Utilising Temporal Information in Behaviour Recognition

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Abstract

The correct recognition of behaviours based on sensor observations in a smart home is a challenging problem; the sensor observations themselves can be noisy, and the pattern activity seen for a behaviour is rarely identical for different occurrences of the behaviour. For this reason, probabilistic methods such as Hidden Markov Models are preferred over symbolic reasoning approaches. However, these models do not deal well with interleaved behaviours, nor do they allow small variations in behaviour to be detected as abnormal, although this might be useful for the smart home, since changes in ingrained habit could be early signs of illness.

We propose methods for using Allen's temporal relations in order to solve these problems, and demonstrate how they can be used to recognise the interleaving of different behaviours, as well as to reason about behaviours that are frequently seen together, and therefore form a behavioural pattern or habit. In this way we have been able to extend our behaviour recognition system to recognise unusual presentations of behaviours.

Introduction

The smart home, i.e., a home equipped with sensors and an ambient intelligent system that monitors its inhabitant and their activities, is a very popular area of current research, e.g., the Gator Tech Smart House (Helal et al. 2005), MavHome (Youngblood and Cook 2007), PlaceLab (Tapia, Intille, and Larson 2004), iDorm (Hagras et al. 2004) and Georgia Tech Aware Home (Kidd et al. 1999). One motivation for developing smart homes is the well-reported fact that the population of the Western world is ageing. For example, in 2005 the number of people over the age of 60 was 10% of the overall world population, and this number is projected to increase to more than 21% by the year 2050 (United Nations 2006).

Unfortunately, the ageing process is often accompanied by decreasing physical and cognitive abilities, with a consequent reduction in quality of life. Even with these problems, many people prefer to stay in the comfort of their own home, and moving the elderly out of a familiar environment can lead to a sudden decrease in their cognitive abilities. Many of the 'activities of daily living' (ADLs) such as eating, dressing, and grooming (Robert et al. 2005), are over-learned and automated processes that become difficult when they are performed in an unfamiliar place (Bucks et al. 1996).

As a solution to this problem, the smart home is a retrospective fitting of sensors into a person's house, with the aim being to observe the behaviour of the elderly inhabitant in order to detect when problems occur. In these events, the system may issue an alert to the inhabitant, or call a relative or caregiver.

An important part of the smart home is the ability to identify when activities go wrong. However, before this can occur, the home needs to recognise the behaviour from its sensor characteristics. This turns out to be difficult because as well as sensor noise and other common problems, there can be wide variation in the way that activities are performed, even by the same person (as an example, consider that the following pair of activities both make a cup of tea):

1. fill kettle with water, boil kettle, get cup, add milk, get teabag, add teabag, pour water, add sugar
2. boil kettle (which still contains water from a previous event), get teabag, get cup, add teabag, pour water, add milk, (decide not to have sugar)

For these reasons, probabilistic models such as Hidden Markov Models (HMMs) (Nguyen et al. 2005), dynamic Bayesian networks (DBN) (Liao et al. 2007) and naïve Bayes classifiers (Tapia, Intille, and Larson 2004) have become popular approaches for recognising human behaviours. The HMM (Rabiner 1989) is a probabilistic graphical model that uses probability distributions to determine the unobservable activities such as 'boiling water' (hidden state) from observable sensor data, such as 'electricity being used at plug C','filling up the kettle' (observations).

However, HMMs do not explicitly utilise temporal information in their recognition, which means that temporal evidence for errors by the inhabitant (e.g., leaving the tea brewing for 3 hours, which is a good sign of forgetfulness, or making dinner at 3 am) is ignored. Another problem is that many activities can be interleaved: while waiting for the kettle to boil a person may occupy themselves by feeding the

