Get Out of the Way - Obstacle Avoidance and Learning by Demonstration for Manipulation

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Abstract: Humans acquire manipulation skills by trial and error within a few trials, whereas programming a robot to perform the same task requires robotic expertise and effort. This paper presents a robot which learns a movement from demonstrations with the ability to generalize the movement to new goal poses and avoid the collision with obstacles in the workspace. The general movement is represented by dynamic movement primitives (DMP) augmented by potential fields in order to modulate the motion in the presence of obstacles. The approach is validated in experiments with a robotic arm in which dynamic obstacles partially blocking the movement are detected by a Photonic-Mixer-Devices (PMD) camera.

Keywords: Robots manipulators; perception and sensing; obstacle avoidance; movement primitives; image processing

1. INTRODUCTION

Since their first industrial application robotic manipulators evolved rapidly in terms of performance and proliferation. Programming a robot (Pires [2006]) to perform a specific task requires expertise and effort and is therefore economically feasible only in case of a large number of manufactured parts. Programming a robot in the conventional way amounts to the specification of several intermediate poses and velocities. In addition small changes to the task such as modification of the movements final pose requires adaptation of the original program. In the context of service robotics in which the tasks are typically provided by a nonexpert in robotics the conventional approach of robot instruction is nonfeasible. Consider a service robot supposed to deliver a cup of coffee. The explicit planning of an appropriate trajectory that is compliant with the task constraints is a painstaking procedure. On the other hand humans possess the remarkable ability not only to acquire such a skill within a few trials but also to generalize the movement onto novel situations even under additional constraints.

Learning from demonstration constitutes a viable alternative to the explicit textual programming of robots (Billard et al. [2008]). The process involves three stages: demonstration, learning and reproduction. During demonstration the movements of an instructor and task specific information such as a goal pose are recorded. In the learning phase, a generalized representation of the movement is adapted such that the model matches the demonstrated movements. In the reproductive phase, this representation enables the optimization and the generalisation of the movement onto a similar motion in novel situations. Dynamic movement primitives simplify the learning and generalisation of demonstrated movements by representing the movement as a dynamic attractor in which state evolves according to a set of non-linear differential equations (Schaal et al. [2007]). The attractor representation generalizes the movement in case of novel start and goal pose without requiring intervention or further adaptation.

In manipulation the task constraints are not only characterized by the start and goal pose but in addition by the presence of objects that confine the robots workspace. The robot is supposed to adapt or delay its original movement in a way that avoids collisions but still eventually accomplishes the task. Potential field methods are a common and well understood approach for collision avoidance in robotics (Krogh [1984]). An obstacle is considered as a virtual repulsive potential field exhibiting a repellent force on the robot that is drawn to the goal by an attractive potential. To avoid non smooth movements, the basic concept is extended to so called dynamic potential fields in (Park et al. [2008]) which consider not only the distance but also the relative velocity between the robot and obstacle. The repulsive force acts upon the link which is closest to the obstacle and thus in immediate hazard of collision. For a kinematically redundant task, the remaining degree of freedoms are exploited to maximize the separation between the obstacle and the closest link (Maciejewski and Klein [1985]). The kinematic redundancy enables the end effector to continue the desired movement, while an escape velocity and direction within the robots null space are generated from a static potential field (Maciejewski and Klein [1985]). This paper integrates the potential field for obstacle avoidance in the null space with the framework of dynamic movement primitives in order to acquire collision free movement of a redundant manipulator from demonstrations. The major novelty is the extension of previous approaches (Park et al. [2008]) to improved generalization of movements in low dimensional subspaces under substantial variations of scale.
The remainder of this paper is structured as follows. The next section introduces the original DMP concept and our proposed extension to improve the generalisation to movements at different scales. Section 3 presents the concept of dynamic potential fields and its application to obstacle avoidance for robot arms. Section 4 details the recording of demonstrated movements and the detection of obstacles in the workspace with the Photonic-Mixer-Devices (PMD) camera. Section 5 reports the experimental validation of the concept on a Katana 5 DOFs robot arm and the paper finally concludes with section 6.

2. AUGMENTATION OF DYNAMIC MOVEMENT PRIMITIVES

This section describes an extension to the representation and training of a DMP system which improves the generalization onto movements at substantially different scales compared to the original DMP.

