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Assistive System for People with Apraxia Using A Markov Decision Process

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Abstract. CogWatch is an assistive system to re-train stroke survivors suffering from Apraxia or Action Disorganization Syndrome (AADS) to complete activities of daily living (ADLs). This paper describes the approach to real-time planning based on a Markov Decision Process (MDP), and demonstrates its ability to improve task's performance via user simulation. The paper concludes with a discussion of the remaining challenges and future enhancements.

Keywords. Markov Decision Process, Task Model, Cognitive Assistive System, Activity of daily living.

Introduction

Stroke survivors suffering from neurophysiological disorders [1, 2] such as Apraxia or Action Disorganization Syndrome (AADS) may be unable to perform simple activities of daily living (ADLs). For example, when making a cup of tea or preparing a snack, patients might perform a wrong sequence of actions, skip steps, or misuse objects with possible safety implications. Caregivers can provide assistance, but patients may be unwilling to accept this as a long-term solution, considering it to be an intrusion into their privacy. Hence, assistive technologies for cognition (ATC) are a key objective in helping stroke survivors to regain independence. This is the goal of the CogWatch system [3], and this paper focuses on its Task Model (TM): a real-time planning system based on a Markov Decision Process (MDP), which can guide and provide meaningful feedback to patients during ADLs. To be more precise, the TM's aim is to make the patients aware of their errors, suggest what should be done to successfully complete the task, and alert them in case of danger.

The potential of ATCs for patients with cognitive impairments in task accuracy and independent task completion has been demonstrated in several studies. Levinson [4] describes an ATC using artificial intelligence (AI) called PEAT, which automatically generates the best plan to complete a task, and assists the user with visual and auditory cues. This project has been enhanced with the integration of sensors [5]. Other computer-based guidance systems, such as Cogorth [6] or Coach [7] were also developed as prototypes before being improved with new technologies. Nevertheless, despite this growing interest in incorporating sensing capabilities and AI techniques in

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ATCs, the studies rarely focus on the effects of the devices on patient performance, and the implication of involving clinical specialists in the system development have also received little attention.

We aim to show that a planning system integrating AI technics can also take into account clinical specialists' knowledge in order to make ATCs' guidance more meaningful. Moreover, even if CogWatch is at its early stage and data involving stroke survivors are still being gathered, we can still demonstrate the ability of its Task Model to improve task performance via user simulation.

1. System Architecture and Method

CogWatch's current goal is to re-train patients with cognitive impairments providing them autonomous guidance during tea making. The complete system (Figure 1) comprises sensorized objects (mug, kettle, milk jug), an Actions Recognition System (AR), the TM and a Prompting System. First, the patient or the clinician chooses the type of tea (i.e. black tea, black tea with sugar, white tea, or white tea with sugar) for which training is believed to be needed. This information is then passed to the TM that enables the system to begin interacting with the patient. When moving the objects, the patient triggers the sensors attached to them; the outputs of the latter, together with estimates of the patient's hand positions, are communicated wirelessly to the AR that tries to comprehend what action has just been performed. Synchronized with Kinect, the AR is a probabilistic system based on Hidden Markov Models. It is implemented as a set of parallel detectors, so that actions occurring at the same time can be identified. It outputs its observations to the TM, which keeps in its memory the patient's actions history, so it can constantly analyses it in order to find potential errors. Flexible, the TM allows the patient to perform the chosen task following all possible valid variations of actions. However, when it detects an error, it determines its type and what action should be performed by the patient for the task to be succeeded. Finally, the TM sends this information to the Prompting System that decides when, how and at which frequency cues (e.g verbal, auditory, visual cues) should be delivered to the patient.