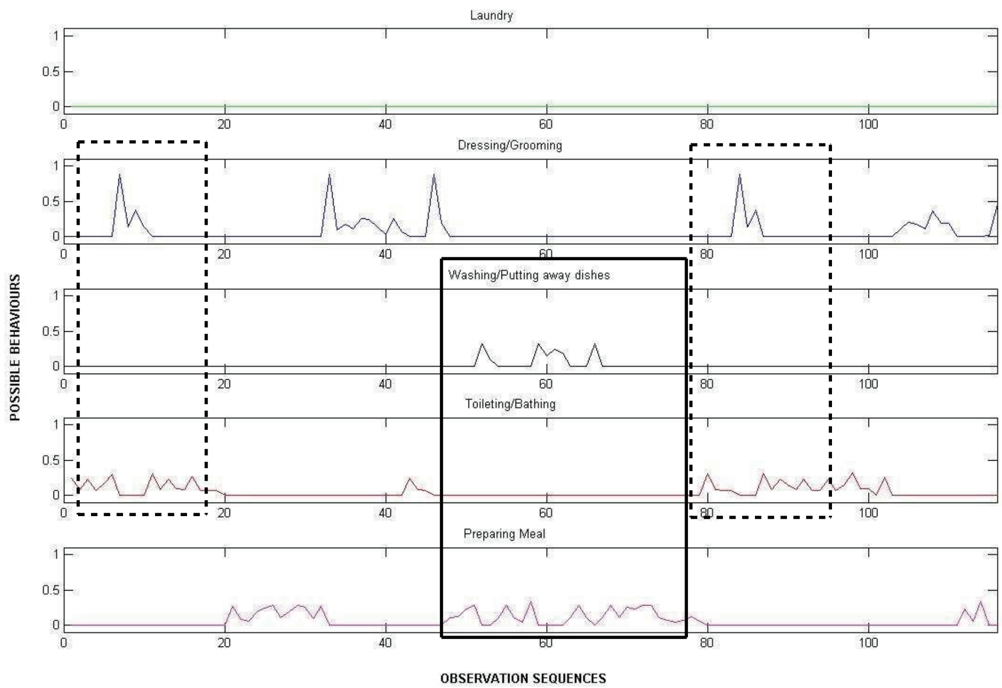

Figure 1: *The likelihood of each of five competing HMMs explaining a set of test data from one day of the PlaceLab data set. A likelihood above 0 means that that HMM matches the data, with higher values being better matches. For an explanation of the boxes, see the text.*

cat or reading the newspaper. However, a behaviour recognition system may recognise a behaviour on the basis of identifying specific parts (sensor readings). It will therefore not realise that the behaviour has been split into two parts and will recognise two separate tea making behaviours instead.

In this paper we propose a method whereby qualitative temporal relationships between the identified behaviours are used to recognise interleaved behaviours and habitual behaviour patterns. We will use Allen's temporal interval relations (Allen 1983) to identify and describe behaviours qualitatively in time. Further, we use these relations to reason about relationships between behaviours that have not been observed directly from the output of the HMMs.

Behaviour recognition using Hidden Markov Models

Our model of the sensor outputs in the house are as a stream of token data, where each token in the sequence represents that a particular sensor has been triggered (we are considering relatively simple sensors such as door open/close, oven on/off, cup moved, rather than cameras, which are obtrusive and also difficult to process).

In (Chua, Marsland, and Guesgen 2009) we proposed a method of automatic segmentation and classification of the token stream. Our method is based on competition: we use a set of trained HMMs, one for each behaviour, and they each compute the statistical likelihood that they explain the current set of observations (where the current set is selected by running a window over the data). The HMM with the highest likelihood then identifies which parts of the window it best recognises, and the other HMMs compete again to see if they can model the other parts of the data better.

Figure 1 shows the output of the system for five different behaviours. The HMMs were trained on hand-labelled data from MIT PlaceLab (Tapia, Intille, and Larson 2004); the data represents the observations of state-change sensors in apartments whose inhabitants kept a record of their activities in order to provide a 'ground truth' about their activities over 16 days. We defined a set of five HMMs identifying behaviours that take place at different locations around the house. The five behaviours are:

- LAUNDRY,
- DRESSING/GROOMING,
- WASHING/PUTTING AWAY DISHES,
- TOILETING/BATHING,
- PREPARING MEAL

Figure 2 shows the HMM for DRESSING/GROOMING. The figure plots likelihood, with values above zero showing that a particular HMM recognises the data. The sequence of activities that are identified for that day were:
TOILETING/BATHING, DRESSING/GROOMING, TOILETING/BATHING, PREPARING MEAL, DRESING/GROOMING, TOILETING/BATHING, DRESSING/GROOMING, PREPARING MEAL, WASHING/PUTTING AWAY DISHES, PREPAR-

ING MEAL, WASHING/PUTTING AWAY DISHES, PREPARING MEAL, WASHING/PUTTING AWAY DISHES, PREPARING MEAL, TOILETING/BATHING, DRESSING/GROOMING, TOILETING/BATHING, DRESSING/GROOMING, PREPARING MEAL, DRESING/GROOMING.

