s profile based on his/her ADL and behaviour. Recognising significant changes in human behaviour early will help the caregiver to take action to address prospective problems early as well.

The majority of existing research work in monitoring concentrates on the detection of normal and abnormal behaviour using appropriate sensory devices installed in older adult’s home. However, more research and experiments are needed to gain more valuable benefits from such a sensory system. Therefore, researchers in this area needs to have data from sensory signal of monitoring system in smart homes. However, it is very difficult to find volunteers to collect data from monitoring their activities, which is one of the most important reasons that forces researchers to build simulators to acquire the data they are looking for.

The aim of this paper is to investigate ways of improving the process of simulator building to mimic an intelligent home environment occupied by an older adult. The presented simulator is created using MATLAB software. The Hidden Markov Model (HMM) combined with the Direct Simulation Monte Carlo (DSMC) are used to model the activities in a defined intelligent environment.
This paper is structured as follows: in Section 2 some previous works are introduced; in Section 3 the modelling of human behaviour for the proposed simulation is presented followed by the implementation of the simulator in Section 4. The validation of the output data, the results of the created simulation and the conclusions are presented in Sections 5, 6 and 7 respectively.

2. RELATED WORK

Many people find monitoring of their elderly very challenging, especially if they suffer from dementia or any other cognitive diseases. Monitoring human behaviour is not easy; they have uncertainty within movement in their living places. Researchers have come up with many ideas to help in elderly monitoring. These ideas include monitoring the change of daily routine for a person living in a smart home, monitoring behavioural change using non-visual sensors, and recognising human actions using visual sensors.

Ambient Assisted Living (AAL) solutions are proposed to allow elderly people to live independently in their preferred environment using ICT technologies for personal healthcare monitoring [5]. Recently, the use of AAL systems and their applications and devices for personal health monitoring and Telehealth services has increased. Furthermore, personal healthcare monitoring is increasing, while awareness and understanding of healthcare concepts and systems are growing, i.e., electronic health medical records, health monitoring systems, and mobile health applications [14]. AAL systems are used to provide people with remote healthcare services using Telehealth and Telemedicine facilities. Most people prefer a non-intrusive technology to help them with their day-to-day activities. For example, using surveillance cameras to monitor their daily activities is not welcomed [8]. The monitored call centre is an essential system for patient monitoring rather than carers[11]. However, using other kinds of monitoring such as sensing systems should become more acceptable.

There are many published research papers in which human activities are simulated to generate a virtual data for health monitoring, location tracking, security etc. Authors in [6] produced an important study of human behaviour modelling methods. These methods are, 1) simple dynamic model, which uses the non trivial models that were considered for modelling human behaviour, 2) multiple dynamic models, 3) Markov dynamic model. A survey of behavioural simulation is reviewed in [19]. They proposed combination of simulations which are: 1) the study of mechanical behaviour based on discretised 3D-geometric models and including observed physical behaviour, 2) simulation of humans based on volumetric virtual humans.

Reducing the burden of patients and nurses’ time is simulated in [4] using adaptive computer programming, and they discussed how use of mobile nursing services in healthcare could save more time than using traditional means (paper-and-pencil testing appraisals). The authors in [13] have built a simulator to generate data representing single occupancy living in a smart home; they have used the simulator to produce a long-term view of the person’s health and an autocorrelation plot is used to distinguish between the trend types of daily living activities. Similarly, the authors in [15] have proposed a simulator representing the activity of the elderly person living independently in a health smart home.

The main challenges of human activities recognition are introduced in [12] and [16], and briefly listed in Table 1. The most used techniques and algorithms in this field are summarised in articles such as [3] which divided activities recognition algorithms into two major groups. The first is based on machine learning techniques including supervised and unsupervised learning methods, which uses probabilistic and statistical reasoning. The second group is based on logical modelling in terms of logical theories and representation formalisms. The author in [12] classifies the methods into statistical and computational intelligence techniques. The authors in [1] categorised the methods into template matching/transductive techniques, generative, and discriminative approaches. A summary of common activity recognition methods is presented in Table 2.

