A Human Robot Interaction Framework for Robotic Motor Skill Learning

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ABSTRACT

A considerable amount of research in the field of human-robot interaction has shown that a human teacher can be an integral component during the learning process of a robot. In this paper, we propose a learning framework that is based on learning from demonstration at a trajectory level. Specifically, we illustrate a scenario where the Sawyer Robotic Arm must learn to pick and place a specific object according to the demonstration of a human teacher. The purpose of the experiment is to facilitate the effectiveness of the proposed method.

CCS Concepts

•Computer systems organization → External interfaces for robotics;

Keywords

Human Robot Interaction, Kinesthetic Teaching, Machine Learning, Neural Networks

1. INTRODUCTION

Learning new motor tasks online while adapting to environmental changes is important for human robot interaction. To cope with the complexity involved in motor skill learning, robots could rely on the insight that humans have when it comes to the decomposition of motor tasks into smaller subtasks. We will address these movement patterns as motor primitives. Thus, motor primitives are a sequence of motor commands, which can accomplish a given task. Learning from demonstration can provide a good framework for motor skill learning as it allows an efficient acquisition of motor primitives through kinesthetic teaching [1], [2].

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2. SYSTEM OVERVIEW

In this section we illustrate an overview of the proposed system. Figure 1 shows the primary modules of the system. Initially, a human is expected to demonstrate the desired task by physically manipulating the robotic arm. During the demonstration, the state of the robot, the users input and any environmental parameter that associate with the given task, will be recorded. These data will be stored in the Library of Motion primitives. Traditionally, data that represent a series of continuous events, such as the data representing the state of the robot, can be exploited with dimensionality reduction techniques. A mapping between the state of the robot (s) and state of the environment (δ) to the actions of the human (α) that were captured during the performance of a demonstration will represent a primitive motion. To generate a new motion, the system learns a policy π(s, δ) = α that maps the captured actions of the user (α), with the equivalent augmented states (s, δ). The policy will be computed by combining each primitive motion according a weight that is assigned from a gating network. Once the policy is learned, the robot is expected to perform a particular action by interpolating between the different primitive motions given the augmented state.

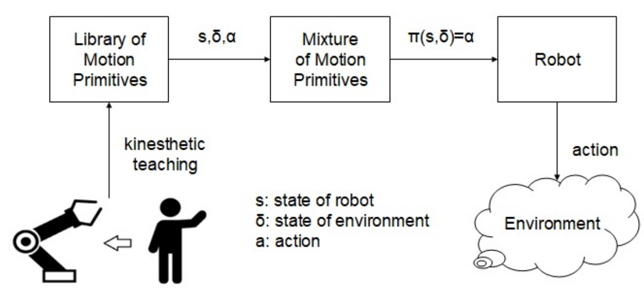

Figure 1: System Overview.

3. KINESTHETIC TEACHING

In this section we will describe an experimental set-up to facilitate the effectiveness of the proposed system. Let us consider the scenario illustrated in Figure 2. The human teaches a robot to pick the objects on the table and place them in the bucket, while the state of the robot and the position of the objects (blue cubes in Figure 2) are being recorded. To achieve this, the human has to grab the end effector of the robot, move it in an appropriate position for the robot to grab the object, order the robot to close the gripper, guide the end effector of the robot to the goal (the black bucket) and then command the robot to open its gripper again, so that the object falls in the bucket.

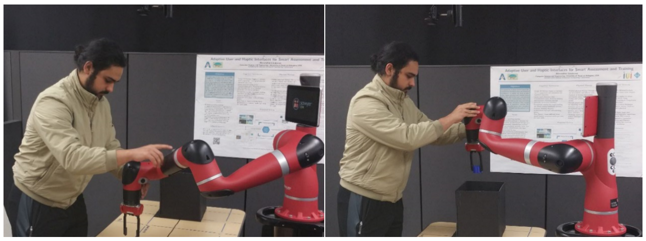

Figure 2: Kinesthetic Teaching.

