Task Assistance for Persons with cognitive Disabilities (TAPeD)

Christian Peters[1]
CITEC
Bielefeld Univ., Germany

Thomas Hermann[1]
Ambient Intelligence Group
Bielefeld Univ., Germany

Sven Wachsmuth[1]
Central Lab Facilities
Bielefeld Univ., Germany

Abstract

TAPeD is a project at the *Cognitive Interaction Technology, Center of Excellence* (CITEC) at Bielefeld University, with the aim to develop an automatic prompting system in the healthcare domain. In comparison to systems applied in individual user's homes to prolong the user's independence in everyday life [2], we aim to develop a system for a residential home where persons with different cognitive disabilities live together and share the same system. We cooperate with *Haus Bersaba*, a residential home belonging to *v. Bodelschwinghsche Stiftungen Bethel* which is a care facility in Bielefeld, Germany. Our user group has problems fulfilling *Activities of Daily Living* (ADLs), in particular in brushing teeth. We describe the progress of development towards an automatic prompting system assisting in brushing teeth and give an overview of our project from a machine learning perspective.

Project overview

The main problem in the development of an automatic prompting system is the transformation from sensory information to the user's progress in the task from which feedback is generated. Specific sensor data is enriched with semantic concepts in a way that users and caregivers can understand the system behavior. From a machine learning perspective, the transformation involves the following steps where learning plays an important role:

Observation model An observation model maps the observations provided by the sensors to internal states of the system.

State transition model A state transition model includes a task model which describes the different steps of task execution in a high-level manner. The task model is usually constructed by hand. The transition between the different steps are mostly learned based on sample data.

Policy learning A policy maps the current state of the system to an action to take, e.g. prompting the user.

A key issue in the three steps is the inclusion of semantic information via a-priori knowledge to restrict the learning problem domain and make the learning process tractable. In order to obtain a-priori knowledge in a comprehensible way, we applied Interaction Unit (IU) analysis similar to [1] as a method of qualitative video analysis by observing real-world videos recorded in *Haus Bersaba*. IU analysis is an approach to interaction modeling describing the conjunction of cognitive and environmental pre- and postconditions for individual actions. Each video shows one trial of a user brushing his/her teeth while being observed and supported by a caregiver if necessary. We extracted three types of a-priori knowledge about the brushing task during IU analysis:

Involved objects The objects involved in the brushing task are mug, towel, toothbrush and toothpaste.

Task-relevant states We identified the *position*, *content* and *condition* of the four objects as relevant state variables. Additionally, we have three state variables describing the content and condition of

[1] `[cpeters,thermann,swachsmu]@techfak.uni-bielefeld.de`

the user's mouth and the condition of the user's teeth. These state variables provide the environmental state space used in the observation model described above.
Task decomposition We decomposed the task of brushing teeth in several subtasks. In conjunction with the caregivers of *Haus Bersaba*, we will construct a model for task execution by hand on which the state transition model will be based.
In our project, we are currently working towards the observation model. In particular, we recognize the task-relevant objects based on sensor technology installed at our washstand setup: We use two 2D cameras observing the scene: one from overhead and one from below the mirror since we identified the sink area and the upper body of the user as the important functional areas during the task. We have not worked on any machine learning problem, yet, but we identified several requirements for solving these problems: The acquisition of training data by conducting evaluations with our user group is very hard since we don't have a working prompting system right now which we can apply directly in the residential home. We aim to develop a first prototype of the system to apply in *Haus Bersaba* for long-term studies in the future. Hence, the machine learning algorithms we will use in our project have to work well with a small amount of training data. Furthermore, they have to generalize well to the huge variance in task execution arising in a user group with several disabilities. The users not only showed huge variance in the execution of the task, but also in the reaction to feedback as shown in a recent experiment [3]: We conducted a Wizard-of-Oz (WOz) experiment with three inhabitants and two caregivers of *Haus Bersaba*: Each of the three persons performed two WOz trials. The user gets the task to brush his/her teeth at the washstand equipped with two cameras, a microphone and a TFT display with speakers for prompting. He is not aware of being supported by a caregiver but thinks that he is faced with an automatic prompting system. However, the caregiver - the wizard in our scenario - operates the system via a graphical user interface and selects and triggers audio or combined audio/video prompts to assist the user in task execution. We analyzed the user's reaction behavior when faced with system prompting instead of direct caregiver prompting. Our results show that an automatic prompting system has to be highly adaptable to the user's needs and abilities in terms of prompting behavior: One user showed an increased rate of correct reactions to video prompts whereas the others were highly distracted and were not able to adapt their behavior according to the prompt. However, all users were able to fulfill the task properly. Machine learning algorithms offer methods to learn appropriate feedback modalities for different users, e.g. a user's individual prompting hierarchy including various modalities on different levels of escalation. A key requirement for user adaptive prompting is the recognition of the user and the assessment of his/her mental state, not only in a single trial, but persistent over a certain period of time. The system has to cope with decline of cognitive abilities due to progress of the disability and with an increase of the cognitive abilities as a result of training. Especially in a residential home, the caregiver's daily assistance in the execution of ADLs is a long-term training process. An automatic prompting system has to cope with this situation and provide user adaptive behavior. A further open challenge is the acceptance of an automatic prompting system in a residential home. In comparison to systems applied in an individual user's home where person are used to fulfill ADLs without the help of a caregiver for their whole life, inhabitants of a residential home are used to be assisted by a caregiver. Hence, the replacement of the caregiver by an automatic prompting system is not suitable. Instead, the caregiver has to be involved in the task, e.g. by customizing the system in the beginning of the trial. In the domain of cognitive assistance, the performance of an automatic prompting system depends strongly on a small number of critical points during task execution. A wrong feedback at these points can have severe impact on the acceptance of the system. In order to apply machine learning algorithms in a suitable way, the optimization criteria on which the learning is based have to be chosen with respect to an appropriate system behavior at these critical points. Hence, the recurring identification of critical points with qualitative methods such as IU analysis is a crucial aspect in an iterative system design process.

References

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