<table>
<thead>
<tr>
<th>The activity</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recognising parallel activities</td>
<td>Doing more than one activity at the same time, e.g., watching TV and talking to a friend.</td>
</tr>
<tr>
<td>Recognising overlapped activities</td>
<td>Activities overlapped to each other, e.g., while a person is cooking in the kitchen and the phone rings, he/she will stop cooking for a while until he/she finishes the call.</td>
</tr>
<tr>
<td>Vagueness in activities interpretation</td>
<td>Interpret similar activities in different ways. For example, opening refrigerator door may considered as a cooking or cleaning operation.</td>
</tr>
<tr>
<td>Multiple occupants</td>
<td>The place occupied by more than a single person.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>The method</th>
<th>Its classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hidden Markov Model (HMM)</td>
<td>Statistical Supervised.</td>
</tr>
<tr>
<td>Bayes Network</td>
<td>Statistical Supervised.</td>
</tr>
<tr>
<td>Various Variants of HMM and Bayes Net</td>
<td>Statistical Unsupervised.</td>
</tr>
<tr>
<td>Support Vector Machine (SVM)</td>
<td>Intelligent Supervised.</td>
</tr>
<tr>
<td>Neural Network</td>
<td>Intelligent Unsupervised.</td>
</tr>
<tr>
<td>Fuzzy Logic</td>
<td>Intelligent Unsupervised.</td>
</tr>
</tbody>
</table>

3. SIMULATION METHODOLOGY

The simulator’s main objective is to generate datasets that can be used for evaluating the performance of the ADL analysis tools representing an older adult living in a smart home. It must be able to mimic sensor activations that show the occupancy behaviour. The underlying problem, in this case, is to monitor the older adult in their own house using sensors, and it has three main components:
Activities are presented into five main categories. They are “Bed Room”, “Living Room”, “Kitchen”, “Bathroom” and “Outside” activities representing sleeping, socialising, eating, cleaning and going out respectively. Each of these activities are represented as a state and they are illustrated in Figure 1. The transition (link between each state) is also presented in the figure.

3.1 Profiling

To simulate different people profiles with different behaviour, a set of parameters describing the characteristics of each person is needed. For example, it is assumed that the duration of staying in the bed room and the start time of going to the bed room are different from one person to another. The sequence of visiting different areas is also different for each person. In addition to the difference in the sequence, the duration of each activity could also be different. Therefore, it is important to identify some parameters in the simulator to represent the user profile. The parameters (together with human and environment constants and variables) give the overall state describing the current situation, and they control the next action to be taken.

The proposed simulation environment is based on a real flat (apartment) environment, which has a basic monitoring system installed. For each activity, the sequence of movement and mean duration of staying in a specific area are recorded. The sequence and duration are stored in a 2-tuple as illustrated below:

\[
\text{Seq} = [(\text{Bed Room}, 25); (\text{Kitchen}, 2); (\text{Living Room}, 50); (\text{BedRoom}, 120); (\text{LivingRoom}, 60); \ldots]
\]

The algorithm will keep the track of the sequential movements and the mean duration of the person’s localisation in each area for the whole day. The following aspects are also taken into our account in the simulation:
The times of movements between the areas for each day is different, and the mean duration time of occupancy is different.

- The algorithm assumed that the occupant has sequential movements starting from one area to another depending on the layout of the environment for a normal pattern.

- Each daily occupancy signal can affect the occupancy signal for the next day. For instance, the next day activity cannot start in bed area if the previous day activity ends in another area.

- Daily observed occupancy pattern can become longer than an expected occupancy pattern, because of interrupts that may happen.

- The first area met on the first day of activity simulation would be the first area of the expected occupancy pattern in the occupant’s profile. In the case of unexpected transitions, if they happen many times it may indicate abnormal activity.

### 3.2 The Simulation’s Modelling

The main assumption made for this work to model the elderly behaviour is that the sequence of occupancy activities could be described by tracking the older adult’s successive occupation of each area and the older adult’s movements from one area to another. For this simulator, only one person living in an environment containing several areas was proposed. The person’s movements are translated into signal transitions and the time spent in each area will be considered as a duration. Therefore, an occupancy signal is created by assuming different levels for each area in the environment. To represent these sequential occupations, a Hidden Markov Model (HMM) is used. The probability of moving from one area to another depends on the time of day and the current activity.

