An Improved Coupling Strategy for Obstacle Avoidance in Dynamic Movement Primitives

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Abstract: Dynamic Movement Primitives (DMPs) are widely used in robotic trajectory generation and imitation learning due to their stability, parameter tunability, and generalization capability. However, most existing DMP-based obstacle avoidance methods rely on conventional artificial potential fields, which often suffer from trajectory oscillations, shape distortion, and loss of demonstrated features in complex environments. To address these issues, this paper proposes an obstacle-avoidance trajectory generation method for DMPs based on an improved artificial potential field. By incorporating an exponential distance attenuation function and a velocity-direction modulation mechanism into the coupling term, the proposed method achieves improved continuity and stability of the obstacle avoidance force in both spatial and directional domains, enabling adaptive local deformation of demonstrated trajectories. While preserving the original convergence property and modular structure of DMPs, the proposed approach significantly enhances trajectory smoothness and obstacle avoidance stability in both single- and multi-obstacle scenarios. Simulation results based on handwritten trajectory data demonstrate that the proposed method outperforms the conventional artificial potential field and steering-angle methods in terms of minimum error and root-mean-square error (RMSE), while better preserving demonstrated trajectory features.

Keywords: Dynamic movement primitives; Trajectory planning; Obstacle avoidance

1. Introduction

With the rapid development of intelligent manufacturing and service robotics, the demand for autonomous robotic manipulation in industrial assembly, collaborative operations, and complex environments has been steadily increasing. Traditional robot trajectory planning methods typically rely on predefined models, static environment assumptions, or strict dynamic constraints, which limits their adaptability to real-time obstacle avoidance and flexible trajectory generation in dynamic environments. Learning from Demonstration (LfD), as an efficient imitation learning paradigm, enables robots to autonomously acquire new skills by imitating human-provided demonstration trajectories, allowing rapid adaptation to diverse and dynamic industrial scenarios without frequent manual reprogramming [1,2].

Among various LfD approaches, Dynamic Movement Primitives (DMPs) have been widely adopted for robotic motion generation due to their stable convergence properties, parameter tunability, and strong generalization capability [3]. DMPs can reproduce target motions from demonstrations and incorporate external coupling terms, making them suitable for real-time obstacle avoidance and dynamic environment adaptation [4]. However, the coupling terms in classical DMPs are usually manually designed and often struggle to simultaneously ensure obstacle-avoidance stability, trajectory smoothness, and generalization performance.

Standard DMP-based obstacle avoidance methods exhibit limited adaptability in high-dimensional or constrained workspaces, and may suffer from unstable avoidance forces, unsmooth trajectories, or insufficient responsiveness to dynamic obstacles. To address these limitations, this paper proposes a DMP trajectory generation method based on an improved artificial potential field coupling term, aiming to enhance trajectory reproduction capability and obstacle-avoidance stability in complex environments.

2 Theoretical Description of the Improved DMP

2.1 DMP Theory

Dynamic Movement Primitives (DMPs) are a robot motion generation method based on dynamical systems. The basic form of the DMP system is defined as:

$$\begin{cases} \tau\dot{v} = \alpha_y\big(\beta_y(g-y)-v\big)+f(x) \\ \tau\dot{y} = v \end{cases} \tag{1}$$

where y denotes the current position, $v=\dot{y}$ denotes the velocity, g denotes the goal point, τ is the temporal scaling factor that controls the execution speed of the trajectory, α_y, β_y is the damping coefficient, The forcing term $f(x)$ is used to learn the motion features contained in the demonstrated trajectory, ensuring that the generated trajectory follows the demonstrated curve. The canonical system in the DMP framework is defined as:

$$\tau\dot{x} = -\alpha_x x \tag{2}$$

where x is the internal phase variable that decays from 1 to 0 over time, and α_x is the coefficient controlling the decay speed. x ensures that the forcing term changes with time and naturally decays as the trajectory approaches the end point.

