Using duration to learn activities of daily living in a smart home environment

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***Abstract*—Recognition of inhabitants' activities of daily living (*ADL*s) is an important task in smart homes to support assisted living for elderly people aging in place. However, uncertain information brings challenge to activity recognition which can be categorised into environmental uncertainties from sensor readings and user uncertainties of variations in the ways to carry out activities in different contexts, or by different users within the same environment. To address the challenges of these two types of uncertainty, in this paper, we introduce the innovative idea of incorporating activity duration into the framework of learning inhabitants' behaviour patterns on carrying out *ADL*s in smart home environment. A probabilistic learning algorithm is proposed with duration information in the context of multi-inhabitants in a single home environment. The prediction is for both inhabitant and *ADL* using the learned model representing what activity is carried out and who performed it. Experiments are designed for the evaluation of duration information in identifying activities and inhabitants. Real data have been collected in a smart kitchen laboratory, and realistic synthetic data are generated for evaluation. Evaluations show encouraging results for higher-level activity identification and improvement on inhabitant and activity prediction in the challenging situation of incomplete observation due to unreliable sensors compared to models that are derived with no duration information. The approach also provides a potential opportunity to identify inhabitants' concept drift in long-term monitoring and respond to a deteriorating situation at as early stage as possible.**

Keywords-probabilistic learning; duration; reasoning; ADL; smart home

I. INTRODUCTION

The world population is aging with the group aged over 65 increasing faster than any other age group. Among elderly adults, it is estimated that nearly 18 million are diagnosed with dementia, with this number expected to reach 35 million by 2050 [9]. People in this age group are more likely to suffer from long term chronic conditions as well as Alzheimer's disease which is the most common cause of dementia, affecting around 417,000 people in the UK alone. These patients have progressive cognitive deterioration thus they suffer difficulties in completing activities of daily living, therefore living independently in their homes is problematic. It is hypothesised that many elder can live an independent life and their stay at home can be extended, by the aid of at-home assistance and health monitoring [1]. Progress is currently being made towards undertaking research to explore techniques for the development of smart homes to support 'aging in place' by providing remote healthcare services and assistive living to automate tasks so to decrease the inhabitants' effort required in the activities. Intelligence is based on learning from inhabitants' activity data collected via a network in the home environment. The assumption is that people have habits and they show periodicity in a number of activities they perform and this periodicity can be observed through sensors [11]. Using the learned model, assistance can be offered based on the predictions given current observations on inhabitants' actions at home. Recognition of Activity of Daily Livings (*ADL*s) is essential in the smart home environment. This promotes the close monitoring of key *ADL*s with which elderly people often have problems, for example, 'eating', 'washing', 'managing medication'. Potentially, when an abnormal situation arises, such as missing a meal, it can then be reported.

The smart home as a distributed environment, in the form of a sensor network, displays the generic characteristics of unreliability, causing challenges for activity prediction in such an environment. One popular cause of uncertain information is the malfunctioning or low-battery condition of sensors, which may not produce a trigger event even if it has been activated correctly. Therefore, under these circumstances, the observed sensor data do not reveal complete information describing the events which may have happened during the course of an inhabitant carrying out an activity. Unreliable sensors will therefore result in incomplete data. Activity recognition is thus required to be able to make a prediction involving data incompleteness. The issue of using low-level sensor data to infer high-level activity can therefore be considered as both a research and practical challenge. Actions carried out in a smart home are recorded by sensors activation indicating the interaction of the inhabitant within the home environment. Activities are often described in a certain context of location, time and ways of performing them. Duration data are available from sensors which routinely generate time stamps with their observations. Duration can be informative on activity recognition as various activities take different time interval to

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complete by an inhabitant, even in the situation of incomplete sensor observation. Duration assists in activity prediction by recovering the most likely activity given observed context information.

