Velocity-Dependent Volumetric Obstacle Avoidance for Dynamic Movement Primitives

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***Abstract*—We propose a novel method to implement obstacle avoidance within the Dynamic Movement Primitives (DMPs) framework. The proposed method is able to deal with volumetric obstacles. Moreover, being dependent on the velocity of the system (and not only on its position), this new method is able to achieve smooth behaviors.**

***Index Terms*—Obstacle Avoidance, Dynamic Movement Primitives, Learning from Demonstration**

I. Introduction

In last years, *Learning from Demonstrations* (LfD) approaches (such as *Gaussian Mixture Models* [1] and *Extreme Learning Machines* [2]) have been developed in order to replicate human gestures in robotics. A widely used LfD technique is the *Dynamic Movement Primitives* (DMPs) framework [3], [4]. DMPs permit to learn a trajectory from just one demonstration by encoding the trajectory in a system of second-order linear Ordinary Differential Equation (ODE), where a forcing term is learned as a linear combination of predefined time-dependent functions. Obstacle avoidance for DMPs has been successfully treated for point-like obstacles (e.g. [4] and [5]). On the other hand, volumetric obstacle avoidance has been treated in our previous work [6] using potential functions.
Here, we propose a new potential function that improves our previous method [6] by extending it so to take into account also the velocity of the system (and not only the position). This allow to achieve a smoother obstacle avoidance behavior.

In Section II we recall the DMP's theory; in Section III we present our proposed method for obstacle avoidance; in Section IV we test it; and in Section V we present the conclusions.

II. DMP Theory

DMPs is a framework for trajectory learning. It is based on an Ordinary Differential Equation (ODE) of spring-mass-damper type with a forcing term. They consist of the following system of Ordinary Differential Equations:

$$\begin{cases} \tau \dot{\mathbf{v}} = \mathbf{K}(\mathbf{g}-\mathbf{x}) - \mathbf{D}\mathbf{v} - \mathbf{K}(\mathbf{g}-\mathbf{x}_0)s + \mathbf{K}\mathbf{f}(s) + \boldsymbol{\varphi}(\mathbf{x},\mathbf{v}) \\ \tau \dot{\mathbf{x}} = \mathbf{v} \end{cases}$$

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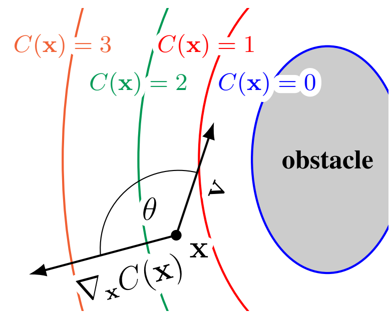

Fig. 1: Depiction of the angle θ in (2).

Vectors $\mathbf{x}, \mathbf{v} \in \mathbb{R}^d$ are, respectively, the *position* and *velocity* of the system; and $\mathbf{x}_0, \mathbf{g} \in \mathbb{R}^d$ are, respectively, the *starting* and *goal positions*. Matrices $\mathbf{K}, \mathbf{D} \in \mathbb{R}_+^{d\times d}$ are, respectively, the *elastic* and *damping terms* of the system. Both are diagonal matrices, $\mathbf{K} = \text{diag}(K_1, K_2, \dots, K_d)$, $\mathbf{D} = \text{diag}(D_1, D_2, \dots, D_d)$, and satisfy the critical damping relation $D_i = 2\sqrt{K_i}$, so that the un-perturbed system, i.e. when $\mathbf{f} \equiv \mathbf{0}$, converges as fast as possible to the unique equilibrium $(\mathbf{x}, \mathbf{v}) = (\mathbf{g}, \mathbf{0})$. Scalar $\tau \in \mathbb{R}_+$ is a *temporal scaling factor* which can be used to make the execution of the trajectory faster or slower. Function $\mathbf{f} : \mathbb{R} \to \mathbb{R}^d$ is the *forcing term*, expressed in term of basis functions. Scalar $s \in (0, 1]$ is a re-parametrization of time $t \in [0, T]$ governed by the so called *canonical system* $\tau \dot{s} = -\alpha s$, where $\alpha \in \mathbb{R}_+$ and the initial state is $s(0) = 1$.
Function $\boldsymbol{\varphi} : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}^d$ is the perturbation term used to deal with obstacle avoidance. Intuitively, it can be seen as a term that 'pushes' the system away from the obstacle. In the next Section, we present our new formulation of function $\boldsymbol{\varphi}$.

III. New Method for Obstacle Avoidance

To define our perturbation term, we start by defining the concept of *isopotential* as any function $C : \mathbb{R}^d \to \mathbb{R}$ that vanishes on the surface of the obstacle and increases as the distance from the obstacle increases. An example in $\mathbb{R}^3$ of isopotential is the function

$$C(\mathbf{x}) = \left(\frac{x_1 - \hat{x}_1}{\ell_1}\right)^{2n_1} + \left(\frac{x_2 - \hat{x}_2}{\ell_2}\right)^{2n_2} + \left(\frac{x_3 - \hat{x}_3}{\ell_3}\right)^{2n_3} - 1, \quad (1)$$

that vanishes on a *pseudo-ellipsoid* of center $\hat{\mathbf{x}} = [\hat{x}_1, \hat{x}_2, \hat{x}_3]^\mathsf{T}$ and semi-axis (ℓ_1, ℓ_2, ℓ_3).