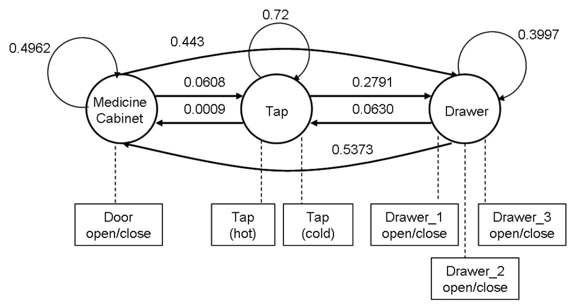

Figure 2: *Hidden Markov Model for* DRESSING/GROOMING. *Rectangles show observations (made by sensors) while circles show the activities, which cannot be directly observed. Edges between activities show probable transitions between states, with the numbers showing the probability of making that state transition at the next timestep. Dashed lines indicate which observations can be seen in each state; there are also probabilities associated with these, but they are omitted for clarity.*

The identified behaviours match with the behaviours that actually went on in the house in the sense that every detected behaviour occurred at the time it was identified. The method needs a relatively small amount of training data and is relatively simple. It is based on recursive computation, which keeps the computational costs significantly lower than many other methods.

However, the above listing contains a period where the algorithm switches quickly between the two behaviours of WASHING/PUTTING AWAY DISHES and PREPARING MEAL. The corresponding output from the HMMs is highlighted in a solid black box in Figure 1. Both behaviours are correctly identified according to their definition and conform to the ground truth provided by the inhabitant. Frequent switching like this between two behaviours might indicate that the two are actually interleaved. In a common sense way we would say that both behaviours are ongoing at the same time.

There are two possible solutions to this. One is to modify the behaviours so that this pattern represents a particular behaviour with its own HMM. However, extending this to all patterns would lead to massively more HMMs, and also increase the chance of misclassification, since many patterns would be similar. Instead, we prefer to introduce temporal relationships between behaviours, and use these to recognise when behaviours are spread out over time. This is discussed next.

Temporal relationships between behaviours

To express relationships between behaviours we use the terms of Allen's interval-based temporal calculus (Allen 1983). The calculus describes all possible relationships between two temporal intervals, A and B, with thirteen jointly exhaustive and pairwise disjoint (JEPD) relations, which are shown in Figure 3. Each interval is clearly defined by its start and end point in time so that the interval relationships can be defined by the relationships of their corresponding start and end time points. For example the relationship 'A contains B' is defined by $A_{start} < B_{start} < B_{end} < A_{end}$.

The observations made by the smart home sensor system are represented by a token stream (observation$_1$, ..., observation$_n$), with certain observations representing the start and end points of the recognised behaviours. We therefore do not need the actual time points of the observations. However, in cases where the inhabitant executes the same behaviour twice in a row, for instance, prepares two beverages, we want to be able to classify these as two separate behaviours if there was a significant pause between them. Therefore, it is important to keep track of the elapsed time between the observations. If the inhabitant actually prepares two beverages in one go, as for example preparing a tea for himself and a coffee for his guest, this would qualify as one single behaviour.

The qualitative temporal relationships observable directly from our model, assuming that only one behaviour occurs at any time, are *before* and *after*. If we include some temporal information (e.g., identifying that no time or very little time has elapsed between the end of one behaviour and the start of the next) and no third behaviour has been executed in between, we are also able to identify the relationships *meets* and *met by*.