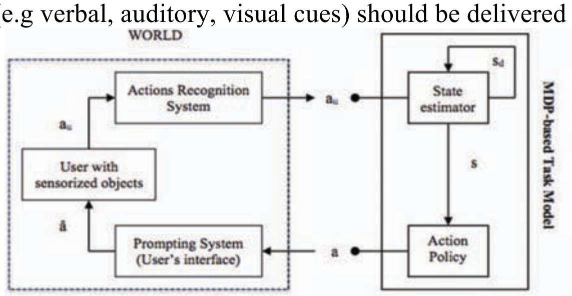

Figure 1. Structure of CogWatch: a_u and a denote the user's action and the TM's strategy, s_d is the user's actions history, s being factorized with a_u and s_d. The circumflex indicates an estimate.

As explained previously, the TM is based on a Markov Decision Process. The MDP is a mathematical tool for planning, learning and describing decision-making in probabilistic environments. It is defined as a four-tuple *(S, A, P, R)* [8], where: *S* is a finite set of states, *A* is a finite set of actions, *P* is the transition function (*P(s, a, s')* denotes the probability of reaching state *s'* from *s* given that action *a* was taken), and *R(s, a)* is replaced by *C(s, a)*, the cost of taking *a* in state *s*. Given an MDP, the problem is to find the optimal strategy π^* which is a mapping from states to actions, where $\pi^*(s)$ is the best action to perform in state s. Its computation is based on the policy value $V^*(s)$, which is the expected sum of costs incurred by a session starting in state s at time $t=0$, and following π^*, until the final state is reached at T_F.

$$V^*(s) = < \sum_{t=0}^{T_F} c(s_t, a_t) >, \tag{1}$$

where $s_0 = s$ and $a_t = \pi^*(s_t)$. It can also be expressed as:

$$V^*(s_t) = min_a[< c(s_t, a) > + \sum_s P(s, a, s_t)V^*(s)]. \tag{2}$$

π^* is then defined by:

$$\pi^*(s_t) = argmin_a[< c(s_t, a) > + \sum_s P(s, a, s_t)V^*(s)]. \tag{3}$$

Those strategies are computed using a Monte Carlo Algorithm [11]. To do so, the four-tuple *(S, A, P, C)* needs to be defined following CogWatch's context:

- **The action space A:** Using the principles of task analysis [9], each type of tea is decomposed into a hierarchy of sub-goals, tasks and sub-tasks. CogWatch currently focuses on the first level, where eight sub-goals have been identified, plus one common error (9), and one potentially hazardous activity (10). These are: *{1. "Fill kettle", 2. "Boil water", 3. "Pour boiling water from kettle into mug", 4. "Add teabag", 5. "Add sugar", 6. "Add milk", 7. "Stir", 8. "Remove teabag", 9. "Pour cold water from jug into mug", 10. "Toy with kettle"}.*
- **The state space S:** States of the MDP-based TM directly correspond to user's states. Specifically, a state is a sequence of actions performed while completing the task that has been chosen by the clinician or the patient.
- **Transition function:** CogWatch is currently used with real participants under the supervision of a clinician. Thus, we make the assumption that the transition function $P(s, a, s')$ is binary. Suppose that the current state s corresponds to the sub-sequence $g_1, g_2, \ldots, g_n$, that a is the sub-goal g, and s' is $g_1, g_2, \ldots, g_n, g$. Then $P(s, a, s')=1$ and $P(s, a, t)=0$ for all states $t \neq s'$.
- **Cost function:** The cost function $C(s, a)$ is a mechanism to incorporate human judgment about the importance of different types of behaviour into the MDP. In our case, it includes a penalty based on the time taken to achieve the task, and a penalty for not doing a specific action in a state where this action is considered to have highest priority. The first type of penalty allows the TM to compute the fastest strategy. However, the fastest strategy is not necessarily the most psychologically plausible. To deal with this, we analysed data from control participants in order to determine which actions are performed most frequently in each state during the task. This knowledge allows the TM to suggest strategies that are not only correct but that clinical specialists also consider being plausible.

2. User Simulation and Results

This section describes an evaluation of the MDP-based TM and measures its ability to guide a virtually impaired simulated user *(SimU)* that interacts with a simulation of CogWatch to make cups of tea. The evaluation with real users is the ultimate measure for the usefulness of a system, we have started it but do not report the data as it is yet in its pilot stages.