Besides the challenge of unreliable sensors, the situation of multi-inhabitants in a single smart home is a very practical occurrence, for example, an elderly couple in the same home, or a patient living with a carer or family members. Distinguishing between multiple inhabitants can promote an opportunity which may be facilitated from a technological perspective and is one of the key areas under investigation within our work. Duration information can be very informative to distinguish among different inhabitants or between a carer and a patient in a single smart home. Such identification facilitates resource saving by providing assistance only to the inhabitant in need. Duration patterns of activities can be learned, stored within personal metadata, and used as thresholds for triggering assistance on personalised intervention on tasks completion. In the long term, duration information can assist detection of the decline of an inhabitant's functionality due to deteriorating health.

Duration is informative on different aspects and is valuable information for the learning process. However, the use of activity duration information is limited in the literature of activity recognition in smart home environments. In this paper, we propose a probabilistic learning mechanism from inhabitants' activities data in a smart home, incorporating duration information. A schema structure is proposed to store activity data with duration information. Inhabitants' behaviours patterns are characterised using the learned probability distribution over various activities. The model is then used to infer the activities, the inhabitants who have carried them out, and how they have done them. Inference is based on low-level sensors readings, where the information can be incomplete.

The rest of the paper is organised as follows. Proposed storage for smart home data of various schema structures is introduced first of all. Then, we show learning on activities data with duration in the smart home environment. A smart kitchen laboratory is introduced for algorithm demonstration and evaluation. This is followed by presentation of activity prediction on observed data in the presence of unreliable sensors. Evaluation is carried out on model performance on identification of daily activities in the environment with unreliable sensors. We conclude with other related work emphasising duration in activity pattern learning and future work.

II. Terminologies and the Data Model

A. *Terminologies*

Attributes are the variables that are used to describe each data entity associated with a database schema. Activities in smart homes are represented by five attributes, namely, *Person*, *ADL*, *Episode*, *Time* and *Duration*. An activity can be seen as the *ADL* carried out in a way described by an *Episode* in the context represented by *Person*, *Time* and *Duration* for the amount of time to complete the activity. Each attribute has a list of categorical domain values. The details are described as follows.

Person: For the situation of multi-inhabitants in a single smart home, each person is represented with an ID number. Individuals normally have different habits and thus different activity profiles. Inhabitants can thus be distinguished and hence the provision of a personalised service is made possible.

ADL: The self-care activities include basic but fundamental tasks of preparing a meal, eating, dressing, bathing or showering, getting in or out of bed or a chair, using the toilet, etc [5, 6]. The necessary amount of *ADL* details to be learned in a smart home can vary and depend on individual applications. The ability to perform *ADL*s is often used to assess an elderly person's abilities for independent living.

Episode: An episode value is a sequence of sensor events activated during the process of carrying out an activity. It is a way of capturing an ADL in low-level information. Episodes capture the inherent patterns of recurrence which reflect the typical routine actions for carrying out an activity. Different episode values for the same activity represent different ways to carry out that activity.

Data are collected automatically from the sensors related to each activity via a home network. The data stream of sensor activations must be partitioned into sub-sequences, each of which represents a possible *ADL*. Transition from one *ADL* to the next is normally indicated by a change of location of the inhabitant, and time duration between two sensor activations, or by the explicit indication of an activity during the training data collection period.

Time: Time is a context variable indicating the time of the day at which an activity is carried out, and is stored as a discretised categorical value of 'Morning', 'Afternoon', or 'Evening'.

Duration: Duration describes the length of the time interval that an activity is carried out and is stored as a discretised categorical value of 'Short', 'Medium', or 'Long'.

B. *The data model*

In this paper, we propose a snow-flake schema structure S to represent activities with duration information in the smart home environment (Figure 1) based on our previous work in [12]. The central fact table is 'Activity Table' that consists of the five attributes of *Person*, *ADL*, *Episode Time* and *Duration*, together with the corresponding aggregates indicating the number of times that an activity has been carried out. The fact table is connected with a set of dimension tables.