Recognising interleaved behaviours

We now consider how these relations can be used to identify the interleaved behaviours of WASHING/PUTTING AWAY DISHES and PREPARING MEAL shown in the solid black box in Figure 1. In order to describe them with Allen's relations, we start by noticing that PREPARING MEAL (which started at observation 47) went on until observation 79, whereas WASHING/PUTTING AWAY DISHES (which started at observation 52) ended with observation 66. This means that PREPARING MEAL started before WASHING/PUTTING AWAY DISHES and ended afterwards. This results in the relationships WASHING/PUTTING AWAY DISHES *contained by* PREPARING MEAL and PREPARING MEAL *contains* WASHING/PUTTING AWAY DISHES.

We can see that the relationships of *overlaps/overlapped by* can also be useful to identify interleaved behaviours. An example of this type of behaviour pattern would be where the laundry is considered. Since the washing machine, once loaded and started, is pretty much left to its own devices, it is very likely that some other behaviour (or behaviours) is identified in the interim. This may well fit into the *contains* relation, but the person may well go back to the intervening behaviour (such as preparing a meal) after they have transferred the washing into the dryer. This leads to the *overlaps/overlapped by* pattern.

We now turn to a more complicated version of the problem, which is illustrated in the two dashed boxes shown in Figure 1. In these boxes, the behaviour sequence of TOILETING/BATHING, DRESSING/GROOMING, TOILETING/BATHING is identified as three separate behaviours. Further, the likelihood of the TOILETING/BATHING be-

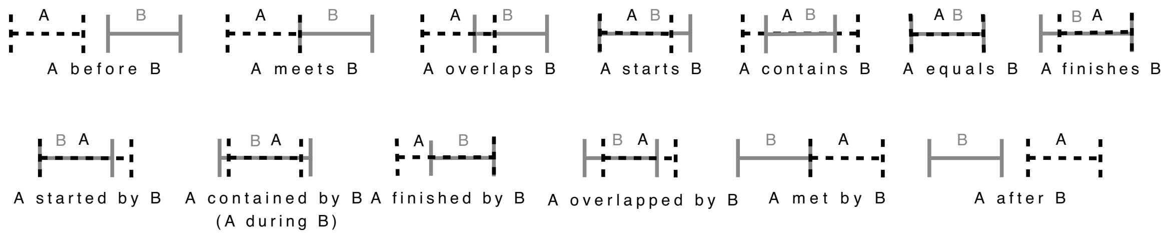

Figure 3: *The thirteen relations of the Interval Calculus.*

haviour is low, suggesting that it is not well-recognised, because not all of the observations are seen during either instance of the behaviour. This is a frequent pattern of observations across the entire dataset.

These two behaviours are related, in the sense that bathing requires activities that are parts of the DRESSING/GROOMING behaviour. Thus, there are examples of TOILETING/BATHING that include DRESSING/GROOMING. One way to approach the problem would be a hierarchy of behaviours, so that DRESSING/GROOMING subsumes TOILETING/BATHING, but this would require a more complex model. However, Allen's relation of *contains* provides us with a useful way to identify this pair of behaviours and to encode their relationship. We could interpret this as DRESSING/GROOMING during TOILETING/BATHING which in Allen's terms also translates to *contained by*.

On the basis of Allen's relations, temporal reasoning about the inhabitant's behaviour is possible. This means that we are able to infer relationships between behaviours that have not been directly observed. This might be quite useful in order to check certain important behavioural relationships as, for instance, taking medications before lunch or taking a shower after coming home from sports and before going to bed. Provided that the person showers sometime before bedtime, they do not need to shower as soon as they arrive home, but can engage in several other behaviours, such as having dinner, watching television, talking on the phone, etc. Temporal logic provides a simple way to describe this constraint.

For other behaviours, certain relationships might be prohibited; for instance, going to bed while cooking. For this scenario, the important interval for cooking is between the moment that the stove is switched on and when it is switched off again. When, during this interval, a GOING TO BED behaviour is recognised, the inhabitant or a carer should be notified. Of course, this discussion does not consider how this information should be learnt by the system, or whether it needs to be pre-installed. It also highlights another interesting feature: for some (potentially dangerous) lapses the behaviour needs to be recognised quickly – if the person is already asleep when the house asks if they realise they have left the stove on then it is unlikely to be useful. This is another benefit of using HMMs, which is that relatively short sensor sequences can still be used to classify behaviours, albeit with less confidence.

