Developing Learning from Demonstration Techniques for Individuals with Physical Disabilities

William Curran
Oregon State University
Corvallis, Oregon
curranw@onid.orst.edu

ABSTRACT

Learning from demonstration research often assumes that the demonstrator can quickly give feedback or demonstrations. Individuals with severe motor disabilities are often slow and prone to human errors in demonstrations while teaching. Our work develops tools to allow persons with severe motor disabilities, who stand to benefit most from assistive robots, to train these systems. To accommodate slower feedback, we will develop a movie-reel style learning from demonstration interface. To handle human error, we will use dimensionality reduction to develop new reinforcement learning techniques.

1. INTRODUCTION

The main goal for our research is to put robots into real homes to help those with severe physical disabilities. These individuals have minimal ability to move and speak, and need extended care all day, every day. The strain on families needing to take care of these individuals is enormous, and it has been shown that inexperienced family caregivers use prescription drugs for depression, anxiety, and insomnia two to three times more often than the average population [2]. Robotics can be used to assist those with extreme disabilities and remove much of this burden on the family.

These disabled individuals are often non-experts, and currently cannot be part of the development process. Yet, most don't want to wait for someone to program autonomous behaviors for all household tasks. We propose to give disabled non-expert users the tools to teach the robot these tasks by themselves. This will give the disabled user both independence and personal customization.

We use a learning from demonstration approach to allow disabled users to teach their assistive robot. In learning from demonstration, users show the robot what actions to execute to perform a task. These user demonstrations are training data for the reinforcement learning algorithm [3]. Using this initialization, the robot can attempt to perform the task, and the user can give feedback as a teacher. Good demonstrations and timely feedback are key assumptions in learning from demonstration approaches [1]. However, our user base is people who suffer from severe physical disabilities. They can't provide a good or timely demonstrations or feedback to guide the learning. These individuals need specially designed interfaces and tools.

State-of-the-art personal robots also need to perform complex manipulation tasks to be viable in assistive scenarios. These complex manipulations need high degree-of-freedom arms and manipulators. The complexity of these robots lead to large dimensional state spaces, which are difficult to learn in. Additionally, the generalization of motor skills to similar tasks become especially important when demonstrations are difficult to perform. This also becomes more difficult in higher-dimensional state spaces.

The contributions of the completed work will be to develop a movie-reel style interface for detailed, time insensitive feedback. This gives the user as much time as they need for demonstrations and feedback. We will also develop a robust, generalizable, and fast learning from demonstration technique. We transform a high-dimensional demonstration to a low-dimensional space. We then perform reinforcement learning in that space, and then execute the learned trajectory back in the high-dimensional space. This reduces the number of demonstrations and increases the resistance to sub-optimal outliers. These are desirable characteristics for non-expert use of the learning algorithm.

HRI'15 Extended Abstracts, March 2–5, 2015, Portland, OR, USA.
ACM 978-1-4503-3318-4/15/03.
http://dx.doi.org/10.1145/2701973.2702710.

2. RELATED WORK

Developing a trajectory using traditional reinforcement learning does not work well in robotics. Finding an optimal or near-optimal solution requires exploration throughout much of the state space. Excessive exploring of the unknown state space risks damaging the robot. Small steps during exploration avoids this problem, but this brings the additional problem of taking longer to find an optimal solution. Initializing, or bootstrapping, the trajectory close to the desired robot behavior removes many of these problems. One approach to this initialization is learning from demonstration.

One current learning from demonstration research focus is on generalizing motor skills to similar tasks. Pastor et al. uses dynamic motor primitives to perform movement generation and generalization to a new goal [5]. However, this approach does not work well with uncertainty. Lee et al. developed belief space learning from demonstration techniques, taking into account uncertainty during learning [4]. In current research, learning from demonstration requires the human teacher to map their movement directly to the joint angles of the robot and assumes an able-bodied user [3].

3. LEARNING FROM DEMONSTRATION INTERFACES

We need to develop a learning from demonstration interface that allows disabled users to teach their assistive robot at their own speed. We propose two interfaces: an early interface for super users, and one for users with severe physical disabilities. In this work we will use RViz, a ROS [6] package that assists users in the visualization of robotic movements and sensors. Our first focus of research is to extend RViz to be an interface for learning from demonstration.