We collect sensor activations during an activity in 'Event' table, each with an activated sensor ID and a time stamp. The values for the variable *Episode* in the table 'Episode dimension' is derived from the '*Event*' table using the corresponding start and end time of this activity from the table 'Class Label'. The value for the *Duration* attribute is obtained by the discretisation of the difference between values of 'End Time' and 'Start Time' in the 'Class Label' table for each activity. Low-level sensor information, namely the 'Sensor' and 'Event' tables, is stored based on homeML [8], an XML

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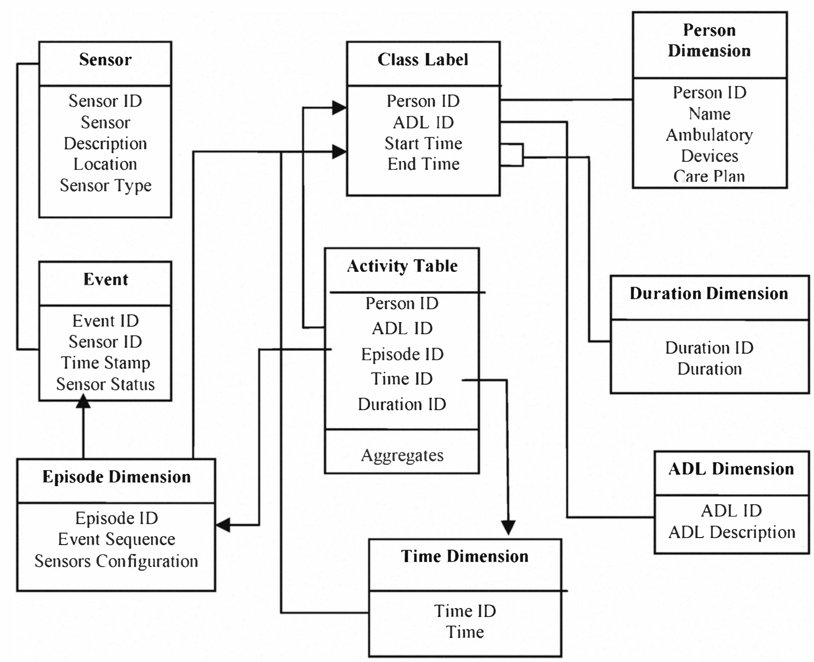

Figure 1. Schema *S* for data collection with *Duration* information in a smart home

based data representation for information in the smart home environment. Variables are connected with metadata information. For each domain value of the variable *Person*, the metadata describing an inhabitant's information including 'care plan', 'ambulatory devices' etc are very informative in providing a personalised intervention service. Activities patterns with duration features can be further used for behaviour monitoring in a longer term, by comparing the models derived in different periods.

Definition 1: A schema *S* of the datacube *D* has five dimensions: *Person*, *ADL*, *Episode*, *Time* and *Duration*. Each attribute j $j \in \{Person, ADL, Episode, Time, Duration\}$ has domain $\{c_1^{(j)},\ldots,c_{k_j}^{(j)}\}$, where k_j is the number of domain values. Cell i of datacube D represented as v_{paetd} is the Cartesian product of the five attributes in the form $\{c_{i_p}^{(Person)} \times c_{i_a}^{(ADL)} \times c_{i_e}^{(Episode)} \times c_{i_t}^{(Time)} \times c_{i_d}^{(Duration)}\}$.

Data are aggregated into five-dimensional datacubes with the corresponding schema structures.

Here, for example, $c_{i_p}^{(Person)}$ is the value of attribute *Person* occurring in cell i of the datacube.

For simplicity of presentation, when writing sum or product over a range of attribute values, we will substitute $k_p = P, k_a = A, k_e = E, k_t = T, k_d = D$, and with, for example, a sum $\sum_{\{c_s^{(p)}\}_{s=1}^{k_p}}$ over attribute values for *Person* as $\sum_{p=1}^{P}$ and a product $\prod_{\{c_j^{(p)}\}_{j=1}^{k_p}}$ as $\prod_{p=1}^{P}$.

Definition 2: A datacube D is defined as the schema S of cells v_{paetd} together with corresponding cardinalities n_{paetd}, representing the number of occurrences of that activity.

Examples of these definitions will be shown for demonstration in the following section using examples from our smart kitchen laboratory.

