Developing Learning from Demonstration Techniques for Individuals with Physical Disabilities

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 using a shared autonomy approach, we will develop a learning from demonstration algorithm that allows those with severe physical disabilities to teach custom routines to the robot 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.

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, but 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 full 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.

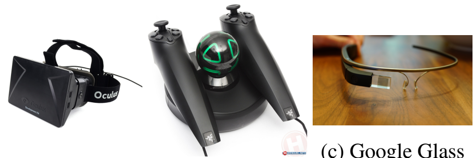
2. LEARNING FROM DEMONSTRATION WITH RIDE

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 efficiently teach the robot through demonstration.

The interface for users with disabilities will use a less direct approach. The robot will come with a motion library of basic autonomous functions, such as turning knobs 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 robot's simulation. The user can then provide feedback on an action or set of actions at his or her 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



(a) Oculus Rift (b) Razer Hydra (c) Google Glass

Figure 1: State-of-the-art hardware tools for providing effective demonstrations.

in a timely manner without direct knowledge of the reinforcement learning algorithm.

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, but without an extensive personal database it cannot know the semantic meaning of all of the objects a user wants to classify.

We plan on developing a shared autonomy interface wherein 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. LEARNING FROM DEMONSTRATION IN HIGH-DIMENSIONAL SPACES

State-of-the-art personal robots need to perform complex manipulation tasks to be viable in assistive scenarios. These complex manipulations require high degree-of-freedom arms and manipulators. For example, the PR2 robot is built with two 7 DoF arms. When learning position, velocity and acceleration control, this leads to a 21 dimensional state space for a single arm. Learning in these large dimensional spaces quickly becomes computationally intractable without optimization techniques. Furthermore, personal robots need to generalize learned motor skills between similar tasks, which in these high dimensional spaces also quickly becomes difficult [5].

To handle these high-dimensional spaces, our plan is to first perform dimensionality reduction (e.g. Principal Component Analysis) on a set of trajectories the user demonstrated to the robot while performing a task. We then transform the high-dimensional space to the first principal component, learn trajectories using the new subspace, and transform back to the high-dimensional space. By transforming to a smaller subspace, learning from demonstration techniques will converge faster to a solution.

In addition to faster learning, we hypothesize that transforming trajectories to a lower dimensional space will allow us to more efficiently parameterize the task-based motor primitives. By parameterizing the motor primitives, we will be able to generalize motor skills to similar tasks, reducing the number of different demonstrations required. Additionally, we know that transforming to a lower dimensional space essentially smooths the trajectory. We hypothesize that this makes the learning more robust to suboptimal outliers caused by human error in the demonstration.

Increasing the robustness to human error in demonstrations and reducing the number of demonstrations are essential aspects of this research. Since we work with individuals with disabilities, demonstrations are difficult, and suboptimal demonstrations are expected.

Preliminary work has shown that while performing a complex sheet folding task, the first principal component represents 58% and 33% of the variance in position and velocity. Additionally, first three principal components represent 85% of all of the variance in the position data and 75% of all of the variance in velocity data. This reinforces the hypothesis that we can reduce the high-dimensional state space to a lower-dimensional space and still represent most of the given trajectory.

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 to 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. By transforming high-dimensional learning from demonstration trajectories to a lower-dimensional space, we hypothesize that we this approach will assist in generalizing between similar tasks, as well as increase the robustness of learning trajectories with suboptimal outliers.

With these new interfaces and tools, individuals with disabilities will be able to accomplish day-to-day tasks without assistance from others. The lack of a human assistant performing the task and the addition of positive experiences like teaching, doing it yourself, and being more independent increases the quality of life for peoples with extreme disabilities.

6. REFERENCES

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