The interface for users without disabilities will take advantage of the direct first-person control aspect of RViz. We will also use the Oculus Rift and Razer Hydra control systems. The Oculus Rift allows a user to see through the sensors of the robot, while the Hydra controls the robot. The Hydra control system computes the exact location and orientation of controllers in your hands, allowing the user natural control of the 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 perform the task. The robot will simulate itself doing the task in RViz. We will extend RViz with a movie-reel style interface for 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. This learning from demonstration interface allows the users to build custom routines for the robot without direct knowledge of the reinforcement learning algorithm.

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 need high degree-of-freedom arms and manipulators. For example, the PR2 robot has two 7 DoF arms. When learning position, velocity and acceleration control, this leads to a 21 dimensional state space per arm. Learning in these large dimensional spaces becomes computationally intractable without optimization techniques. Furthermore, personal robots need to generalize learned motor skills between similar tasks. This also becomes difficult in these high-dimensional spaces [5].

To handle these high-dimensional spaces, our plan is to first perform dimensionality reduction on a set of demonstrated trajectories. We will use Principal Component Analysis to transform the high-dimensional space to a subspace. We then 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.

By parameterizing the motor primitives, we will be able to generalize motor skills to similar tasks. This will reduce the number of different demonstrations required. We hypothesize that transforming trajectories to a lower dimensional space will make it easier to parameterize the task-based motor primitives. Additionally, dimensionality reduction smooths the lower-dimensional trajectory. We hypothesize that this makes the learning more robust to suboptimal outliers caused by human error. Increasing the robustness to human error in demonstrations and reducing the number of demonstrations are essential. Since we work with individuals with disabilities, demonstrations are difficult, and expect suboptimal demonstrations. Since demonstrations are difficult, fewer demonstrations are also a desirable quality.

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 the variance in the position data and 75% of all the variance in velocity data. This reinforces the hypothesis that we can represent a high-dimensional trajectory in a low-dimensional space.

5. EVALUATION

To analyze the initial efficacy of the movie-reel style interface there will be a within-subjects study, in which the users will be able-bodied. We will take objective measurements such as the total task time and the user's cognitive load, as well as subjective measurements with questionnaires. We will then perform another study with individuals from an ALS house that have previously worked with our lab. Comparing the results will give us a full understanding of the efficacy of the interface. To analyze our dimensionality reduction research, we will compare learning speed and efficiency to the dynamic motor primitive work by Pastor et al. [5] and the belief state planning by Lee et al. [4].

6. CONCLUSION

Those suffering from ALS and quadriplegia need assistive robots now. These individuals cannot wait for someone to program autonomous behaviors for all household tasks. This work intends to help those suffering from severe physical disabilities by giving them the ability to teach the robot themselves.

This work introduces 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 suboptimal. By learning in a lower-dimensional space, we hypothesize that it will be easier to generalize between similar tasks, as well as ease the learning of trajectories with outliers.

With these new interfaces and learning advances, individuals with disabilities will be able to do day-to-day tasks without help 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 people with extreme disabilities.

7. REFERENCES

[1] Argall, B. D., Chernova, S., Veloso, M., and Browning, B. A survey of robot learning from demonstration. *Robot. Auton. Syst. 57*, 5 (May 2009), 469–483.

[2] Gallagher, D., Rose, J., Rivera, P., Lovett, S., and Thompson, L. W. Prevalence of depression in family caregivers. *The Gerontologist 29*, 4 (1989), 449–456.

[3] Kober, J., Bagnell, J. A. D., and Peters, J. Reinforcement learning in robotics: A survey. *International Journal of Robotics Research* (July 2013).

[4] Lee, A., Duan, Y., Patil, S., Schulman, J., McCarthy, Z., van den Berg, J., Goldberg, K., and Abbeel, P. Sigma hulls for gaussian belief space planning for imprecise articulated robots amid obstacles. In *Proceedings of the 26th IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (2013).

[5] Pastor, P., Hoffmann, H., Asfour, T., and Schaal, S. Learning and generalization of motor skills by learning from demonstration. In *International Conference on Robotics and Automation (ICRA2009)* (2009).

[6] Quigley, M., Conley, K., Gerkey, B. P., Faust, J., Foote, T., Leibs, J., Wheeler, R., and Ng, A. Y. ROS: An open-source robot operating system. In *ICRA Workshop on Open Source Software* (2009).