III. THE SMART KITCHEN LABORATORY

For our initial experiment, a 17 m^2 smart kitchen laboratory was used, which is located at the University of Ulster at Jordanstown (Figure 2 (a)). Daily activities of 'making a drink' are studied and monitored within this environment, for multiple users, through a suite of sensors (contact switches) embedded in the related objects. Movement detectors are installed on the inside and outside of the kitchen doors to monitor the presence of an inhabitant in the area. Real data were collected over a period of four weeks in this environment.

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In our experiment, the task of 'making a drink' refers to nine possible activities: ={'making black tea', 'making tea with milk', 'making tea with sugar', 'making tea with both milk and 'making coffee with sugar', 'making coffee with both milk and sugar' and 'making a cold drink'} (j=1,…,9). The task of 'making a drink' can be also described by higher-level concept values, namely, HA_1= 'making a cup of tea', HA_2= 'making a cup of coffee' and HA_3= 'making a cold drink'. In our laboratory two people were participating during this period of experiment. We use virtual names to represent the two users as P_1= 'Emma' and P_2= 'David'. Their behaviour patterns of 'making a drink' are learned and monitored. To obtain labelled data, an interface has been designed for users to select labels of *Person* and *ADL* for the activities they are about to carry out. This is followed by clicking the 'start' and 'end' button to enable making a record of the timestamps of an activity and thus to partition a sequence of sensor activations into episodes.

Objects relevant to our target activities are equipped with sensors, for example, sugar jar and kettle (Figure 2 (b)). Actions carried out in the kitchen environment are detected from the sensors. Each sensor sends a signal when it is activated, which otherwise remains as a '0' value whilst in a static state. For writing simplification, the initial letter of the object name is taken and capitalised to represent the sensor attached to it, for example, '*K*' for the sensor on the 'Kettle' in the rest of the paper. Class labels of training data are obtained through the labels collected using the designed interface and stored as two attributes in the table 'Class Label'. Using the start and end times for this activity, the corresponding episode value is extracted from sensor events in the 'Event' table.

(a) (b)

Figure 2. The smart kitchen laboratory in the University of Ulster at Jordanstown: (a) an overall kitchen view; (b) a coffee jar attached with a contact sensor

Finally, by matching up dimension tables of 'Episode Dimension', 'Class Label', and 'Time Dimension', we derive data of the schema *S* for table 'Activity Table'. A sample is shown in the Table I.

TABLE I. A SAMPLE DATA WITH ATTRIBUTES' VALUES IN 'ACTIVTY TABLE'

Activity ID	*Person*	*ADL*	*Episode*	*Time*	*Duration*
…	…	…	…	…	…
19	David	'making tea with milk and sugar'	CFK	Morning	Medium
31	Emma	'making coffee with milk'	TSKF	Afternoon	Long
…	…	…	…	…	…

The discretisation of the duration is carried out based on the real duration values for activities collected during the training data collection period. We show the distribution of the activity durations values collected in Figure 3. From the figure, we make the divisions based two large duration values gaps.

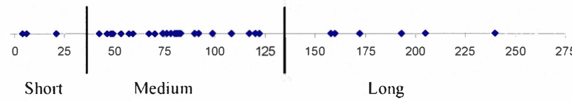

Figure 3. The distribution of duration values from collected dataset and the discretisation into three categories separated by two vertical lines

IV. LEARNING ACTIVTIES OF DAILY LIVING IN A SMART HOME INCORPORATING DURATION

Our work is carried out through three stages: firstly, the data collection and pre-processing stage including the integration of low-level sensor data and class labels for further aggregation to form data for learning, secondly, the training stage to build up the inhabitants' activity model, thirdly, the reasoning stage for the activity recognition, prediction and any other potential applications. At the training stage, patterns of inhabitants carrying out daily activities are learned. Data labels are required in training a model, in terms of the activities performed and by whom. This information is stored in the table 'Class Label'. The learned activity model is of a joint probability distribution over different activities represented by cells in schema *S*. Given the learned model, prediction is carried out based on the current observations of sensor activations in the 'Event' table to identify the activity being carried out and the inhabitant who performed it.

