Task Space Behavior Learning for Humanoid Robots using Gaussian Mixture Models

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Abstract

In this paper a system was developed for robot behavior acquisition using kinesthetic demonstrations. It enables a humanoid robot to imitate constrained reaching gestures directed towards a target using a learning algorithm based on Gaussian Mixture Models. The imitation trajectory can be reshaped in order to satisfy the constraints of the task and it can adapt to changes in the initial conditions and to target displacements occurring during movement execution. The potential of this method was evaluated using experiments with the Nao, Aldebaran's humanoid robot.

Introduction

Learning by Demonstration is a wide area of research by which we are able to teach a robot new behaviors without extensive programming. A human, playing the role of the demonstrator, has the task of effectively communicating the required behavior to the artificial learning agent through various methods of interaction. The mode of interaction that is used in this paper is Kinesthetic Teaching, whereby the human communicates behaviors by manually controlling the robots end-effectors. This form of interaction is less prone to error as the correspondence problem is simplified. However it is important to understand the limitations associated with the demonstrator as well as the imitator. Demonstrating complex tasks which involve controlling multiple robot actuators in parallel, can be impossible for a single human and similarly the complexity of the task is limited by the hardware and software capabilities of the robot. A complex robot task, involving a set of motor actions to be performed in a sequential manner, is decomposed into known sets of actions, performable by both the demonstrator and the imitator. This step helps in extracting and encoding low-level features, e.g. primitives of motion in joint and task space. A recent survey (Argall et al. 2009) summarizes the current algorithms used for Learning by Demonstration.

The approach used focuses on learning reaching gestures by extracting and generalizing the constraints associated with the task. Gaussian Mixture Models (GMM's) are ideal for efficient learning as they are robust to noise, can efficiently generalize, and can capture correlations between continuous features (constraints). Gaussian Mixture Regression (GMR) is then performed on the learned model to reproduce the required task trajectory. It is known that Gaussian process regression does not scale with an increase in the dimensions of the state space. This makes them inefficient for online learning in robots with large degrees of freedom. For such cases, the framework employs a form of Approximate Nearest Neighbor Search (ANNS) (Arya et al. 1998) to efficiently compute the required task trajectory. The framework was tested by performing reaching gestures like Obstacle Avoidance and Ball to Goal tasks and it was observed that the model was able to adapt to unseen conditions and unexpected online perturbations with minimal user interaction.

The next section briefly introduces the concept of Task Space Learning and generalization of continuous data using GMM's. The last section discusses the Experiments and Results, followed by the Concluding remarks.

Task Space Trajectory Learning

Given a behavior in the task space, it is important for us to characterize the set of constraints that are vital to completing the task. Consider an example - let state A represent the starting position of a robot, state B represent the position of a ball and state C represent the position of the goal. The aim is to move the robot from start position (A) to the ball (B) and take it to the goal (C). The constraints for such a task can be achieved by calculating, at each time step, the relative positions of the robot with respect to the ball and goal. Therefore given the cartesian coordinates of the robots actuators from the demonstrations, we calculate the relative distances with respect to the ball and goal. The state space (dimensions of the constraint data) is dependent on the number of the robot actuators required for the task. The extracted constraints, being continuous and highly correlated, are temporally aligned, sampled and generalized using Gaussian Mixture Models.

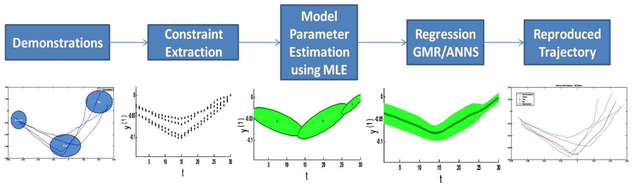

Figure 1: Block diagram explaining the individual steps of the algorithm.

Gaussian Mixture Models

Mixture modeling is a popular approach for generalizing continuous correlated data (Calinon and Billard 2008). A probabilistic representation of the sampled constraint data was used to estimate these correlations across the constraint variables. A mixture model consisting of K components is defined by the probability density function:

$$p(\epsilon_j) \quad = \quad \sum_{k=1}^{K} p(k)p(\epsilon_j|k) \tag{1}$$

where ϵ_j is the input dataset, K is the number of Gaussian components, $p(k)$ the Priors and $p(\epsilon_j|k)$ is the Gaussian function represented by,

$$p(\epsilon_j|k) = \frac{1}{\sqrt{(2\pi)^D|\Sigma_k|}} e^{-1/2((\epsilon_j-\mu_k)^T\Sigma_k^{-1}(\epsilon_j-\mu_k))} \tag{2}$$

From the above equation, we need to calculate the mean μ_k, covariance matrices Σ_k and priors $p(k)$. The value of K is task specific and can be estimated by trial and error or by using the Bayesian Information Criterion (BIC). These statistical parameters of the model are computed using Maximum Likelihood Estimation (MLE). Depending on the dimensions of the state space, regression is performed on the model using a combination of the ANNS algorithm (Arya et al. 1998) and GMR (Calinon and Billard 2008) to reconstruct trajectories for new unseen conditions. An overall layout of the steps of the algorithm is shown in Figure 1.

Experiments and Results

Three experiments were performed with the Nao robot to test the validity of the framework. The Nao has 25 degrees of freedom and the experiments utilized the robot arm chains. *Fawkes*, *http://www.fawkesrobotics.org*, an open source robot software designed for the Robocup platform, was used to communicate with the Nao. The reaching gestures that were used for testing were Robot Arm Obstacle Avoidance and a Ball to Goal task. A video of the outcome of these tests is available online at *http://www.ece.rutgers.edu/∼kausubbu/research.html*. Each of these tasks was given 4 to 10 demonstrations on which the generalization was performed. Results:

- The generalized model was robust to the noise associated with the servo motors of the robot. The memory utilized in these experiments was very small as only the means and covariance matrices needed to be stored.
- The robot was successful in completing the defined tasks in positions and orientations that were not included in the demonstrations.

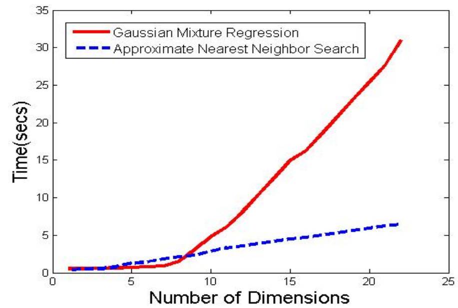

Figure 2: Comparison of Computation Time between the GMR and ANNS regression models

- We tested the robustness of model to sudden changes in the positions of the objects while the robot was executing the behavior. The model was able to overcome the online perturbations and go on to complete the task.
- When using many of the robots actuators, it was observed that GMR was accurate up to 7 dimensions (Figure 2), above which it started to slow down the computations. However the experiments showed that ANNS was efficient for online learning of tasks up to 20 dimensions.

Conclusion

This paper offers a brief overview of a probabilistic framework that extracts the essential features characterizing a skill by handling constraints in task space. Using a robot, it was demonstrated that the GMM approach along with appropriate regression models (ANNS, GMR) could be applied successfully to learn generically new behavioral skills. The limitations of the system are that the task space constraints do not completely satisfy the high levels of accuracy required in real world models. The reproduced trajectory at times contains sharp unexpected movements while attempting to reach the goal. Further work will focus on building a kinematics model that will take into account joint space constraints.

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