2.1 Dynamic movement primitives

The concepts of DMP was first introduced in (Schaal et al. [2007]). Discrete or rhythmic movements are represented and generated by a dynamic attractor. The following differential equations represent a linear system, which differential equations represent a linear system, which [40x808]in which Schaal denotes as a dynamic movement primitive (DMP) system (Schaal et al. [2007]):

\[ \tau \dot{v} = K (g - x) - D \dot{v}, \]
\[ \tau \dot{x} = v, \]

which in D denotes the damping factor, K the spring constant and \( \tau \) the temporal rate of the dynamic system. The parameters K and D are designed such that the system is aperiodically damped. The motion is modulated by adding a nonlinear term \( f_2(\theta) \) to the mass spring damper system which Schaal denotes as a dynamic movement primitive (DMP) system (Schaal et al. [2007]):

\[ \tau \dot{v} = K (g - x) - D \dot{v} + (g - x_0) f_2(\theta). \] (3)

The nonlinear function has the form:

\[ f_2(\theta) = \frac{\sum_{i=1}^{N} \omega_i \psi_i(\theta)}{\sum_{i=1}^{N} \psi_i(\theta)}, \] (4)

which evolution does not explicitly depend on time but on the phase variable \( \theta \). The kernels \( \psi_i(\theta) = e^{-h_i(\theta - c_i)^2} \) with centers \( c_i \) and widths \( h_i \). The weights \( w_i \) enable the approximation of \( f_2 \) to a general nonlinear function by superposition of the kernels. The so-called "canonical system"

\[ \tau_k \dot{\theta} = -\alpha \theta \] (5)

describes the relation between the phase and the time variable. Together, the set of equations (1) to (5) establish a dynamic movement primitive which exhibits the following characteristics:

- Convergence from \( x_0 \) to the goal \( g \) is guaranteed as the system (1) is asymptotically stable and the term \( f_2 \) with limited weights \( w_i \) converges to zero at a rate \( \tau_k \).
- Adaptation of \( w_i \) allows it to approximate universal movements.
- Modulation of the original trajectory in time and space by adaptation of the time constants \( t \) and \( \tau_k \) and the goal \( g \).

In order to learn from a demonstrated movement, the positions, velocities and accelerations (\( \dot{x}, \ddot{v} \) and \( \dddot{a} \)) are recorded with a uniform sampling time during the demonstration. These samples provide the target function to be approximated by \( \hat{f}_2 \):

\[ \hat{f}_2 = \frac{\tau \dddot{a} - K (g - \dot{x}) + D \ddot{v}}{g - x_0}. \] (6)

It is learned by minimization of the squared error \( \varepsilon = (f_2 - \hat{f}_2)^2 \) with respect to the parameters \( w_i \) in equation (4). The minimization problem assumes a fixed number \( N \) of Gaussians with fixed centers \( c_i \) and widths \( h_i \). The least square solution \( w_i \) is obtained by linear optimization.

2.2 Modified DMP learning

The DMP approach assumes that the magnitude of the demonstrated and the reproduced movement are of similar scale. If this assumption is violated even along a single dimension, e.g. start and goal pose coincide in one coordinate, the generalisation fails. The learning of the DMP in equation (3) is restricted by the disappearance of the nonlinear function \( f_2 \) at the goal \( g \) which causes two problems in case that one coordinate of the start pose is close to the goal \( x_0 \approx g \):

- If the reproduced movement mostly takes place within a low dimensional subspace of the original workspace, the learned trajectory can not be reproduced.
- If the scale of the demonstrated and reproduced movement varies along a component, the reproduced movement exhibits disproportionate accelerations. Figure 1 (left) illustrates this effect for a planar movement, in which the y-coordinates of the start and goal in the demonstrated movement coincide, whereas they differ for the reproduced movement. The effect of changing the y-coordinate of the goal is an overamplification of the reproduced path along this dimension.