First of all, a probabilistic learning approach is proposed to obtain inhabitants' behavioural patterns characterised by a joint probability distribution over typical activities in various contexts. Given data collected in a smart home environment over a period of time, the distribution is obtained using the maximum likelihood estimation approach. We denote parameter π_{paetd} as the probability of cell v_{paetd} in datacube *D*, representing the activity '*Person=p, ADL=a, Episode=e, Time=t,* and *Duration=d*'; n_{paetd} is the corresponding cardinality for the number of occurrences of this activity. Since the aggregates in the datacube *D* follow a multinomial distribution, the likelihood is therefore given in Equation (1).

$$L \propto \prod_{p=1}^{P}\prod_{a=1}^{A}\prod_{e=1}^{E}\prod_{t=1}^{T}\prod_{d=1}^{D}\pi_{paetd}^{\;n_{paetd}} \qquad (1)$$

Maximisation of this likelihood by setting $\frac{\partial L}{\partial \pi_{paetd}} = 0$ subject to the constraint $\sum_{p=1}^{P}\sum_{a=1}^{A}\sum_{e=1}^{E}\sum_{t=1}^{T}\sum_{d=1}^{D}\pi_{paetd} = 1$ gives model parameters as follows:

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$$\pi_{paetd} = \frac{n_{paetd}}{N}, \ where\ N = \sum_{p=1}^{P}\sum_{a=1}^{A}\sum_{e=1}^{E}\sum_{t=1}^{T}\sum_{d=1}^{D} n_{paetd} \qquad (2)$$

V. EVALUATION FRAMEWORK

A. Performance criterion

Inhabitants' life styles in terms of their activity management and daily routines provide information about their overall well-being. The ability for us to identify key activities carried out by inhabitants is important to detect any abnormal situations. Therefore, our evaluation criterion is the performance on activity prediction given low-level sensor observations. This is a classification process. A model is developed from the training data, which are then used to classify new data into the predefined activity categories. In our multi-inhabitant situation, it is also essential to distinguish the individual who has carried out the task as well as the activity itself especially when it is required to provide a personalised service.

1) Prediction given complete data

The prediction of class (*Person, ADL*) (*PA* for abbreviation) indicates who is performing what activity. The derived model is in the form of a probability distribution over activities with their class information. Therefore, activity prediction is carried out using Equation (3) for the given observation data D.

$$\Pr(c_k|D) = \frac{\Pr(D|c_k)\Pr(c_k)}{\sum_{c=1}^{G}\Pr(D|c_c)\Pr(c_c)} = \frac{\Pr(D,c_k)}{\sum_{c=1}^{G}\Pr(D,c_c)} \qquad (3)$$

where c_k is a (*Person, ADL*) class variable (p_i, a_j), and G is the total number of classes.

For each class $c_k = (p_i, a_j)$, $\Pr(p_i, a_j)$ represents the probability of the person p_i carrying out the activity a_j at time t^o via episode e^o with duration d^o:

$$\begin{aligned}\Pr(c_k|D) &= \Pr(p_i, a_j|e = e^o, t = t^o, d = d^o) \\ &= \frac{\Pr(p_i, a_j, e^o, t^o, d^o)}{\sum_{c=1}^{G}\Pr(c_c, D)}\end{aligned} \qquad (4)$$

where

$$\sum_{c=1}^{G}\Pr(c_c, D) = \sum_{i=1}^{P}\sum_{j=1}^{A}\Pr(p_i, a_j, e^o, t^o, d^o) = \sum_{i=1}^{P}\sum_{j=1}^{A}\pi_{p_i a_j e^o t^o d^o} \qquad (5)$$

and $\pi_{p_i a_j e^o t^o d^o}$ is the probability of activity $v_{p_i a_j e^o t^o d^o}$ in the learned model. This gives:

$$\Pr(p_i, a_j|e = e^o, t = t^o, d = d^o) = \frac{\pi_{p_i a_j e^o t^o d^o}}{\sum_{p=1}^{P}\sum_{a=1}^{A}\pi_{p,a,e^o t^o d^o}}. \qquad (6)$$

The prediction can be then assigned to the class of highest probability

$$(P, A) = \arg\max_{p_i a_j} \Pr(p_i, a_j|e^o, t^o, d^o). \qquad (7)$$

Classification performance is evaluated by the prediction accuracy, defined as the number of observations for which both the activity and the individual who carried it out are correctly identified, in relation to the total number of activity observations in the evaluation dataset. Results are averaged over 10 repetitions to obtain the mean value and the standard deviation for all the measurements.