4. MIXTURE OF MOTION PRIMITIVES

Each demonstration will be learned in a supervised manner by estimating a non-linear function from the equivalent (s, δ) to (α). To achieve this, we will employ shallow sigmoid feed forward neural networks which act as function approximators. Figure 3 below depicts the role of each expert neural network in the overall module of the system which constitutes a mixture of experts architecture [4], [3]. The gating network acts as a soft-max layer that assigns a probability to each expert according to the state of the robot and the environment. The final output is the weighted sum of all the experts according to their assigned probability.Thus, the role of the Mixture of Primitive Motion module is to act as a manager neural network that decides, which is the most efficient local estimation that represents a Primitive Motion.

Note, that to increase the training time of the network, certain preprocessing techniques can be applied. Redundant experts can be eliminating by classifying the different input state and action trajectories in an unsupervised learning manner. This means that an expert may specializes in a cluster of similar trajectories. Moreover, research has shown that before the clustering of the trajectories, data that represent a series of continuous events, such as the data representing the state of the robot, are susceptible for to dimensionality reduction techniques. Lastly, it must be mentioned that the expert neural networks and the gating network will be trained separately.

5. EXPERIMENTAL RESULTS

In this section we will briefly present simulated experimental results, which were produced through the conduction of two kinesthetic teaching sessions with the Rethink Robotics Sawyer Robotic Arm. In Figure 4, each expert (1 & 2) represents a recorded trajectory acquired through kinesthetic teaching. The Mixture of Motion Primitives module acts as a high level manager that decides, how much each local expert is going to contribute in the construction of the final learned motor skill.

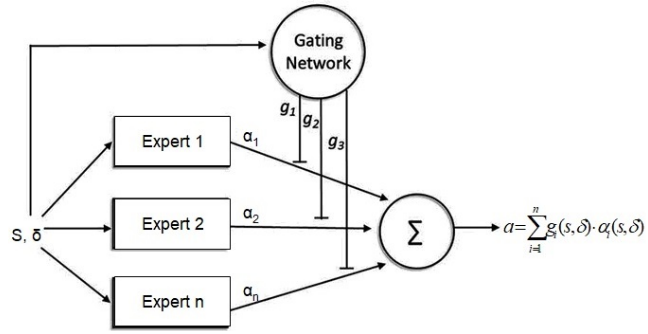

Figure 3: Mixture of Motion Primitives Architecture.

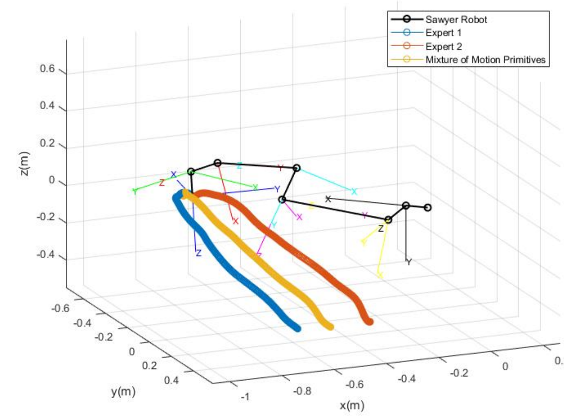

Figure 4: Experimental Results.

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7. REFERENCES

[1] B. Akgun, M. Cakmak, J. W. Yoo, and A. L. Thomaz. Trajectories and keyframes for kinesthetic teaching: A human-robot interaction perspective. *Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction*, pages 391–398, 2012.

[2] K. Gräve, J. Stückler, and S. Behnke. Learning motion skills from expert demonstrations and own experience using gaussian process regression. In *Robotics (ISR), 2010 41st International Symposium on and 2010 6th German Conference on Robotics (ROBOTIK)*, pages 1–8. VDE, 2010.

[3] M. I. Jordan and R. A. Jacobs. Hierarchical mixtures of experts and the em algorithm. *Neural computation*, 6(2):181–214, 1994.

[4] M. I. Jordan and D. E. Rumelhart. Forward models: Supervised learning with a distal teacher. *Cognitive science*, 16(3):307–354, 1992.