In this paper we suggest a novel approach to represent and train the DMP system, which overcomes the restriction of the original DMP with respect to variations in scale. The original DMP in equation (3) is augmented by an additional nonlinear term \( f_3(\theta) \) described in equation (4) such that the resulting DMP is described by two independent, superimposed nonlinear components:

\[ \tau \dot{v} = K (g - x) - D \dot{v} + K f_1(\theta) + (g - x_0) f_2(\theta), \] (7)
\[ \tau \dot{x} = v. \] (8)

Notice, that the evolution is largely dominated by the term \( (g - x_0) f_2 \) and the residual term \( f_1 \) merely influences the movement in the vicinity of the goal \( g \approx x_0 \) for which
As described in section 2, the DMP generates the trajectory of the end effector in the Cartesian space. The trajectory of the end effector in the Cartesian space. The trajectory of the end effector in the Cartesian space. The trajectory of the end effector in the Cartesian space. The trajectory of the end effector in the Cartesian space.

\begin{equation}
\lambda \left( -\cos \alpha \right) \frac{\|v\|}{d(x)} \left\{ \begin{array}{ll}
0 & \text{if } 0 < |\alpha| < \frac{\pi}{2} \\
\frac{\beta}{d} \nabla \left( \cos \alpha \right) - \lambda \frac{\cos \alpha}{d^2} \nabla \left( d(x) \right) & \text{if } \frac{\pi}{2} \leq |\alpha| \leq \pi
\end{array} \right.,
\end{equation}

where $\lambda$ denotes a positive gain and $v$ and $x$ represent the relative velocity and distance between the robot and the obstacle. The angle between the relative velocity and the obstacle location in robocentric coordinates is $\alpha$:

\begin{equation}
\alpha = \arccos \left( \frac{\mathbf{v}^T \mathbf{x}}{\|\mathbf{v}\| \|d(x)\|} \right).
\end{equation}

The repellent force is strongest if the robot approaches the obstacle head-on. The virtual force exhibited by the potential field $\varphi(x, v)$ is defined as the negative gradient of the potential $U_{\text{dyn}}(x, v)$:

\begin{equation}
\varphi(x, v) = \lambda \left( -\cos \alpha \right)^{\beta - 1} \left( \frac{\beta}{d} \nabla \left( \cos \alpha \right) - \lambda \frac{\cos \alpha}{d^2} \nabla \left( d(x) \right) \right).
\end{equation}

Figure 2 illustrates an example of a dynamic potential field for two different relative robot velocities. It is apparent that the potential field in the vicinity of the obstacle is dynamic and varies with the relative velocity between the robot and the obstacle.

3. OBSTACLE AVOIDANCE WITH DYNAMIC POTENTIAL FIELDS

3.1 Dynamic potential field

Collision avoidance for robots with potential fields is presented in [Krogh 1984]. The obstacle creates a virtual repulsive potential field $U(x)$, which depends on the distance between the robot and obstacle. The robot is considered as a point mass that moves under the influence of the force exhibited by the potential field. To achieve smooth trajectories, (Park et al. [2008]) introduced the concept of dynamic potential fields which in addition to proximity depends on the relative velocity between the robot and obstacle. The dynamic potential field is given by:

$$U_{\text{dyn}}(x, v) = \left\{ \begin{array}{ll}
\lambda \left( -\cos \alpha \right) \frac{\|v\|}{d(x)} & \text{if } 0 < |\alpha| < \frac{\pi}{2} \\
0 & \text{if } \frac{\pi}{2} \leq |\alpha| \leq \pi
\end{array} \right.,$$

(11)

The repellent force is strongest if the robot approaches the obstacle head-on. The virtual force exhibited by the potential field $\varphi(x, v)$ is defined as the negative gradient of the potential $U_{\text{dyn}}(x, v)$:

$$\varphi(x, v) = \lambda \left( -\cos \alpha \right)^{\beta - 1} \left( \frac{\beta}{d} \nabla \left( \cos \alpha \right) - \lambda \frac{\cos \alpha}{d^2} \nabla \left( d(x) \right) \right).$$

3.2 Dynamic potential fields for obstacle avoidance of a kinematically redundant robot arm

Potential field approaches consider the robot as an isolated point mass. Potentially, every part of the extended robot arm structure might collide with the obstacle, thus a reduction of the arm onto a single point is not feasible. An approach of obstacle avoidance for kinematically redundant manipulators is introduced in [Maciejewski and Klein 1985]). The repulsive potential field is determined with respect to the point of the arm structure that is closest to the obstacle. The corresponding force effects the null space movement. The kinematic redundance enables it to avoid a collision while preserving the trajectory of the end effector. Our approach combines the two frameworks of dynamic potential fields (Park et al. [2008]) and dynamic movement primitives.