Based on real participants data, the *SimU* incorporates a complete psychologically plausible behavior, which allows it to deal with all possible situations encountered while interacting with the CogWatch Simulator. It can output all the sub-goals part of the MDP action space and virtually interact with the Prompting System from which it can receive cues or ask for help. The CogWatch Simulator follows the same structure of the real system described in Figure 1; the *SimU* replacing the module corresponding to the 'user with sensorized objects'. During this experiment, the *SimU* tried to make each type of tea 1189 times. Table 1 shows its success rates when being compliant to the TM (i.e when executing the strategy suggested by it) and when ignoring it, which means to perform the task by itself. The results highlight the fact that the use of the CogWatch Simulator increases the ability of the *SimU* to succeed each type of tea. In other words, when the MDP-based TM detects a recoverable error made by the *SimU*, the strategy it suggests and to which the *SimU* complies helps the latter to succeed each task more often.

Table 1. Simulated User's success rates when interacting with the CogWatch Simulator.

Type of tea	Assisted by TM	Ignoring TM
Black tea	86.7%	79.1%
Black tea with sugar	35.4%	16.3%
White tea	63.3%	43.9%
White tea with sugar	64.5%	19.1%

Table 2 shows the error rates of specific types of errors made by the *SimU* when trying to make a white tea with sugar, complying with and ignoring the Task Model. One can see that the TM's assistance results in significantly fewer toying and omission errors being made by the *SimU*. Defined by specialists working with cognitively impaired people, the errors highlighted in this table are part of the thirty errors the MDP-based TM is able to detect and to compensate with its strategy.

Table 2. Error rates of specific types of errors made by Simulated User's when making a white tea with sugar. E30 – sequence error: removing the teabag from the mug before adding hot water to it; E13 – toying error: misusing the water jug; E29 – omission error: omitting to stir the tea (if pre-defined as compulsory).

Type of error	Assisted by TM	Ignoring TM
E30	12.6%	12.7%
E13	9.4%	61.3%
E29	0.6%	0.9%

3. Discussion

In our experiments, we have shown that the assistance of the MDP-based Task Model integrated in a simulation of the current CogWatch System permits to increase the success rates of a virtually impaired simulated user for each type of tea. It also decreases the error rates of specific types of errors commonly performed by people suffering from apraxia. Thus, following the strategy provided by the TM helps the *SimU* to increase its task performance. We believe that similar results will be observed when experiments being run with real participants will come to an end. From an architectural and computational point of view, to have implemented this virtual simulation of CogWatch allowed us to validate the Task Model's capability to fulfill the requirements needed for the system to be an intelligent assistive device. In the future, the TM will be extended to other types of tasks, such as snack making and teeth brushing. The flexibility of its current structure already allows such extensions, but specific errors definitions will have to be defined and integrated. Another issue that will be tackled is the granularity of the actions the TM analyses. Indeed, we would like to deal with actions that are at a lower level of hierarchy. For example, we would like the TM to understand that if the patient fails adding an ingredient it is because an object is hold with a wrong grip, or because he/she fails other complex dexterous movements. Beyond these examples, numerous challenges remain such as the amount of human supervision needed by CogWatch.

Currently, when used with real participants, a clinician supervises CogWatch. This allowed us to make the assumption that the observations made by the AR of the user's state are always correct. As our goal is to have a fully automatic assistive device with as little human supervision as possible, in the next prototypes we will have to take into account the uncertainties associated to the AR. Indeed, the AR may misrecognize some actions performed by the user during the task, which means that the observations of the user's state received by TM might not be true all the time. Such uncertainties are inevitable, and as a MDP-based Task Model cannot cope with them, a solution will be to replace the MDP with a Partially Observable MDP (POMDP) [10] that can accommodate uncertainties in the state space. So, when the AR will output an observation, instead of choosing a strategy based on the most probable state, a POMDP-based TM will base it on a probability distribution over all states. In the context of a fully automatic system, we believe that such enhancements will permit obtaining a more accurate representation of the environment, and a more robust guidance under uncertainty.

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