An Intervention Framework for Cognitively Impaired Patients

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ABSTRACT
People suffering from memory impairments experience decreased concentration, with difficulty in recalling and thinking. Inhabitants in a smart home are surrounded by multiple sensors and the sensor data collected provide information about the inhabitant’s interaction with the environment. Sensor data can be used to monitor the cognitive disabilities of the person by studying their behaviour in relation to carrying out Activity of Daily Living (ADLs). In this paper we propose an intervention framework for assistance that incorporates duration information along with the partially observed low-level sensor information and time. The framework learns probabilistically about the user and the ongoing activity and then provides decision support to monitor and assist in completing the ADLs. Our results verify that adding duration information consistently improves the accuracy in predictions from partial observation of sensor activations.

Keywords
Activity recognition, partially observed data, smart homes, duration.

ACM Classification Keywords

General Terms

INTRODUCTION
Mental disorders in patients affects their day-to-day function and causes difficulty in paying attention so more clues are required for recall [1]. These memory deficiencies have severe to mild effect on cognitive abilities of the patient and make it difficult for them to remember simple sequence of steps to be followed to complete the ADL. A patient with these kinds of disabilities needs caregiver for assistance. However their memory impairments can be reduced by providing slight assistance. Distributed and ubiquitous computing environments have become a popular and emerging technology with devices integrated into everyday objects and activities. An example of ubiquitous computing is in smart homes which can help in solving the problem of care giving and health monitoring. It compensates disabilities and assures better quality of life. The wellbeing of the person can be monitored by examining the changes in their activity patterns over time [2]. The assumption is that people carry out activity in a habitual way and this can be measured by monitoring the key ADLs such as ‘washing’, ‘eating’ and ‘managing basic needs’ [2].

The theory of ubiquitous computing aims to develop scattered and networked processing infrastructure to assist user activities, while being hidden from the user. Inhabitants in a smart home are surrounded by multiple sensors that report about the inhabitant and the activity. Sensors provide the low level information that the system processes to know about the inhabitants’ behaviour. Different sensors report different type of information about the inhabitant and the activity, which can be integrated together to derive a model that predicts inhabitants’ behaviour. Time and duration are characteristics of sensor data that encode lot of hidden information that can be utilised for improving predictions. The duration of an activity is indicative of the characteristics of individual behaviour. For example, each individual might do the same activity at a different point of time, with a different duration and using a different sequence. Duration can also indicate the person’s wellness and if more time is taken to complete the activity it can be a possible indication of deterioration so according we can decide the degree of assistance required. Smart home data incorporates a notion of time and we can utilise this information to build an intervention framework. Our approach is novel in the way that duration is used for monitoring wellness. We are here concerned with assistive living and mental wellness of the patients. We aim at learning an inhabitants’ activity profile through sensor activations during the activity, time at which the activity occurs and duration of the activity, thus building a model that can predict the inhabitant and the activity in order to assist in the ongoing activity.
RELATED WORK
A lot of ongoing research in the area of smart homes addresses the issue of cognitive disabilities and work towards developing technical solutions for assistance. People suffering from dementia forget things, to assist them objects were embedded with RFID tags and the system can issue then audio and video clues to find those objects [3]. In order to improve cognitive disabilities behaviour tracking is done and the build system provides cognitive assistance in carrying out ADLs through mobile and pervasive computing [7]. For assisting people with dementia in hand washing the system can take video as input and prompt the user [4].

Activity duration is an additional and informative source of data obtained from sensors. Duration information was used in [6] to detect anomalies when the temporal constraint is not met. Temporal rules can be derived from duration of activities and normal activities can be modelled as temporal checks. Abnormality can be detected when these rules are violated [5]. Durations have also been used to monitor hazardous situations in which the device is left unattended for long time [2]. Duration is therefore potentially useful information that can be used for enhancing intelligence and solves complex problems.