As described in section 2, the DMP generates the trajectory of the end effector in the Cartesian space. The
trajectory is controlled in terms of the robot joint motion by an inverse kinematics scheme (Sciavicco and Siciliano [2005]). For kinematically redundant manipulators, the relationship between the joint and the end effector velocities is described by:

$$\dot{q} = J^\dagger (\dot{x} + Ke) + (I - J^\dagger J) \dot{q}_0,$$

(14)

in which $e$ denotes the Cartesian trajectory error of the end effector, $I$ the identity matrix and $J^\dagger$ the Jacobian pseudo inverse. Figure 3 illustrates the closed loop control block structure.

![Block scheme of inverse kinematics control](image)

**Fig. 3.** Block scheme of inverse kinematics control

The term $(I - J^\dagger J) \dot{q}_0$ in equation (14) corresponds to the null space movement with velocity $\dot{q}_0$. It effects the joint configuration in the null space for a fixed end effector motion. Assume, $x_0$ denotes the Cartesian coordinates of the point on the arm that is closest to the obstacle and $J_0$ its Jacobian. Its Cartesian velocity according to equation (14) is given by

$$\dot{x}_0 = J_0 J^\dagger (\dot{x} + Ke) + J_0 (I - J^\dagger J) \dot{q}_0$$

(15)

and its null space joint velocities become

$$\dot{q}_0 = (J_0 (I - J^\dagger J))^\dagger (\dot{x}_0 - J_0 J^\dagger (\dot{x} + Ke)).$$

(16)

Substitution of this solution into (14) yields:

$$\dot{q} = J^\dagger (\dot{x} + Ke) + (I - J^\dagger J) (J_0 (I - J^\dagger J))^\dagger \cdot (\dot{x}_0 - J_0 J^\dagger (\dot{x} + Ke)),$$

(17)

where $\dot{x}_0 = -\nabla (U_{dyn}(x_0,v_0))$ is the force exhibited by the dynamic potential field described in (3.1). Figure 4 shows two different configurations of a kinematically redundant planar robot arm. The null space movement transforms the arm from configuration (1) to (2) under the influence of the dynamic potential field which increases the separation between the arm and the obstacle.

![Different configurations of a redundant manipulator within the null space](image)

**Fig. 4.** Different configurations of a redundant manipulator within the null space

Obstacle avoidance in the null space fails if the end effector itself is the point on the arm closest to the obstacle. In that case the movement does not converge as the arm only exhibits a null space movement but no end effector motion. The remedy to this problem is to correct the end effector trajectory in the presence of obstacles. The end effector collision avoidance is achieved by adding the negative gradient of the potential field as an additional repulsive force to the original DMP in equation (7):

$$\tau = K (g - x) - D \dot{v} + KE (\theta) + (g - x_0) F_2 (\theta) + \varphi(x,v)$$

(18)

in order to obtain a DMP system with self adaptive path planning.

4. DEMONSTRATION RECORDING AND OBSTACLE DETECTION WITH PMD CAMERA

A Photonic-Mixer-Devices (PMD) camera tracks the demonstrated movement and detects dynamic obstacles in the robots work space. In addition to an intensity the PMD camera provides depth information for each pixel. In conjunction with an appropriate background segmentation the Cartesian pose of a ping pong ball is easily extracted in the image. The teacher demonstrates the desired trajectory by moving the ping pong ball across the workspace while the PMD camera captures its position. During reproduction, when the robot is supposed to mimic this trajectory, the ping pong ball serves as a dynamic obstacle. The ball is segmented in the depth image by a region growing algorithm (Ballard and Brown [1982]). Region growing groups neighboring points according to their similarity. In our case similarity is defined in terms of depth thus segmenting the ball from its background. The left image in figure (5) shows the original depth image and the right part depicts the corresponding image segmented according to depth. The ball is recognized among the different objects in the segmented image.