The forcing term in traditional DMPs adopts a linear combination form:

$$f(x) = \frac{\sum_{i=1}^{N}\psi_i(x)w_i}{\sum_{i=1}^{N}\psi_i(x)}x(g-y_0) \tag{3}$$

where the basic functions are Gaussian functions:

$$\psi_i(x) = \exp\left(-h_i(x-c_i)^2\right) \tag{4}$$

where c_i denotes the center of the basis function, h_i denotes the width parameter, w_i and denotes the weight, which must be obtained by learning from the demonstration trajectory. Given a demonstration trajectory $(y_{demo}, \dot{y}_{demo}, \ddot{y}_{demo})$, the target forcing term of the DMP can be expressed as:

$$f_{\text{target}}(t) = \tau\dot{v}_{demo}(t) - \alpha_y\left[\beta_y\big(g-y_{demo}(t)\big)-v_{demo}(t)\right] \tag{5}$$

which $\dot{v}_{demo}=\ddot{y}_{demo}$ is obtained by substituting the demonstrated trajectory into the DMP dynamic equation and solving backward. The weights w_i can be computed using local weighted regression (LWR).

2.2 Improved Artificial Potential Field Method

The artificial potential field (APF) method is a classical robot trajectory planning method, first proposed by Khatib and widely applied in robot trajectory planning [5]. It is defined as:

$$F_{\text{rep}}(y) = \begin{cases} \dfrac{\eta}{2}\left(\dfrac{1}{d(y)}-\dfrac{1}{d_0}\right)^2, & d(y) < d_0 \\ 0, & d(y) \geq d_0 \end{cases} \tag{6}$$

where $d(y) = \|y - y_{obs}\|$ denotes the distance between the robot and the obstacle, d_0 denotes the action radius, and η denotes the gain coefficient. A smaller distance results in a larger force, and when the distance exceeds the action range, no force is applied.

In conventional potential field methods, the repulsive term depends solely on distance, which may cause abrupt force variations and severe trajectory oscillations. To address these issues and integrate obstacle avoidance into DMPs, an improved APF coupling term (iAPF-DMP) is proposed by incorporating exponential distance attenuation and a velocity influence factor. the proposed method jointly considers both distance and velocity, it is defined as

$$C = k \sum_{i=1}^{N} w_v \frac{r_i}{\|r_i\|} \exp\left(-\frac{\|r_i\|}{d_0}\right) \tag{7}$$

where k denotes the gain coefficient of the coupling term, $r_i = o - p_i$ denotes the relative position vector, o denotes the obstacle position, p denotes the current robot position, d_0 denotes the influence radius of the obstacle, and w_v is defined as:

$$w_v = 1 + \lambda \cdot max\left(0, \frac{v}{\|v\|} \cdot \frac{o - p_i}{\|o - p_i\|}\right) \tag{8}$$

where λ denotes the velocity sensitivity coefficient and $w_v$used to adjust the influence of velocity on the coupling term. The improved transformation system is therefore written as:

$$\tau \dot{v} = \alpha_y\left(\beta_y(g - y) - v\right) + f(x) + C \tag{9}$$

where C represents the additional force coupling term added to the DMP.

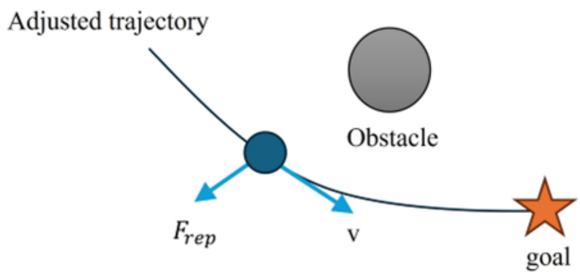

Figure 1: Artificial Potential Field Method.

Figure 1 illustrates the trajectory adjustment process of DMP combined with the improved artificial potential field method for obstacle avoidance. When the robot moves along the demonstrated trajectory in the direction of its velocity vector v, it is affected by the repulsive force F_{rep} generated by nearby obstacles. This repulsive force typically varies with the distance and the v between the trajectory and the obstacle, ensuring stronger repulsion as the robot gets closer to the obstacle, thereby enabling trajectory adjustment. The adjusted trajectory balances the two core goals of DMP obstacle avoidance: maintaining progress toward the target point and achieving collision-free motion through real-time potential field modulation.

3. Experimental Study

The experiments in this section aim to quantitatively analyze the effectiveness of the method introduced in Chapter 3. The trajectories in the handwriting dataset are used as demonstration data [6]. The proposed method is compared with the traditional artificial potential field method (APF-DMP) and the classical steering-angle method (Steer-DMP).