TERMINOLOGY
An activity can be defined as an ADL carried out by the Person using sequence of steps, i.e. Episode, at a particular Time and for a specific Duration. The details of each attribute are described as follows:

**Person (P):** We consider the possibility of multi-inhabitants in the home. Multi-inhabitants can be the situation in which more than one patient or family member or caregiver stay in the same home. To track such cases each person is given a unique identity.

**ADL (A):** ADLs are defined as the activities performed in daily living such as bathing, eating, dressing, etc, [2].

**Episode (E):** We define an episode as a sequence of sensor activations triggered during an activity and extracted from low-level sensor information received as a stream of data in a smart home. A single activity can have more than one episode value as people have diverse behaviour and follow different combinations of objects to complete the same activity. Figure 1 illustrates the scenario of making tea with two different episodes. Using a tilt sensor attached to the kettle (K), contact switches attached to the tea bag container (T), a sugar container (S) and a fridge (F). Thus the episode 'TKSF' represents the situation where the inhabitant first uses a tea bag container, then the kettle, followed by sugar and finally milk from the fridge to carry out the activity of 'making tea'.

**Time (T):** Time indicates the time of the day at which the activity is carried out. Time is categorised as 'Morning', 'Afternoon' or 'Evening' according to [2].

**Duration (D):** We consider duration of an activity as the amount of time taken to complete the activity. We categorise duration as ‘Short’, ‘Medium’ or ‘Long’ based on length of time taken and calculated from sensor timestamp data, where the door sensor is activated at the start of an activity and again at the end of the activity.

**Definition 1:** A schema $S$ of datacube $D$ has five dimensions: Person, ADL, Episode, Time and Duration. Each attribute $j$ has a set of domain values $\{c_1^{(j)}, ..., c_k^{(j)}\}$, where $k$ is the number of unique values for the attribute. Thus each cell $i$ of datacube $D$ is represented by $v_{p,a,e,t}^{j}$ which is the Cartesian product of five attributes in the form $\{c_1^{(p)} \times c_1^{(a)} \times c_1^{(e)} \times c_1^{(t)} \times c_1^{(d)}\}$.

**Definition 2:** A datacube $D$ is defined of type schema $S$ with each cell $v_{p,a,e,t}^{j}$ containing the value $n_{p,a,e,t}^{j}$ representing the number of occurrences of the corresponding combination of values from Person, ADL, Episode, Time and Duration.

EXPERIMENTAL SETUP
To investigate our preliminary study, we have set up an environment to carry out the activity of ‘making drink’ in the laboratory located at the University of Ulster at Jordanstown. We study the behavioural patterns of inhabitants doing the following three activities: (1) ADL$_1$ = ‘making tea’ (2) ADL$_2$ = ‘making coffee’ (3) ADL$_3$ = ‘making a cold drink’. Contact switches were embedded in the related objects and movement detectors were installed for tracking the entry and exit of the inhabitant. A user interface is designed to obtain the label data. A user selects labels of Person and ADL before they start the activity during the training phase. A ‘start’ and ‘end’ button is used to record the timestamp of the activity and this information is also used to partition the sequence of sensor activations into episodes. When the sensors are activated time-stamped data is sent to the server and stored in the database. We carry out the discretisation process and divide the continuous interval of duration into discrete values of ‘Short’, ‘Medium’ and ‘Long’ as in [2]. Table 1 presents the sample data collected.

