Developing Learning and Multi-Robot Coordination Techniques for Individuals with Physical Disabilities (Doctoral Consortium)

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ABSTRACT

The field of Human-Robot Interaction (HRI) has recently emerged as an area of research dedicated to understanding and evaluating robotic systems to be used by humans. Traditionally, HRI has focused on a psychological analysis of how an able-bodied individual can cooperatively accomplish tasks with a robot. Our work removes the assumption that the user is able-bodied, and focuses on developing interfaces and reinforcement learning tools for people with amyotrophic lateral sclerosis (ALS) and quadriplegia to effectively teach and use a personal assistant robot.

Those suffering from ALS and quadriplegia need robots in the world now, and cannot wait for full autonomy of every task. By applying a shared autonomy approach, we will develop a learning from demonstration algorithm that allows those with severe physical disabilities to teach the robot custom routines and give accurate feedback to guide the learning. This approach will be built upon the Robot Interactive Display Environment (RIDE) interface as a hands-free addition utilizing the Google Glass hardware.

Categories and Subject Descriptors

I.2.9 [**Artificial Intelligence**]: Robotics

General Terms

Algorithms, Design, Experimentation, Human Factors

Keywords

Human-Robot Interaction, Learning from Demonstration, Shared Autonomy

1. INTRODUCTION

Putting robots into real homes to help those with severe physical disabilities, such as amyotrophic lateral sclerosis (ALS) and quadriplegia, is a long-term goal for our research. Autonomy is one aspect of this goal, however, developing full autonomy for all household tasks for an individual is not possible. We propose to give the user the tools to teach the robot themselves, giving the disabled user both independence and personal customization.

We promote using a shared autonomy approach. We can separate the low-level reactivity from the higher level reasoning, and give the higher level reasoning task to the user. This gives the user far more control over the robot, relieving many of the issues of pure autonomy [2].

We will combine this approach with learning from demonstration. Using demonstration to initialize reinforcement learning provides supervised training data of what actions to perform in states that are encountered [4]. Using this initialization, the robot can perform the task to a small degree, and the user can take the role of a teacher, giving feedback.

However, our user base is people who suffer from severe physical disabilities. These individuals require specially designed interfaces and tools. This work will look at how to apply learning from demonstration for people who can't provide a good demonstration physically, and who cannot provide timely feedback to guide the learning.

## 2. LEARNING FROM DEMONSTRATION USING RIDE

The Robot Interactive Display Environment (RIDE) was developed by Karulf et al. to satisfy the need of a robotic control interface that allows a single user to effectively control a large number of robots [3]. In RIDE, operators are able to switch between direct control of a robot and supervisory control over all robots. This allows the operators as much control over the robots as the situation warrants.

Our first focus of research is to extend RIDE to be an interface for learning from demonstration. Traditionally, learning from demonstration requires the physical movement of the robot, which is inefficient, requires the human teacher to map their movement directly to the joint angles of the robot, and assumes an able-bodied user [4]. We propose two interfaces, one as an early interface for super users, and one for users with severe physical disabilities.

The interface for users without disabilities will take advantage of the direct first-person control aspect of RIDE and the usability of the Oculus Rift (Figure 1a) and Razer Hydra (Figure 1b) control systems. The Oculus Rift allows a user to see through the sensors of the robot, while the Hydra can compute the exact location and orientation of controllers in your hand, allowing the user direct control over robotic arms. Using these tools the user can teach the robot through demonstration, initializing the reinforcement learning algorithm to a fine level of detail.