![Object detection from distance image](image)

**Fig. 5.** Object detection from distance image

There are several approaches to detect a disk or a circle within an image, e.g. Hough transform or RANSAC method. In our case ball detection relies on a simple method. For each segmented object the length of the major and minor axis are compared, which become equal if the object is a circle. This constitutes a necessary albeit not sufficient condition to recognize a ball. The circularity of an object is defined by the ratio of the area $A$ and the perimeter $C$ of the object

$$h = \frac{4\pi A}{C^2},$$

(19)

which in case of a disk, becomes equal to one. An object is recognized as a ball if both features are within an interval around their nominal value.
Upon detection of the ball its position in the camera coordinate frame is computed from the depth information. The scan points of a PMD depth image consist of the pixel coordinates $u$ and $v$ and the distance information $r$. The relation between the pixel and the camera coordinate system is given by:

$$u = \alpha_x \frac{X}{Z} + u_0, \quad v = \alpha_y \frac{Y}{Z} + v_0,$$

(20)

(21)

in which $\alpha_x$, $\alpha_y$, $u_0$, $v_0$ denote the intrinsic camera parameters, obtained from the calibration method proposed by (Bouguet [2008]).

The depth information is related to the coordinates in the camera frame by:

$$r = \sqrt{X^2 + Y^2 + Z^2}, \quad (22)$$

The camera coordinates $X, Y, Z$ are determined from the equations (20) to (22):

$$Z = \frac{r}{\sqrt{\left(\frac{u - u_0}{\alpha_x}\right)^2 + \left(\frac{v - v_0}{\alpha_y}\right)^2 + 1}}, \quad (23)$$

$$X = \frac{u - u_0}{\alpha_x} Z, \quad (24)$$

$$Y = \frac{v - v_0}{\alpha_y} Z. \quad (25)$$

Fig. 6. Transformation between two coordinate systems

The ball position $p_K$ in the camera coordinate system is transformed to the position $p_R$ in the robot coordinate system by a homogeneous transformation

$$p_R = T^K_R p_K, \quad (26)$$

in which the matrix $T^K_R$ describes the translation and rotation between two coordinate systems and is obtained once through a calibration measurement. The extracted ball position is provided at run time to the motion recording scheme as well as the movement controller with obstacle avoidance.

5. EXPERIMENTAL RESULTS

This section reports experimental results of the application of the approach to obstacle avoidance on a 5 DOFs robot arm. Figure 7 shows the architecture of the overall system including learning from demonstration, ball detection and trajectory generation. Even though the robot arm only possesses five degree of freedom, it is still kinematically redundant as the task only prescribes the end effector position but not its orientation. Thus, there remain two degrees of freedom to maximize separation between the arm and the obstacle. The PMD camera is installed in a static eye-to-hand configuration and the transformation between camera coordinate and robot coordinate system is obtained from prior calibration. Several trajectories are demonstrated with the ball and recorded as described in sections 2.2 and 4. From these demonstrations the learner computes the DMP parameters that best reproduce and generalize the obstacle free movements.

In figure 8 the dashed line depicts the demonstrated ball movement whereas the black line corresponds to the reproduced trajectory of the end effector. The reproduction is precise considering the accuracy of the underlying inverse kinematics controller. The grey line shows the robot movement for a scenario in which the original trajectory is partially blocked by an obstacle. The controller achieves a smooth adjustment of the original trajectory in the vicinity of the obstacle while preserving its basic shape and curvature.

Fig. 7. Block scheme of control architecture

Fig. 8. Obstacle avoidance of the end effector on the Katana robot arm

The next experiment is concerned with a scenario in which during the reproduced free movement a robot link rather than the end effector is at risk to collide with the obstacle. The gray line in figure 9(a) shows the link trajectory as it collides with the obstacle in case of inactive obstacle avoidance in the null space. The black line depicts the same scenario with activated collision avoidance. Notice, that both end effector trajectories (dashed lines) coincide but that in the second case the dynamic potential field prevents the link obstacle collision. The influence of the potential field on the null space movement becomes more
apparent in figure 9(b) which shows the separation between the link point at highest risk of collision and the obstacle during the motion.

Fig. 9. Obstacle avoidance of a kinematically redundant manipulator

Figure 10 shows snapshot sequences of three different experiments. The top row images show the reproduction of a demonstrated trajectory without obstacle avoidance in which the end effector collides with the ball in the right snapshot. The middle row images show the same scenario with activated obstacle avoidance. It is apparent that the controller maintains a clear separation between end effector and obstacle. In the third scenario the obstacle is located close to a robot link. The motion of the end effector coincides with the original movement in the first scenario but the trajectory of the link at collision risk is altered to avoid contact with the obstacle.

Fig. 10. Comparison of the movements with and without obstacle avoidance

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