#### 3.2.1 Hidden Markov Model

Hidden Markov Model is a generative probabilistic function of Markov chains based on the first order Markov assumption of transition. HMM is consisting of a hidden variable and an observable variable at each time step. The basic idea of HMM is based on the Markov first order assumptions, which is that the future state depends only on the current state[7], [9].

To model an older adult’s behaviour using HMM, suppose that the occupancy state is tracked. In this model, the hidden state is discrete and consists of two possible outcomes: “occupied” and “not occupied” for each defined area. It is assumed that the occupancy state of the person can be changed over time and is sometimes unpredictable (as in real life). Assume that if a change of the occupancy happened with probability of ($a$) then state with probability of ($1 - a$) remains the same. For example, when $a = 0.1$, it is expected that on average 1 out of 10 of the transitions will be associated with a change in occupancy state.

In addition, a prior $P(X_0)$ needs to specify over states at the first time step, which is assumed to be uniform. To complete the model, the observations are assumed to be discrete and consist of only two possible outcomes: “duration” and “vacancy” for each area. As might be suspected, the model is parametrised such that duration is more likely in the occupied state and vacancy is more likely in not occupied state. Specifically, with probability of ($b$) a person produces an outcome that is consistent with their occupancy state is assumed. The model is parametrised such that “occupied” is more likely in a duration state and “not occupied” is more likely in a vacancy state. Specifically, it will be assumed that with probability $b$, a person produces an outcome that is consistent with his/her an occupancy state. Instead of using symbols, the states “occupied” and “duration” by the number 2 and “not occupied” and “vacancy” by the number 1. Therefore, $X_t = 2$ represents a occupancy state at time $t$ and $X_{t-1} = 1$ represents an observed vacancy at time $t$. This leads to the following HMM equations[15]:

**State Probability**

$$P(X_{n+1} = j | X_n = i) = P(X_1 = j | X_0 = i)$$

(1)

and the Transition Matrix:

$$T(i, j) = P(X_t = j | X_{t-1} = i), 1 < t \leq N$$

(2)

with

$$T(i, j) \geq 0, \forall (i, j) \in N^2$$

(3)

and

$$\sum_{N} T(i, j) = 1, \forall i \in N$$

(4)

#### 3.2.2 Direct Simulation Monte Carlo

In this step, the concept of Direct Simulation Monte Carlo [2], [18] is applied on the state-space to ensure that the generated data is modeled as a dynamic system and data covers the whole day. This technique is used to model the evolution of the created system over time, and measurements are assumed to be available at discrete times. For dynamic
state estimation, the discrete-time approach is widespread and convenient.

The direct simulation algorithm has two steps - the first step is the sampling proposal for the current hidden state and the second step is to assess the likelihood of the data given each proposal. However, any proposed particles that may produce unlikely projected distributions for the observed data may be ignored. At the same time, the “prior” distribution from the state transitions and the “evidence” from the observed data are weighted.

This procedure will product simulated data, which is displayed in a matrix of [Duration, Area, Date-Time], therefore the state of each area in the specific time will be known. The following equations were used to consider the occupancy date and time for the simulation:

\[ N = S * (j, i) \]  
where S is the state of each Area

\[ j \in [\text{Startday, Endday}] \]  
\[ i \in [1, 86400] \text{ Seconds} \]  
\[ N \in [1, \text{No. of Areas}] \]

### 3.2.3 The Proposed Algorithm

In this work the HMM with DSMC is combined, to build a simulator for a single occupancy model to represent the elderly person’s movements and occupancy duration in the proposed environment. This system can provide long-term pattern data, which is needed for our research. Generally, focusing on finding out a long-term patterns and trends in elderly activities are key areas of concern; they are necessary to estimate the progress or deterioration in these activities which could help the medical assistant or caregiver. Here is the summary of the proposed procedure that is used to generate the data:

**Algorithm 1 The Simulation Algorithm.**

1: procedure HMMDS 
2: Input the Start day and End day of the simulator 
3: Generate the person’s sequential movements 
4: calculate the mean time of each occupancy state 
5: repeat
6: For time t, session m 
7: repeat 
8: Sample a random particle i 
9: \( i \sim \text{Uniform}(1, \ldots, M) \) 
10: Sample a proposal \( X^* \sim P(X_t|X_{t-1}) \) 
11: Sample \( u \sim \text{Uniform}(0, 1) \) 
12: if \( u < P(Y_i|X^*) \) then 
13: accept the proposal. 
14: Set \( X^*_m = X^* \) 
15: until all required sessions covered 
16: until all required time covered

### 4. IMPLEMENTING THE SIMULATION

The simulator was developed within the MATLAB software environment. The process contains three stages: data preparation, profiling and generating the simulated data for each day for a whole period that is needed i.e. couple of months.

#### 4.1 Data preparation

The real dataset that is available to this work contains binary data which has been collected from indoor sensors such PIR, door contact switch, and pressure sensors. The data is stored in sets with date and time, sensor type, sensor value, and the location of the sensor. An example of the data is shown in Table 3.

In this stage, the real data was modelled. The idea from this is to have clear raw data which could be simulated. This operation was started by discarding the redundancy from real data and clustering it into days, then the resultant data was stored in a matrix. Therefore, the final signal in the form of a time series was gained.

#### 4.2 Create the profiles

As it was explained in 3.1, the idea behind it is to create different people profiles and generate different patterns of data. This stage starts with defining the sequential movements between the areas and generate new movements after training with the real data. In this stage used is HMM.

#### 4.3 Generate the simulated data

In this phase, using a predefined function in the HMM toolbox the primary data is simulated. Then the primary data is handled by the concept of the Direct Simulation Monte Carlo to generate the simulated data in its final format, and store it is a matrix containing the duration, the area and the start time of occupying this area. A sample of the simulated data is presented in Table 4.

### 5. VALIDATION

Probably the validation step is the most challenging phase; it is not easy to validate simulation models of human behaviour. This process is to evaluate the software during or at the end of its development to determine whether it meet the specified requirements. The author in [10] provides a survey on how to validate a simulation models based on statistical techniques. He assumed that “the type of technique actually applied depends on the availability of data on the real system. Regarding this data availability, I distinguish three situations: (i) no real-life data are available, (ii) there is only data on the real output (not the corresponding input or scenario). (iii) besides the output data, the corresponding input or trace is also known, which is used to perform so-called trace driven or correlated simulation”.

In this work, the main goal is to create models that aim to provide better understanding of the activity of daily living for elderly. To assess the quality of the model, the proposed approach to validate the simulation statistically is a goodness-of-fit measure. This technique is used to match the proposed model outputs to the real database that is available for the authors.

#### 5.1 Goodness-of-fit measures

There are a number of goodness-of-fit measures methods could be used to evaluate the overall performance of simulation models. Popular among them are the root-mean-square error (RMSE), goodness-of-fit for a Binomial distribution and goodness-of-fit for a Poisson distribution. In this research, the goodness-of-fit for a Poisson distribution is used.
Table 3: A sample of real data.

<table>
<thead>
<tr>
<th>Date and Time</th>
<th>Sensor Type</th>
<th>Location</th>
<th>Sensor Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014 − 02 − 07 11 : 04 : 17.656</td>
<td>PIR</td>
<td>Living Room</td>
<td>00011</td>
</tr>
<tr>
<td>2014 − 02 − 07 11 : 05 : 03.766</td>
<td>PIR</td>
<td>Master Bedroom</td>
<td>00011</td>
</tr>
<tr>
<td>2014 − 02 − 07 11 : 06 : 03.796</td>
<td>PIR</td>
<td>Kitchen</td>
<td>00011</td>
</tr>
</tbody>
</table>

Table 4: A sample of simulated data.