2) Prediction given incomplete data

In an environment with unreliable sensors, due to malfunctioning or low-battery conditions, sensor signals cannot always be collected even if a sensor has been activated. Therefore, with *Episode* value representing the sequence of sensor activations, an observed episode for an activity in such circumstances can correspond to a number of possible episodes that would be obtained when all sensors were working properly, defined as base episodes with complete information. The schema structure S for the complete data is correspondingly defined as the base schema and contains the finest level of information available. Incomplete data are stored in the corresponding schema S_w according to the structure. For incomplete data, the dimension *Episode* has coarser values compared to values in the base schema. Mappings can then be made between the observed episodes and the base episodes. We represent the mapping from episode e_j^w in its corresponding schema S_w to episode e in the base schema S as $q_{e_j e}^w$, where the value is 1 if there is a mapping between the two episodes, and 0 otherwise. For example, we consider the activity of 'making a coffee'. In the situation of the 'Sugar' sensor not working, we observe an episode with sensor activation sequence 'Coffee', 'Kettle' represented by e_j^w=CK. We are not able to know from this observation if the inhabitant put sugar in the coffee or not, and if so where in the sequence he put it in. Thus, the observed episode 'CK' can map to several base episodes, namely e='SCK', 'CSK', 'CKS' or 'CK', indicating different ways of making the coffee with and without sugar.

We show the formulas for hierarchical predictions from the learned activity profile model, given the observed information

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of *Episode* e^o, *Time T* t^o and *Duration* d^o. The *PA* (*Person, ADL*) prediction task is formulated as follows:

$$\begin{aligned}\Pr(p_i, a_j \mid e^o, t^o, d^o) &= \sum_{k=1}^{E} \Pr(p_i, a_j, e_k \mid e^o, t^o, d^o) \\ &= \sum_{k=1}^{E} \left(\frac{\pi_{p_i a_j e_k t^o d^o}}{\Pr(e = e^o, t = t^o, d = d^o)} \right)\end{aligned} \quad (8)$$

The marginal probability of *Episode* e^o, *Time T* t^o and *Duration* d^o is calculated using Equation (9):

$$\Pr(e = e^o, t = t^o, d = d^o) = \sum_{i=1}^{P} \sum_{j=1}^{A} \sum_{k=1}^{E} (\pi_{p_i a_j e_k t^o d^o} \times q^{w}_{e^o e_k}) \quad (9)$$

where $q^{w}_{e^o e_k}$ is the mapping from the observed episode e^o of its corresponding schema S_w to the episode e_k in base schema S, giving

$$\begin{aligned}\Pr(p_i, a_j \mid e^o, t^o, d^o) &= \sum_{k=1}^{E} \Pr(p_i, a_j, e_k \mid e^o, t^o, d^o) \\ &= \sum_{k=1}^{E} \left(\frac{\pi_{p_i a_j e_k t^o d^o}}{\sum_{i=1}^{P} \sum_{j=1}^{A} \sum_{k=1}^{E} (\pi_{p_i a_j e_k t^o d^o} \times q^{w}_{e^o e_k})} \right)\end{aligned} \quad (10)$$

Crisp prediction can then be assigned to the *PA* class c^{PA} of the highest conditional probability value

$$c_k^{PA} = \underset{(p_i\, a_j)}{\arg\max} \Pr(p_i, a_j \big| e^o, t^o, d^o). \quad (11)$$

In the prediction in the presence of incomplete observations due to unreliable low-level sensors, we compare the prediction performance by models derived with and without duration information.

