DMP-Based Cartesian Trajectory Learning from Multiple Demonstrations

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ABSTRACT

Robot learning plays a critical role in the field of robotics, particularly in industrial applications where robots are required to perform complex, repetitive tasks with high precision. Traditional motion planning methods are often time-consuming and struggle with environmental changes, limiting their use in dynamic settings when tackling complex tasks such as assembly, manipulation, and human-robot collaboration. With the increasing demand for robots capable of handling complex tasks, robot learning methods that can autonomously learn from demonstrations and adapt to new scenarios are gaining importance. Learning from Demonstration (LfD) has emerged as a powerful approach in this domain, allowing robots to acquire skills by observing demonstrations. This method enhances the robot's adaptability to complex environments while reducing the time and costs associated with reprogramming[1].

Dynamic Movement Primitives (DMPs) provide a robust LfD method, known for their high adaptability, reliability, and strong performance in encoding complex trajectories. However, DMPs are traditionally limited to learning from a single demonstration. To address this, Prados [2] et al. introduced a DMP-based Gaussian Model Regression (GMR) approach to analyze multiple demonstrations and generate new imitating trajectory. With its strength in handling uncertainties, Fanger [3] et al. proposed integrating DMPs with Gaussian Processes Regression (GPR) to learn from multiple demonstrations. Despite its advantages, GPR complexity remains a challenge, particularly for large datasets. Another limitation of DMPs is their reliance solely on positional data, making it difficult to express trajectories in Cartesian space. Ude [4] et al. improved and extended the classic DMP to represent trajectory orientation, developing DMPs based on rotation matrices and quaternion method respectively.

To enhance the overall capability of trajectory learning, we integrate classic DMP for position with quaternion DMP for orientation, while employing sparse GPR to improve adaptability across multiple demonstrations. This framework enables simultaneous learning of both position and orientation, with GPR predicting non-linear terms from demonstrations. The use of sparse representation reduces computational complexity, making the approach more efficient.

In the proposed framework, the principle of DMP is to transform the simple attractor dynamic system model into a nonlinear dynamic system through the learning of attractor landscapes to generate the desired goal. The DMP model could be consider a damp and spring system which present by the equations (1) and (2). Meanwhile the quaternion DMP can be writen as euqations (3) and (4).

Table 1: Classic and Quaternion DMP

	Classic DMP	*Quaternion DMP*
Main part	$\tau\dot{z} = \alpha_z(\beta_z(g-y)-z)+f(x)$ (1) $\tau\dot{y} = z$ (2)	$\tau\dot{\eta} = \alpha_q(\beta_q \log(q_g \cdot \bar{q}) - \eta) + f_0(x)$ (3) $\tau\dot{q} = \frac{1}{2}\eta \cdot q$ (4)
Non-linear term	$f(x) = \frac{\sum_{i=1}^{N}\varphi_i(x)w_i}{\sum_{i=1}^{N}\varphi_i(x)}(g-y_0)$ (5)	$f_0(x) = \frac{\sum_{i=1}^{N}\varphi_i(x)w_i}{\sum_{i=1}^{N}\varphi_i(x)} \cdot 2\log(-q_g \cdot \bar{q}_0)$ (6)
Gaussian function	$\varphi_i(x) = \exp(-h_i(x-c_i)^2)$ (7)	
Canonical system	$\tau\dot{x} = -\alpha x$ (8)	

In Table 1, the parameters α and β are positive time constants, τ is a temporal scaling factor, g is the attractor point and q_g is the goal quaternion, y and $\dot{y}$ correspond to the position and velocity respectively, f and f_0 are the non-linear term, Equation (7) is Gaussian function and equation (8) is the canonical system.

GPR is a Bayesian non-parametric regression method widely used for modeling complex functional relationships[5]. The advantage of GPR lies in its ability to naturally quantify uncertainty in the predictions without requiring a predefined functional form, making it robust in applications with small sample sizes or noisy data. The probability model of GPR $p(y_* \mid X, y, x_*) \sim \mathcal{N}(\mu^*, \Sigma^*)$ is build by observing the mapping from inputs X and outputs y to predict the values at new input locations x_*, the mean μ^* and covariance Σ^* of the new output y_* are computed as $\mu^* = k(x_*, X)\left[K(X,X)+\sigma_n^2 I\right]^{-1} y$ and $\Sigma^* = k(x_*, x_*) - k(x_*, X)\left[K(X,X)+\sigma_n^2 I\right]^{-1} k(X, x_*)$. Here $k(x_*, x)$ is kernel function, $k(x_*, X)$ is the covariance vector between the test point x_* and the training points X, $K(X,X)$ is the

 DOI: 10.17185/duepublico/82615

covariance matrix of the training points, σ_n^2 is the noise variance. The time complexity of GRP is $O(n^3)$, n is number of samples. To mitigate this limitation, the K-means clustering algorithm is used to to select the inducing point, thereby enabling the construction of Sparse GPR. This approach reduces the complexity to $O(n^2m)$, m is the inducing number chose by the K-means algorithm.

