From Symbolic to Probabilistic Models

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Abstract. We argue, that generative probabilistic models should be used to detect user activities, and we discuss two approaches to create those model from symbolic descriptions.

1 Motivation

In many application areas, a computer needs to recognise the user's current activity. Examples are the automatic creation of diaries, user assistance in instrumented environments and many others. Unfortunately, activity recognition is by no means a simple problem, because we have to deal with the problems of noisy sensor data, incomplete descriptions of the domain, unpredictable behaviours of humans and many others. In this paper, we argue that we need (i) generative probabilistic models for activity recognition and (ii) high-level description of these models in a human readable form. And we show two possible approaches currently under investigation in our lab.

2 Probabilistic Models and Abstract Description

As mentioned above, we have to deal with noisy sensor data while trying to recognise the user's activity. Probabilistic models, for example hidden Markov models or more general dynamic Bayesian networks, have been applied successfully. We believe that generative models should be used for the high-level activity recognition because they allow an easy integration of prior knowledge and we can not only recognise the user's activity but also predict and simulate it.

Unfortunately, probabilistic models quickly become rather complex. Therefore, they are neither easy to construct nor to debug by humans. Both problems could be solved, if we were able to automatically construct complex models based on a symbolic description, and to extract such a description from a (trained) model later.

Below we discuss the creation of hidden Markov models (HMM) from (a) grammars and (b) STRIPS descriptions [2]. While the first is a top-down approach (starting at the highest level, which is then detailed) the latter works in a bottom-up fashion (starting from atomic actions that are composed into sequences).

We propose to use a extension of probabilistic context free grammars [2] (EPCFG) to define the language of human activities of daily living such that

$\mathsf{Day} \xrightarrow{0.7} \mathsf{WDay} \ \mid \ \xrightarrow{0.3} \mathsf{Weekend}$

$\mathsf{WDay} \xrightarrow{0.3} \mathsf{Car}, \mathsf{work}[8h], \mathsf{Car}$

$\mathsf{Car} \xrightarrow{0.5} \mathsf{carfast}[1min], @0.9$

$\mathsf{Car} \xrightarrow{0.3} \mathsf{carslow}[1min], @0.9$

$\mathsf{Car} \xrightarrow{0.2} \mathsf{carstop}[1min], @0.9$

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(:action present :parameters(?who)
 :precondition (and (at ?who stage)
  (forall (?x - user) (or (=?x ?who) (at ?who seat))))
 :effect (and (has-presented ?who)))
(:action move :parameters(?who ?from ?to)
 :precondition (at ?who ?from)
 :effect (and ((at ?who ?to)(not (at ?who ?from)))))
(:goal (forall (?p - person)
       (and (has-presented ?p) (has-discussed ?p))))
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Fig. 1. Excerpts of an extended grammar describing a human's life (on the left) and a STRIPS formalisation of a smart meeting room (on the right).

the underlying terminal symbols correspond to observable primitive activities. I.e., for each of them we can define a probability distribution over the raw sensor data. Figure 1 shows a grammar which is annotated by probabilities and timing information. For a speedometer, the terminal carfast can be defined as a normal distribution with mean "50 km/h" and variance of "10km/h". The EPCFG is translated into a hierarchical HMM, which then is flattened. The resulting HMM can be used for annotation. But, we can also assign labels to the states of the model which allows the detection of high-level activities.

As a second approach, we propose to use STRIPS operators as known from planning [2, 1]. These operators define pre- and post-conditions of actions. A simple example is shown in Figure 1 on the right, in which we model the activities during meetings. Those meetings are hard to model using grammars, because all possible sequences of actions have to be modelled. By employing the STRIPS formalism, we can generate all possible meeting sequences via expansion from an initial state, given the number of participants and the agenda of the meeting. This allows a straight-forward integration of prior knowledge of the domain, e.g., social norms. Those sequences of states can easily be modelled using HMMs.

3 Discussion

We have discussed two approaches to create probabilistic models for high-level activity recognition based on symbolic descriptions. Both allow the automatic generation of such models based on a symbolic description. The training and the extraction of symbolic descriptions from the revised models needs to be investigated in the future. Furthermore, we need to evaluate our approach using real problems.

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References

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