B. Data simulation

Realistic data are simulated based on the patterns indicated in the real data collection for evaluation purposes. The evaluation of our learning algorithm using synthetic data provides the opportunity for systematic evaluation from various aspects in a controlled way. To generate synthetic data, inhabitants' behaviour model is required with parameters of an overall probability distribution, and the size of data samples. Random data values between 0 and 1 are generated in Matlab® [4]. Seeds are used in order to be able to reproduce the experimental results. In a datacube D of schema S, each cell v_{paetd} corresponds to a numeric interval according to the accumulated probability distribution. Generated random numbers that fall into an interval thus represent observations that correspond to the activity indicated by that cell in the datacube. The categorised random data are then aggregated, where the cardinality for each cell is the number of random values that fall in the corresponding interval. In this way, the simulated data follow the correct probability distribution. The synthetic datasets for training and evaluation purposes are generated separately, based on the same distribution presenting the behavioural model.

VI. EVALUATION RESULTS

In this section, we carry out an experiment to investigate how duration information affects the performance of activity prediction.

A. Evaluation on the distiction of higher-level ADLs

In the first experiment, the learning is based on data with only one attribute of *Duration*, the output is the class of higher-level activities of daily living: c_1='Cold drink, c_2='Hot drink'. Probabilistic learning is carried out on activity data with duration information. The evaluation results (Figure 4) demonstrate that duration can be informative on the activity prediction, where activity classes are of high-level. The result is indicative and encouraging considering our limited number of collected data for experiments. Duration in general should be informative on prediction for more detailed levels of activity classes, especially in the situation of incomplete observation of an activity.

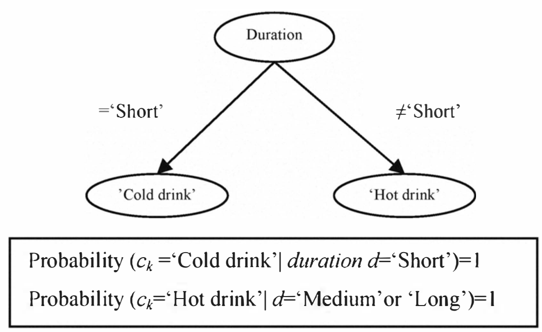

Figure 4. Learned model in a tree representation with rules

B. Evaluation on the distinction of (Person ADL) in the presence of incomplete data

In this section, we investigate the prediction of activity and person by model learned by incorporating duration data on the incomplete data due to unreliable low-level sensors.

In the situation of prediction completely observed information, based on the learned model derived from data with duration information, the performance is 0.97975 on average and with a standard deviation of 0.00786. However, in an environment with unreliable sensors, due to malfunctioning or low-battery conditions, the sensor signals cannot always be collected even if a sensor has been activated. Therefore, with *Episode* value representing the sequence of sensor activations, an observed episode in such circumstances corresponds to a number of possibilities. Such probabilities correspond to the

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sequences that would be obtained when all sensors were working properly, defined as base episodes with complete information. We need to be able to make prediction given incomplete observed episode information which is of a coarser level compared to the base episode values.

We investigate the model performance with duration when a sensor is unreliable. An illustrative example is shown with the intermittent 'Fridge' sensor for different fraction of test data. The performance of prediction on incomplete observed data using the model learned with duration is shown in Figure 5 along with its comparison to the prediction performance of the model learned without duration using our previous approach [13], on a typical task of (*Person*, *ADL*).

