Task Models for Inferring Team Intentions

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Emerging smart environment infrastructures provide users with a large number of interconnected assisting appliances. Inferring the intention of a team within such an area becomes a central challenge, especially if multiple user are observed by noisy heterogenous sensors. We propose a team task model based on hierarchical Dynamic Bayesian Network (DBN) for inferring the current task and activity of a *team* of users online. Given (noisy and intermittent) sensor readings of the team members' positions in a meeting room, we are interested in inferring the team's current objective.

1 Introduction

Mobility of computing devices makes information technology accessible for user activities that are temporally and, especially, spatially distributed[1]. Ubiquity of appliances enables seamless incooperation of user tasks in smart environment infrastructures. The important consequence here is that the structure of a user task becomes visible to the computing system. This creates the *opportunity of proactive assistance*: If the devices in the user's environment are able to infer his current activity, they are able to trigger actions (such as providing information), without explicit user interaction.

To use the opportunity of proactive assistance, a basic concept is being investigated in current research: providing the system with an *explicit model* of the user's task, a *task model*.

Our own contribution to this technology is:

- The development of task models that allow to recognize activities of individual users from observable noisy sensor data.
- The enhancement to a *team task model* to further recognize team objectives from observable actions of the team members.

The paper is organized as follows: Next, we will briefly look at the concept of *task models*. In Section 3 we discuss related work and introduce our own contribution. Section 4 outlines the scenario, describes our *team task model* and addresses some sensor issues. Finally in Section 5 we present a first outcome and give an outlook regarding the next steps.

2 Task Models

By a *task model* we mean a breakdown of a composite activity into individual atomic steps, between which a partial order may be defined (induced by the preconditions and effects of the individual atomic steps), roughly speaking: a "plan". Cooking recipes or construction manuals are everyday examples for such plans that can easily be transformed into a machine-readable format. The term "activity" will hence denote an atomic step of a task.

Task models originate from two research areas:

[1] We will use the term "task" for such a composite activity.

In *cognitive psychology*, task models have been developed as means for formally describing human problem solving behavior. The well known GOMS[2] model [2] is a very good example for this class of models. It is the foundation of several proposals for model-based user interface design (for instance, [11]). These models can be used in two ways: (i) for *analyzing* the cognitive complexity of a given user interface by deriving, for instance, its equivalent GOMS description from which the complexity can be estimated, and (ii) for *designing* user interfaces by first developing a model of the task at hand and *then* choosing appropriate dialogue elements for the individual atomic activities (the overall dialogue structure can be directly derived from the task model).

In *signal processing*, "task models" have been developed as a means for estimating the actual behavior of a signal source, for which only incomplete and noisy observations are available. The challenge here is to identify the most probable behavior as cause for a set of observations. Tracking of moving physical objects based on noisy sensor data is the classical example. The fundamental algorithmic approach is *Bayesian filtering*: Given a hypothesis about a signal source's behavior repertoire, a hypothesis about which behavior will cause what observation, and a set of noisy observations, a Bayesian filter will yield the most probable explanation for the observed data – i.e., the most probable behavior of the signal source given the observations[3].

The relation between these two origins for task models becomes clear once we try to track a human user: The observations may be data from (noisy) location sensors (e.g., Beacon-based, GPS, UbiSense), accelerometers attached to the user's body (or her mobile phone), microphones and ambient light sensors, or information about objects touched by the user (using, e.g., RFID-Tags). The challenge is then: given a set of sensor data – what task is the user trying to perform? – Clearly, a model correctly describing a human's strategy for achieving a certain goal (i.e., a task model for this goal), is an ideal hypothesis for a Bayesian filter: given a set of task models and a set of sensor readings, a Bayesian filter will output the user's most probable goal. (A Bayesian filter will provide even more: it will give a probability distribution across *all*

[2] The acronym "GOMS" stands for the key modeling elements: Goals, Operators, Methods, Selection rules.

[3] This account of Bayesian filtering is *really* brief. See e.g. [4] for a nice introduction.

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