<table>
<thead>
<tr>
<th>ADL ID</th>
<th>Person</th>
<th>ADL</th>
<th>Episode</th>
<th>Time</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>49</td>
<td>David</td>
<td>Making tea</td>
<td>TKFS</td>
<td>Afternoon</td>
<td>Short</td>
</tr>
</tbody>
</table>

**Table 1. A sample of data collected**

Figure 1. Making of tea with two different episodes

LEARNING ACTIVITIES IN SMART HOME
A probabilistic learning approach is used to obtain inhabitants’ behavioural patterns and is defined by the joint probability distribution over different activities [2]. Data analysis is used to find the probability distribution that is the most likely to have produced this data. Using the collected data over a period of time in the lab, the
distribution is obtained using Maximum Likelihood Estimation (MLE). The parameter is denoted by $\pi_{paed}$ as the probability distribution of cell $v_{paed}$ in datacube $D$ of type schema $S$, representing the Person, $p$, ADL, $a$, Episode, $e$, Time, $t$ and Duration, $d$: $n_{paed}$ is the corresponding cardinality for the number of occurrences of these attribute values. Since the aggregates in the datacube $D$ follow a multinomial distribution the likelihood is given by equation (1):

$$L \propto \prod_{p=1}^{P} \prod_{a=1}^{A} \prod_{e=1}^{E} \prod_{t=1}^{T} \prod_{d=1}^{D} \pi_{paed}^{n_{paed}}$$

The maximization of this likelihood is obtained by setting $\frac{\partial L}{\partial \pi_{paed}} = 0$, subject to the constraint:

$$\sum_{p=1}^{P} \sum_{a=1}^{A} \sum_{e=1}^{E} \sum_{t=1}^{T} \sum_{d=1}^{D} \pi_{paed} = 1$$

This gives the model parameter as:

$$\pi_{paed} = \frac{n_{paed}}{N}, \text{where } N = \sum_{p=1}^{P} \sum_{a=1}^{A} \sum_{e=1}^{E} \sum_{t=1}^{T} \sum_{d=1}^{D} n_{paed}$$

**EVALUATION**

The learned model accuracy is evaluated on how well it is able to predict the inhabitant and the activity performed by him. Thus the number of correct predictions of Person and ADL from the observed values of Episode, Time and Duration defines the model accuracy.

**Prediction of Person and ADL**

The prediction of class (Person, ADL) (PA for short) identifies what activity is carried out and by whom. The derived model is in the form of probability distribution over activities with their class information (i.e. Probability of particular combination of person, ADL, episode, time and duration stored in each cell of datacube $D$). Therefore the activity prediction is carried out using following equation:

$$Pr(p_i, a_j | e^o, t^o, d^o) = \frac{Pr(p_i, a_j, e^o, t^o, d^o)}{\sum_{p=1}^{P} \sum_{a=1}^{A} Pr(p, a, e^o, t^o, d^o)}$$

This can be solved by:

$$Pr(p_i, a_j | e^o, t^o, d^o) = \frac{\pi_{p_i, a_j, e^o, t^o, d^o}}{\sum_{p=1}^{P} \sum_{a=1}^{A} \sum_{e=1}^{E} \sum_{t=1}^{T} \sum_{d=1}^{D} \pi_{p, a, e, t, d}}$$

where, $\pi_{p_i, a_j, e^o, t^o, d^o}$ is the probability of the person $p_i$, carrying out activity $a_j$ at time $t_i$ via episode $e^o$, with duration $d^o$ of the cell $v_{p_i, a_j, e^o, t^o, d^o}$. The denominator $\sum_{p=1}^{P} \sum_{a=1}^{A} \sum_{e=1}^{E} \sum_{t=1}^{T} \sum_{d=1}^{D} \pi_{p, a, e, t, d}$ is the sum of all the possible combination of Person and ADL that could be formed, for given episode $e^o$, timestamp $t^o$, and duration $d^o$. The prediction is then assigned to the class with the highest probability of Person and ADL:

$$(P, A) = \arg \max Pr(p_i, a_j, e^o, t^o, d^o)$$

**Data Simulation**

Data was collected in the lab for 47 activities in 9 days. For evaluating the performance of the learning algorithm, we simulate data based on the patterns shown in the real data. Generating synthetic data for the evaluation of the learning algorithm permits evaluation in controlled way. Given the base probability distribution and the size of data samples required, we generate random values between 0 and 1 in Matlab. The generated random values are grouped according to probability distribution. Thus the values in each interval signify the observation that represents particular combination of Person, ADL, Episode, Time and Duration. The categorised random values are aggregated to obtain the cardinality of each cell of datacube $D$. Thus the simulated data follow the observed probability distribution. We generate synthetic data separately for both learning and testing the model. Seeds are used to reproduce the result.