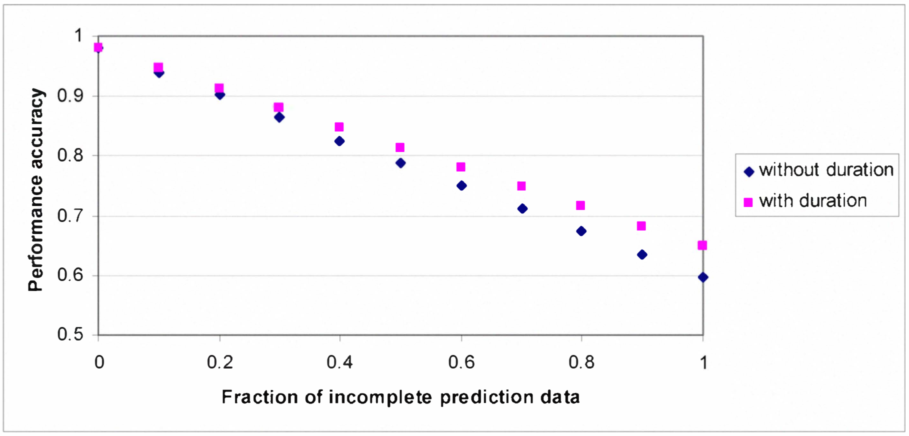

Figure 5. (*Person*, *ADL*) prediction performance comparison among models learned with and without duration data on incomplete data due to an unreliable *Fridge* sensor

From the result in Figure 5, it is observed that with increasing fraction of incomplete data, the prediction performance decreases for the prediction task, as we would expect. Compared to the performance of the model learned from data without duration information, our models learned with duration have increased accuracies. When the fractions of incomplete data are quite large, the advantage is the most obvious. The prediction performance shows similar prediction trend on incomplete data due to other unreliable sensor to intermittent 'Fridge' sensor.

The prediction time is less than 0.001 second on average for both the models derived from data with and without duration information. Data with duration has one more dimension on the schema than the schema for data without duration information. Therefore, the data pre-processing stage may take a slight longer time than the same stage for data with less attributes. However, since the data pre-processing and the learning process can be carried out off-line when not many events are happening, the training time is not a crucial issue.

VII. Related Work

Activity duration can be very informative. Temporal information along with sequential information can be useful in predicting activities. Time is a property of all sensor data which is time-stamped. Very few approaches here tried to use temporal information in activity prediction. Temporal features can be divided into two category as absolute and relative. The day can be segmented into continuous interval and each activity that is carried out is part of single high level category. It is assumed that a person's routines can cause daily patterns in absolute temporal features. Even though activity can occur throughout the day, there can be peaks at some part of the day. Relative temporal features can be inferred from relationships with other activities. The occurrence of activity can exhibit rich temporal semantics such as overlapping, containing, preceding, co-starting and co-ending [10]. Although smart home actions are instantaneous, most of them occur over an interval of time. These temporal relationships between events can be defined using Allen's temporal logic [3]. Temporal rules can be obtained from a time series representation of observed inhabitant activities. Normal activities are modelled as temporal constraints. An abnormal situation may occur if a temporal constraint is not satisfied [2]. For other sensor data, time acts as metadata. Temporal semantics can be applied to sensor data so that the same sensor values can be mapped to different activities according to the time of day [10]. Temporal information can also be used in calculating the hazardous condition of the device [7]. Temporal information is therefore useful for enhancing intelligence and solving complex problems.

VIII. Conclusion

We have proposed learning inhabitants' activity profiles in a smart home environment by incorporating duration information. We address the uncertainty in environmental information which resides in unreliable sensor readings, and the uncertainty in inhabitants' behaviours including situations when his/her activity varies according to contexts such as

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different locations and time, and multi-inhabitants may have different patterns for completing a particular task. We have shown in the experiments that duration information is informative on aspects of recognising higher level activities; and distinguishing between multiple inhabitants to potentially support personalised service. Promising results show the improvement of using duration information on the performance of identification of activities and inhabitants in the presence of unreliable low-level sensors. Dealing with uncertainty is important for both the deployment of activity recognition and intervention for assistive living in a smart home environment.

Duration can be used as thresholds for triggering assistance on personalised intervention on tasks completion in our previously proposed decision-making mechanism [12]. Duration also has the potential for application in long-term health pattern monitoring. Concept drift means a departure from the probability model that we use to capture inhabitant behaviour patterns. Activity models for the same inhabitant along different time periods can change over time in an unseen way. This can be an indication of falling health condition. Duration can be a good indicator of concept drift. Therefore, future work will include detection of such changes using duration and enable the provision of possible alert to carers, healthcare professional or emergency services. In our current evaluations, synthetic data for training and test are both generated based on the distribution derived from limited number of real data. Greater amount of real data will be necessary for further evaluations.

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