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SULTAN: SIMULTANEOUS USER LEARNING AND TASK EXECUTION, AND ITS APPLICATION IN ASSISTIVE ROBOTICS

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INTRODUCTION

The main objective of this work is to present a mechanism called Simultaneous User Learning and TAsk executioN (SULTAN). In SULTAN the model of the user maintained by the system's learning module and the system's representation of the physical interaction tasks are concurrently refined (in analogy with SLAM), keeping explicit account of the user's own learning. The process is as such seen as a mutual adaptation learning process. It aims to augment the users' ability to perform daily tasks by a new concept of intelligent service robotic system capable of physical and cognitive collaboration. One of the potential applications is in assistive robotics (see Figure 1), and the main focus is on creating a human+robot binomial in which: a) the robotic system will use, not ignore, the human perception and cognitive abilities in order to safely achieve the tasks that would be too complex to perform in a purely autonomous way, and b) the human will not be a mere teleoperator of the robot but will take advantage of the acquired knowledge of the robotic system to augment her/his action and perception capabilities.

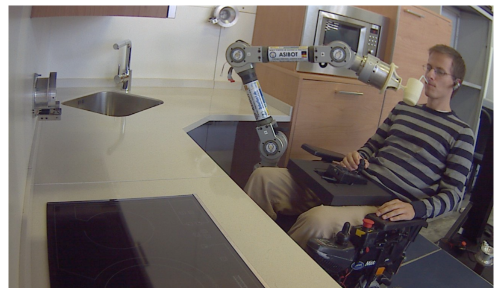

Figure 1. ASIBOT robot [1] working with a user in a real kitchen environment.

THE SULTAN CONCEPT

The SULTAN learning process is based on hierarchical Bayesian networks [2,3,4]. Building on the Bayesian Approach to Cognitive System (BACS) EU project, see for example [5], a probability is assigned to all possible interpretations of the available human+robot sensory and motor information, on the basis of sensory or motor noise and priors designating the most likely interpretation. The motor output (following a Robot Parametric Path, RPP, a parameterized and probabilistical representation of a given task) corresponds to the interpretation that has the most probable, or the most desirable, outcome. The SULTAN concept sets the problem in a user-task-object domain to solve the challenge of how to robustly perform a set of tasks for different users in different environments by the same robot, see Figure 2. For example, a situation where a user (Martin) commands the robotic system to perform a specific task (pick) with a specific object (can), using the user's perception abilities (eye tracking) and his satisfaction index (quality of the path). The storyline of the SULTAN system begins with the KDB (Knowledge Data Base) empty, except for some information of the robot and the user. During the first stage of SULTAN the user moves the robot in a fully teleoperated mode, using his/her knowledge and his/her perception, and interacting with the real world. The KDB is learning by the continuous updating of the RPPs parameters. While the user repeats the tasks, the robot's control changes from fully teleoperated to semi-autonomous mode with less and less intervention of the user. Some of the

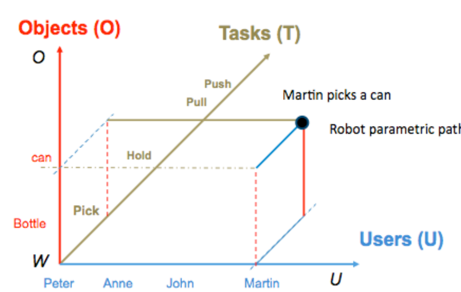

Figure 2. The SULTAN dimensional relationships.

parts of the RPP will be executed in a fully autonomous way. When the number of tasks is sufficient and the RPP parameters adjustment is finished, the robot can move fully autonomously using its own perception and control system and the updated KDB. The users only supervise the system. This process will be repeated for different users (Peter-pick-can), different tasks (Martin-hold-can) and different objects (Martin-pick-bottle), this way creating the full KDB. At this point the storyline is finished and the robot will work with a certain degree of autonomy.

FIRST IMPLEMENTATION

The scope of the software architecture required for realizing SULTAN ranges from high (user interaction-level) to low (hardware interaction-level) aspects of design. The multimodal interaction will be interpreted at a semantic level and used to plan a desired task. This process uses information that has been collected from the environment and the knowledge that exists about a given user (in the before-mentioned KDB). A learning agent generates this knowledge by observing the user inputs, task progress and contextual information, simultaneously learning with the user. The generated task is performed and monitored using information from the external sensors and the robot's own propioceptive sensors. Benchmarks for human performance on typical DLAs are being established. See for example the trajectories for two users (without disability) performing simplified DLAs in a virtual environment in Figure 3. These benchmarks can be used to put the performance of the human+robot binomial in perspective and to aid in the design of shared control and intent recognition capabilities. A pilot study was also performed, in the same environment, to investigate the adaptation of the interaction for a robot capable of providing physical assistance to disabled users. The subjects were three non-disabled users. A simple shared control scheme was implemented, which limits the velocity of the end-effector commanded by the user in the direction where obstacles are detected, proportionally to the distance measured. All sessions, except the control session, had Gaussian noise added which was low-pass filtered at 2 Hz and which increased in magnitude proportionally with the magnitude of the velocity commanded by the user. As it can be seen from Figure 4, the noise added did seem to have a negative effect of the performance of the subjects. The average Mean Time (MT) over subjects was increased from 6.15 to 10.04 seconds. This was seen even clearer in the predictive information metric, $I(A_t;A_{t+1})$, the mutual information across the shared control output (A) at subsequent moments in time [6]. This indicates this metric's sensitivity to the reduction in the "predictability" of the trajectories with the noise added. The shared control had a positive effect, reducing MT to 7.43 seconds. This improvement was seen also in the other two metrics, especially in the mutual information across the noise added, Z, and the shared control output, i.e. $I(Z_t;A_t)$.

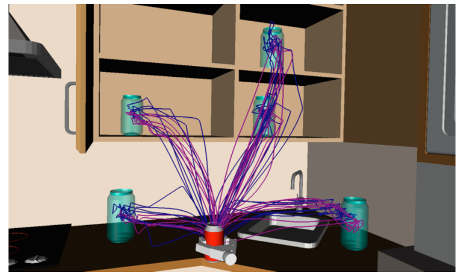

Figure 3. Trajectories for two users placing a can in a virtual kitchen.

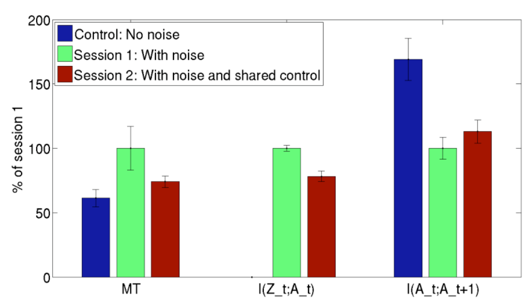

Figure 4. Preliminary results for the effect of noise and a simple shared control system.

CONCLUSIONS AND FUTURE WORK

In this paper we have presented the novel SULTAN concept as a mechanism that allows the augmentation of personal capabilities to perform daily tasks through the creation of a human+robot binomial in which physical and cognitive collaboration is achieved as a whole. The novelty of this approach is discussed and in order to demonstrate the applicability of the SULTAN idea, the first experimental results from its implementation have been given. Further research will focus on the implementation of the complete SULTAN architecture, closing the loops between all its levels and integrating it in different robotic systems, including assistive robots.

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