<table>
<thead>
<tr>
<th>Duration in Minutes</th>
<th>Location</th>
<th>Date and Time</th>
<th>Sensor Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>12.229</td>
<td>Bathroom</td>
<td>2014 − 02 − 17 : 56 : 15.45</td>
<td>PIR</td>
</tr>
<tr>
<td>66.145</td>
<td>Bed Area</td>
<td>2014 − 02 − 18 : 8 : 29.321</td>
<td>PIR</td>
</tr>
<tr>
<td>3.045</td>
<td>Bathroom</td>
<td>2014 − 02 − 19 : 14 : 38.674</td>
<td>PIR</td>
</tr>
<tr>
<td>24.964</td>
<td>Kitchen</td>
<td>2014 − 02 − 19 : 17 : 40.239</td>
<td>PIR</td>
</tr>
</tbody>
</table>

Before this method was used, a day was divided into four time slots; morning, noon, evening and night. Suppose that, the mean time and the number of times a particular event occurs in each of major times (one of four) are observed. Therefore, the mean time of occurrences of each activity at the period of time could be deduced. To calculate Poisson probabilities the Equation 9 was used. Then, the \( \chi^2 \) test was used to see how closely the observed data agree with the simulated data; Equation 10 was used to calculate the \( \chi^2 \) test.

\[
P(X) = \frac{e^{-m} m^x}{x}
\]

for \( x=0,1,2,3,... \)

Here \( P(X) \) means the probability of the activity \( x \) to randomly occur per time, \( m \) the mean time of each activity in the time.

\[
cal X^2 = \sum \frac{(R - S)^2}{R}
\]

where \( R \) is the real data and \( S \) is the simulated data.

6. THE RESULTS

Two profiles of elderly people are designed. Those people are assumed to be living in different flats with the same layout. The simulator is operated to generate the data of sequential occupancy of their entire day. The simulator has the ability to generate data for any number of days. The real database that available from our partner is exploited to develop and benchmark the proposed algorithm and simulator. Once the simulator has been developed and its data is displayed, the feasibility of the proposed simulator would be demonstrated by presenting some results of simulated data, then comparing it with the available real data. The main purpose of this simulator is to find out any trend that could be in the data, such that from the simulated data signs of trends could be seen.

Figures 3 to 8 illustrate the time of occupancy in each area, the duration of each period and the movements between these areas. In each figure, the circles represent the time period of occupying the area in hours and the areas’ line is shown the main areas in the house including “Outside” which is describing the time which is may be the person spent it outside the house. The movements between the areas could be seen by tracking the circles.
6.1 Lazy Profile Experiment
The first profile is designed for a person with less movement. Figures 3, 4 and 5 are three of the days chosen from an amount of generated data with movement of this person from a state to another over a period of 24 hours. These figures seem to show that this person spends more of his time in the living room, and he has a good sleeping time.

6.2 Energetic Profile Experiment
This profile is for a person with more movements. Figures 6, 7, 8 are three of the days chosen from an amount of generated data with movement of this person from a state to another over a period of 24 hours. These figures have shown that this person more often keeps moving between living room and other areas, and he has a good sleeping time.

6.3 Real Data vs. Simulated Data
The data was created using the proposed method. Then the simulator was validated using statistical methods. The similarities between real and simulated data were graphically estimated. Comparing Figures 9, 10 representing simulated data and with Figures 11, 12 representing real data, the similarity between the real and simulated data could be seen clearly.

7. CONCLUSION
The proposed model demonstrated the feasibility of producing virtual data that mimics real data to support our needs for data in our future work. However, it has a number of limitations compared to a more realistic simulation of daily activities that could be required in other applications. The model is built to mimic realistic data in terms of occupancy, to help us understand any trends in the long-term activities of daily life of elderly people. In future work, some ‘rules’ will be integrated into the model to interpret the activities in an understandable way. In the current implementation of the simulator, several possible sequences of movements and occupancies can be defined for a particular activity. The simulator has parameters that allow us to change the factors in the experiments to generate the simu-
lated data. This feature helps to generate different types of simulated data.

Evaluation of the model is a very challenging task. In this work, the virtual data against the real data is compared using statistical comparisons methods. Further work should include investigating the evaluation of this model and its assumptions on different scenarios of lifestyle. The difficulty of performing effective field evaluations is the main obstacle for the next generation of intelligent Telecare systems’ creation. Therefore building such systems for pre-evaluation using virtual data would be beneficial in this area.

8. REFERENCES