The proposed approach is evaluated through a simulation experiment where a robot arm grasps a cylindrical object initially positioned horizontally on a lower platform and places it upright on a higher platform as shown in Figure 1, involving the adjustment of the object's orientation from horizontal to vertical. The process begins by constructing a dataset comprising multiple Cartesian trajectories, which are generated with the assistance of human guidance over time. Each trajectory's position and orientation are then analyzed separately using both classic DMP and quaternion DMP to compute the corresponding non-linear term. Sparse GPR is subsequently applied to derive the final non-linear term. Following the learning phase, the robot arm is capable of autonomously executing the pick-and-place task. This ability persists even when the pick-and-place locations or the object's orientation vary. The Figure 2 illustrates the execution of the proposed method. The demonstration trajectory includes three components of position data (x, y, z) and four components of quaternion orientation data (q_w, q_x, q_y, q_z), shown in the upper and lower parts, respectively. Each dimension's force term is computed, with the GPR-based probability distribution indicated by the blue dashed area. The mean output serves as the force term, enabling DMP to compute the generated Cartesian trajectory.

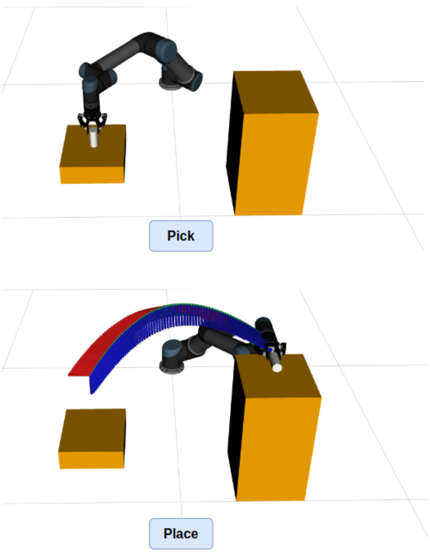

Figure 1: Robot Pick and Place

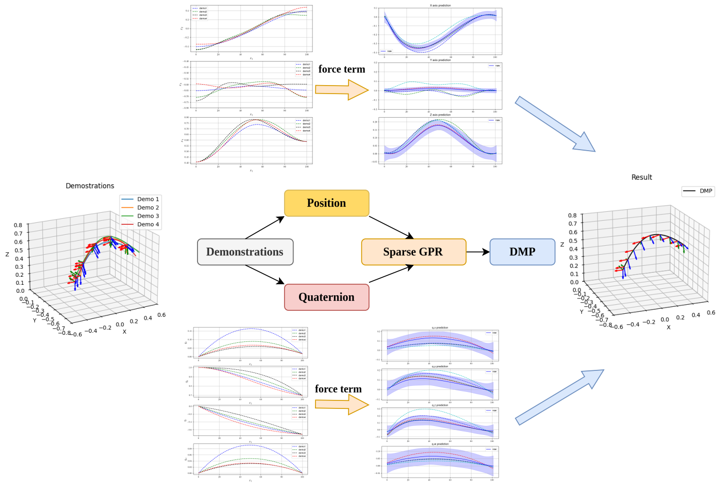

Figure 2: DMP based Cartesian trajectory learning

This abstract presents a trajectory learning process in Cartesian space by combining classic DMP with quaternion DMP. To enhance efficiency, we optimized the approach using sparse GPR, allowing for learning from multiple demonstrations with reduced computational complexity. The proposed method was evaluated through a robotic arm learning pick-and-place task, demonstrating its effectiveness. It provides a robust foundation for robot learning in more complex tasks and environments.

Acknowledgments

This research did not receive any specific funding or financial support.

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DOI: 10.17185/duepublico/82615
URN: urn:nbn:de:hbz:465-20241118-135814-9

1st IFToMM Young Faculty Group Symposium on Emerging Fields in Mechanism and Machine Science 2024: 19.11. - 21.11.2024, Online Symposium