Another thing that can help to identify interleaving is using additional data that the house has access to, such as context information from other sensors around the house, statistics of execution time for certain behaviours, or orderings of behaviours from past experience. It is quite common that behaviours include appliances that do part of the job for us, for instance washing machines, dryers, dishwashers or coffee machines. While these machines run, the inhabitant can easily attend to other behaviours while waiting for the machine to finish and to be able to continue the 'paused' behaviour. If, for example, the time elapsed for the behaviour indicates that a laundry behaviour might have been paused instead of finished, the sensor for the washing machine can be used to confirm that the laundry behaviour is still ongoing in the background. Then any behaviour, such as tea making, that happens is interleaved with the ongoing laundry behaviour.

Contextual information can be very useful in assisting the HMMs and competitive process by using the fact that people's days are often based on habits, and if these can be identified and reasoned about (for example, 'it is Tuesday morning so the person will probably do the laundry', or 'they have just made lunch so they will probably have a nap now') then the process of recognising behaviours is much simpler. Another benefit is that it could provide an early warning of illness, when habits are broken.

Identifying habits

Once all observable relationships are collected over a reasonable number of days, we can look for patterns that frequently reoccur. The temporal reasoning process can enable us to identify patterns that occur in the relative orderings of behaviours, such as that having a nap comes after eating lunch. They can also be useful to supplement the data within the HMM of a particular behaviour. For example, some actions within a behaviour are ingrained by habit – in the example of tea making, people often do it in a relatively fixed ordering, so that filling and switching the kettle on happens first.

Since boiling water is a part of several behaviours (such as making tea, preparing water for cooking pasta, and filling a hot water bottle), the behaviour cannot be identified from this observation. However, if the temperature is warm and it is dinner time, then the cooking behaviour can be made more likely than the others. In this way we can change the probability of behaviours as individual observations occur, without requiring more observations to be seen, based on previous experience. In terms of Allen's temporal relationships we can say that putting the kettle on *starts* the behaviour pattern for preparing tea, cooking pasta, and preparing hot water bottle. We can also see that besides the relationships

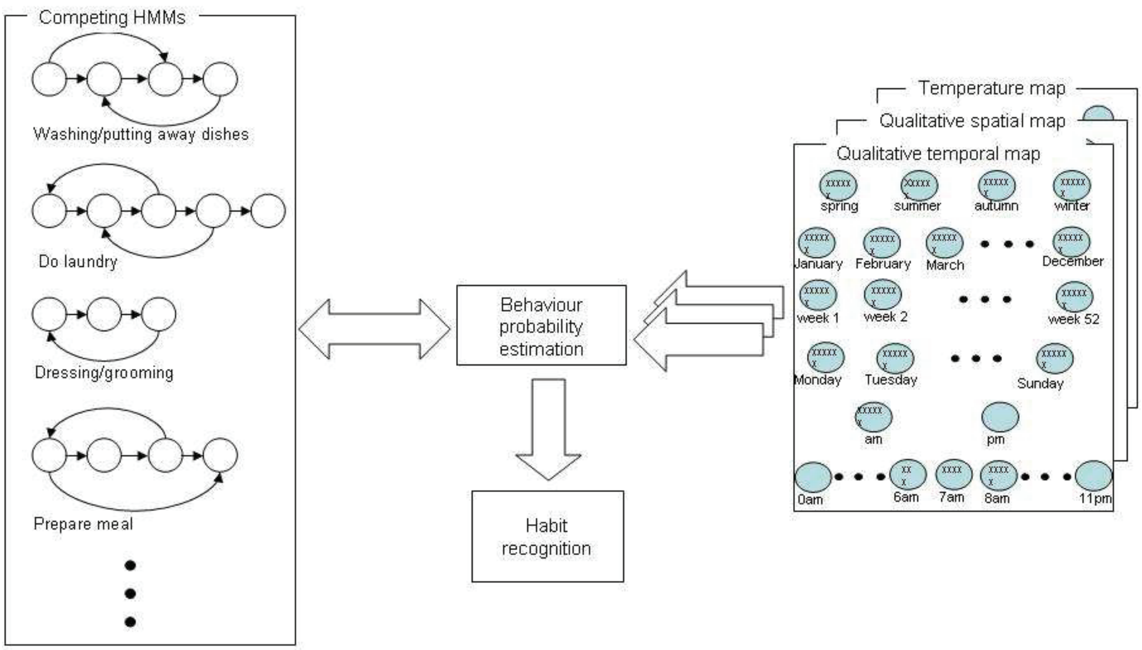

Figure 4: *Behaviour recognition with HMMs and Context maps. The likelihoods from the competition between HMMs is used in conjunction with the various spatial and temporal maps in order to form a probability that each behaviour is observed. This can assist in the recognition of behaviours, and also in identifying habits or behavioural patterns.*