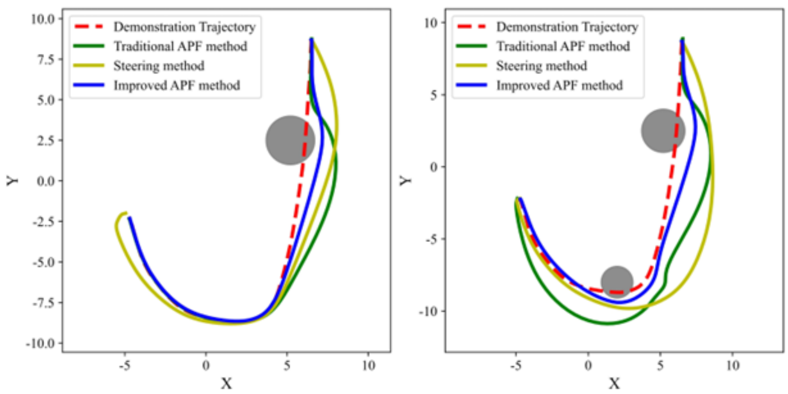

Figure 2: Comparison for letter J.

Figure 2 compares the regenerated obstacle-avoidance trajectories produced by the traditional artificial potential field method, the steering-angle method, and the proposed improved potential field method. In this experiment, the same demonstration trajectory is used, with obstacles located at (5.2, 2.5) and (−2, −8) and radii of 1.5 and 1.1, respectively. Although both the traditional potential field and steering-angle methods can achieve obstacle avoidance, they exhibit notable limitations, including loss of key trajectory features in obstacle regions. The traditional potential field method significantly degrades trajectory smoothness, while the steering-angle method causes large local deformations and may introduce premature avoidance, resulting in insufficient feature preservation. These issues arise because the repulsive force in the traditional potential field method depends solely on spatial distance, leading to unstable directional disturbances near obstacle boundaries, whereas the steering-angle method may apply strong corrections before collision risk becomes significant. In contrast, the proposed method better preserves the overall trajectory shape while maintaining smoothness and the characteristic "J" pattern during obstacle avoidance.

The results show that the proposed method can avoid obstacles under different scenarios, fully demonstrating its effectiveness. To more intuitively present the trajectory learning ability and feature-preservation capability, the minimum error and RMSE are used as evaluation indicators for quantitative analysis, and the results are shown in Tables.

Table 1: Results for Letter J.

Method	Single obstacle		Multiple obstacles	
	Minimum error	RMSE	Minimum error	RMSE
APF-DMP	0.0069	0.7097	0.0120	1.8674
Steer-DMP	0.0021	0.8178	0.0021	1.4279
iAPF-DMP	0.0015	0.6507	0.0006	0.9782

The regenerated "J" shaped trajectories produced by different methods demonstrate that, whether in single-obstacle or multi-obstacle scenarios, the trajectories generated by the DMP with the improved potential-field-based coupling term are smoother, and their minimum errors are lower than those of the other two methods. Meanwhile, the RMSE performance is significantly better than that of the traditional APF method and the steering-angle method, indicating that the proposed method shows superior performance in maintaining and matching trajectory features.

4. Conclusion

This paper addresses safe trajectory generation for robotic manipulators in complex and constrained environments and proposes a DMP-based obstacle-avoidance method using an improved artificial potential field. To overcome the limitations of conventional DMP coupling terms in stability and trajectory feature preservation, an exponential distance attenuation mechanism and a velocity-direction modulation factor are introduced, enabling continuous, smooth, and direction-aware trajectory adjustment during obstacle avoidance.

Simulation results demonstrate that the proposed method achieves stable obstacle avoidance in both single- and multi-obstacle scenarios and outperforms the traditional artificial potential field and steering-angle methods in terms of minimum error and RMSE. The method effectively preserves the overall shape of demonstrated trajectories while improving smoothness and adaptability. Future work will extend the approach to high-degree-of-freedom manipulators and dynamic obstacle environments and integrate sensor feedback and learning-based strategies to enhance robustness in real robotic systems.

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