**Results**

We evaluate the performance of the model learned from different sizes of dataset. The result is averaged over 10 repetitions to obtain mean value and standard deviation. Each model is tested with a dataset of 150 observations. Learning performance is shown in Figure 2 for different sizes of dataset. There is rise in performance as the size of dataset increases as expected. The model shows stability at N=150 and this would be sufficient, but we conservatively fixed the size of dataset as 175.

![Figure 2. Prediction accuracy for different size of dataset](image)

**INTERVENTION FRAMEWORK**

The learned model permits us to characterise behavioural patterns of inhabitants. Patients with mental illness find it difficult to remember order of steps required to complete the ADL. In this paper we address this issue and try to build an intervention framework that predicts the activity from the partial sensor activations during the ongoing activity. We propose a real-time decision making based on the incomplete observed episodes denoting the first few steps taken for the ongoing activity. Decision support is activated only when the inhabitant has been inactive for a long time and no sensor activations have taken place. In such cases it is most probable that he/she has forgotten the next step and needs assistance. Based on the observed partial episode, current time and tentative duration required to complete the activity, the model predicts the most probable Person, ADL and Episode. Predicted episode is used to determine the next step in the activity and the system issues a prompt to the user.
For doing this, we define the base episodes that denotes a set of all the episodes having starting sub-string as this partially observed episode (partially observed episode can correspond to one or more episodes). Here we examine the performance of decision making and effectiveness in making decisions based on the partial observation and duration incorporation. A partially observed episode is denoted by $E^o$ and $\Omega(E^o)$ is defined as set of all the possible base episodes (Episodes with $E^o$ as starting sub-string). Using the learned model, partially observed episode $E^o$, time and duration prediction is made as follows:

$$Pr(p_1,a_j,e_k|E^0,t^o,d^o) = \frac{Pr(p_1,a_j,e_k,t^o,d^o)}{Pr(E^0,t^o,d^o)}$$

Where $e_k \in \Omega(E^o)$ and the probability $Pr(E^0,t^o,d^o)$ is $Pr(E^0,t^o,d^o) = \sum_{p=1}^{P} \sum_{d=1}^{D} \sum_{e_k \in \Omega(E^o)} \pi_{p,a,t^o,d^o}$, giving

$$Pr(p_1,a_j,e_k|E^0,t^o,d^0) = \frac{\pi_{p_1,a_j,e_k,t^o,d^o}}{\sum_{p=1}^{P} \sum_{d=1}^{D} \sum_{e \in \Omega(E^o)} \pi_{p,a,t^o,d^o}}$$

this probability is 0 if $e_k \notin \Omega(E^o)$.

The prediction accuracy is tested for different size of dataset. Figure 3 shows the predictions accuracies in determining the Person, ADL and Episode using different number of observations made for different size of dataset with no duration information included. There is rise in performance of predictions and the model is able to predict better when duration information is included. Figure 4 shows the rise in prediction performance when duration information is included. It is more visible in the case of small number of observations where including durations achieves nearly 20% of rise in prediction accuracy. In both cases the prediction is increased when the number of sensor activations increases i.e. the inhabitant has done more steps towards the activity thus increasing the observation count.

CONCLUSION

The cognitive assistance supports the patient in completing the ADLs in a non-intrusive way. Including duration information consistently improves the accuracy of system in making predictions form partial observation of sensor sequences. We will further try to explore duration and time information for deriving temporal rules that can be applied to the models for better decision making.

REFERENCES

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