(a) Oculus Rift
(b) Razer Hydra
(c) Google Glass
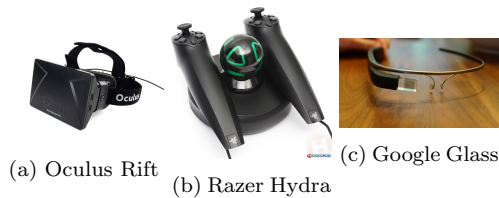
The interface for users without disabilities will use a less direct approach. The robot will come with basic learned autonomous functionality, such as turning knobs, movement and picking up objects. First, the user will give the robot a sequence of these high level actions to accomplish the overall task. The robot will simulate itself doing the task in RIDE. We will extend RIDE to give a movie reel style interface, allowing rewinding and fast forwarding of the robots simulation. The user can then provide feedback on a action or set of actions at their own speed. To combine the autonomous and learned routines the robot will be applying hierarchical reinforcement learning [1]. This shared autonomy approach allows the users to build custom routines for the robot to perform in a timely manner without direct knowledge of the reinforcement learning algorithm.

We will follow this research with a user study analyzing the effectiveness of the less direct approach.

3. SEMANTIC MAPPING WITH GLASS

Google Glass (Figure 1c) is a wearable computer with a head-mounted display and camera. It can be used hands-free through voice commands, making it ideal for users with disabilities. It can be used as a computer vision tool to classify objects in the world, however, without an extensive personal database, it cannot know the semantic meaning of all of the objects a user wants to classify.

This next focus of research will involve developing a shared autonomy approach between the user, Google Glass, and the robot. The user can label objects using the Glass interface, and have that semantic mapping wirelessly sent to the robot. This semantic mapping can then be used as additional information when learning by demonstration and when giving tasks to the robot.

4. MULTI-ROBOT COORDINATION

RIDE was originally created to allow one user to control many robots directly, or take a supervisory role. However, the current supervisory role can be expanded to include giving high level goals, such as bringing the user a book. Combining the abilities learned through demonstration in Section 2 and the semantic information obtained during object classification in Section 3, we can build a new interface allowing users to give high level goals to a group of robots. This interface will look like a classic real time strategy game, where user gives high level commands to a large number of troops.

When using RIDE to assign tasks, the user will be able to select one or more robots, and then select an object which has been given a semantic mapping. The RIDE interface will display to the user tasks that had been learned which involve interaction with this object and the selected number of robots. The selected robots will then coordinate to accomplish the task given to them by the user. These goal-based tasks will utilize previously learned actions from Section 2. For example, we have two robots, a PR2 and Turtlebot.

The PR2 is large and slow, but has limbs, while the Turtlebot has no ability to interact with the environment, but is fast. Through learning by demonstration the PR2 has learned to pick up a book, and has learned to set it down, and the Turlebot has learned to move from one location to another. If the user gave these robots a task to bring a book to himself, they can coordinate these smaller tasks together to perform the larger goal. The PR2 can put the book on the Turtlebot, and the Turtlebot can delver it.

To accomplish this, each robot will know what tasks it is capable of performing and how well it performs the task. They will will be able communicate this information with each other and coordinate. The previous example required three tasks: picking up book, setting down book, and moving. The PR2 will know it is efficient at the first two tasks, but slow at the third, where the Turtlebot knows it cannot perform the first two tasks, but performs the third task well. Applying this coordination allows simple robots to be able to perform much more complicated tasks.

5. CONCLUSION

Those suffering from ALS and quadriplegia need robots in the world now, and cannot wait for full autonomy of every task. This work intends to help those suffering from severe physical disabilities by giving them the ability to teach the robot themselves, as well as easily give positive and negative feedback. By using our shared autonomy approach we separate the low-level reactivity from the higher level reasoning, and give the higher level reasoning task to the user.

This work also helps further the state of the art in reinforcement learning by introducing a new learning from demonstration technique that utilizes human demonstration from non-experts. This requires robots to learn from human demonstrations, even when those demonstrations are highly suboptimal. It also furthers the field in robot coordination, allowing a robot to evaluate its own performance, and utilize that information to efficiently coordinate.

With these new interfaces and tools, individuals with disabilities will be able to accomplish day-to-day tasks without human assistance. The lack of a human assistant performing the task and the addition of positive experiences like teaching, doing it yourself, and being more independent gets us closer to our goal of putting robots into real homes to help those with physical disabilities.

6. REFERENCES

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