starts/started by the relationships *finishes/finished by* can occur for behaviour patterns.

This kind of habit identification might be especially useful in combination with the unobtrusive sensors that do not allow for an exact identification of what the person does at any moment in time, as they can allow a behaviour to be identified as wrong when the actions occur in the wrong order, or when one action is missed, something that the HMM alone may not see as a problem. For example, making a cup of tea without adding a tea bag, or boiling the kettle only after pouring the water in the cup, are both mistakes that a confused person may make, but the HMM will still recognise the behaviour without realising the mistake.

As a supplement to the habit identification we suggest the use of contextual maps, one for each context class as e.g., time, space, temperature, heart rate, blood sugar level etc., providing additional information. This is shown in Figure 4. The qualitative temporal map, for example, provides a classification of time. Each occurrence of the same behaviour is annotated (by an x) in its corresponding qualitative temporal map describing when the behaviour occurred with regard to each class. Possible temporal time categories are: year, season, month, week, weekday, part of day (*am/pm*), hour. As an example we can think of the PREPARE BREAKFAST behaviour that occurs every morning between seven and eight o'clock. Whenever the behaviour is recognised we list its occurrence in each category. In the season category we will not see any pattern of the occurrence of the behaviour, as the person has breakfast at about the same time throughout all seasons. The same is true for the month, the week, and the weekday categories. For the category part of day we see that the prepare breakfast is always in the class *am* and never in the class *pm*, which gives us the first clue that breakfasts are usually prepared in the first half of the day. In the category hour, we will find many entries scattered around between *seven am* and *eight am*, which leads to the conclusion that this person likes to eat breakfast at that time.

Whenever the HMMs recognise a PREPARING BREAKFAST behaviour we can check using the context information of the present time and the qualitative temporal map to see if this behaviour fits the usual habits. We can also use the context information to double check the output of the behaviour recognition algorithm. If the context information does not support the chosen winning behaviour, we might decide to ignore this behaviour and run the behaviour recognition algorithm again on the remaining possible behaviours, or to flag this as an unusual occurrence.

By simply counting the entries in the map for each class we can calculate the probability of a behaviour, given the context information, e.g., $P(\text{breakfast}|7am)$ using Bayes' Rule. The use of further contextual maps allows for even better estimations. Suppose that the inhabitant has his breakfast at five o'clock in the morning, which is rather unlikely regarding the qualitative temporal map, but taking into account that his blood sugar level was very low the likelihood of this behaviour, $P(\text{breakfast}|5am, \text{Low blood sugar})$, increases. It may, however, lead to the so-called curse of dimensionality.

Discussion

In this paper we have considered how temporal data can supplement a behaviour recognition system for a smart home by allowing interleaved behaviours, both related to each other and not, to be recognised, and how it can be used as contextual data to assist in the behaviour recognition process. This system can be added to our current behaviour recognition system, which is based on competition between a set of trained HMMs, each of which recognises a different human behaviour. We have also suggested that the use of temporal information can identify when habits of house inhabitants change, since minor changes in the ordering of activities are not noticed by the HMM.

This last is an interesting feature of HMMs: it is often a benefit, since it enables behaviours – which are almost never identical to previous examples – to be recognised, but at the cost of missing possible errors that the house inhabitant is making, which could be early signs of illness. By adding some temporal reasoning it is possible to have the benefits of HMMs without losing the diagnostic ability.

We have solved this problem by identifying habits, which are behavioural patterns (both within a behaviour and across several behaviours) that recur frequently. In the case of these habits, and changes to them, it really is all in the (relative) timing.

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