Combining dynamic movement primitives and potential fields for online obstacle avoidance

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Robots in a human environment need to be compliant. This compliance requires that a pre-planed movement can be adapted to an obstacle that may move or appear suddenly. Here, we present a general framework for online adaptation to obstacles. Using the dynamic-movement-primitive formulation, we represent a pre-trained movement in end-effector space with a differential equation. This equation allows adding a perturbing force without sacrificing stability. As perturbation, we use a repellent force around a point-like obstacle. We demonstrate our framework in simulations and with the Sarcos Master robot arm

Humans can adapt a movement plan online to adjust for obstacles in the intended path. This flexibility is also required in robots operating in a human environment, where humans may move unpredictably forbidding a robot to strictly follow a pre-planned path. At the same time, we like to program a robotic movement in a simple way, i.e., through demonstration.

We combine movement reproduction from demonstration with the flexibility to react to perturbances using the dynamic movement primitive (DMP) framework [1]. A DMP can represent any recorded movement with a set of differential equations [2]. Representing a movement with a differential equation has the advantage that a perturbance can be automatically corrected for by the dynamics of the system. Moreover, the DMPs are formulated in a way that convergence to a goal position is guaranteed.

For online obstacle avoidance, potential fields are a common approach. A potential field is defined around an obstacle, and the gradient of this field results in a repellent force on the robot. This approach has been particularly popular for motion planning in mobile robotics [3], but has been also used for robotic manipulators; e.g., Brock and Khatib [4] used the potential-field method for real-time re-planning.

In the following, we show the combination of DMP with potential fields, present our potential-field equation, and show results in simulation and in the Sarcos robot.

Dynamic movement primitives

Dynamic movement primitives can be used to generate discrete and rhythmic movements [2, 1]. Here, we focus on discrete movements. A movement is generated by integrating the following set of differential equations (which we will refer to as 'transformation system'):

$$\tau \dot{v} = K(g-x) - Dv - K(g-x_0)\theta + Kf(\theta) \quad (1)$$

$$\tau \dot{x} = v \ , \quad (2)$$

where x and v are position and velocity of the system; x_0 and g are the start and goal position; τ is a temporal scaling factor; K and D are constants; D is chosen such that the system is critically damped, and f is a non-linear function which can be adapted to allow the generation of arbitrary complex movements [2]. Equation (1) is slightly different from perviously published versions. It fixes a problem when start and end points are equal. This equation is motivated from human behavioral data and force fields observed on the frog's leg after stimulating the spinal cord [5].

The equation of motion does not depend explicitly on time, but instead on a phase variable θ, which goes from 1 towards 0 during a movement and is obtained by the equation

$$\tau \dot{\theta} = -\alpha \theta \ . \quad (3)$$

where α is a pre-defined constant.

To learn a movement from demonstration, first, a movement $x(t)$ is recorded and its derivatives $v(t)$ and $\dot{v}(t)$ are computed for each time step t. Second, (3) is integrated and $\theta(t)$ evaluated. Using the resulting arrays, $f(\theta(t))$ is computed based on (1), and its parameters are determined.

For combining a DMP with a potential field for obstacle avoidance, we add to (1) a repulsive accleration, the negative gradient of a potential U around an obstacle,

$$\tau \dot{v} = K(g-x) - Dv - K(g-x_0)\theta + Kf(\theta) - \frac{\partial U}{\partial x} \ . \quad (4)$$

Using the transformation system, we generate movements in operational space. Thus, the variable x describes the end-effector position, and the obstacle's position is encoded in the same space.

Potential field for obstacle avoidance

We designed the potential field to achieve a human-like obstacle avoidance. In experiments, we found better results with a velocity-dependent field. The field is computed relative to the position and velocity of the obstacle. Let $\mathbf{x}_r$ and $\mathbf{v}_r$ be the relative position and velocity vectors of the end-effector. Our potential U is defined as

$$U(\mathbf{x}_r, \mathbf{v}_r) = \left\{ \begin{array}{lll} \lambda(-\cos\gamma)^{\beta} \frac{||\mathbf{v}_r||}{||\mathbf{x}_r||} & : & \frac{\pi}{2} \leq \gamma \leq \frac{3\pi}{2} \\ 0 & : & \text{else} \end{array} \right\} \quad (5)$$

where λ is a constant for the strength of the entire field, β another constant, and γ the angle between $\mathbf{x}_r$ and $\mathbf{v}_r$.

Simulation

We tested the movement generation with potential fields in a simulation of a moving point (Fig. 1 and 2). The transformation system describes the movement in the xy-plane. Complex trajectories could be adapted for obstacle avoidance (Fig. 1), and furthermore, the system could also react to a moving obstacle (Fig. 2).

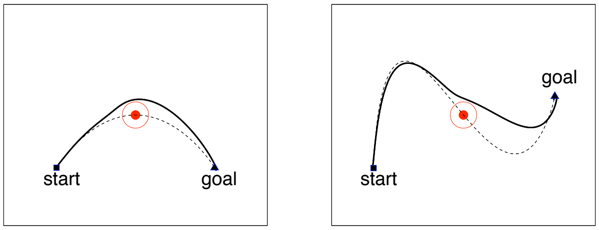

Fig. 1: Movement generation with potential field (solid curve). The original movement is shown with a dashed line.

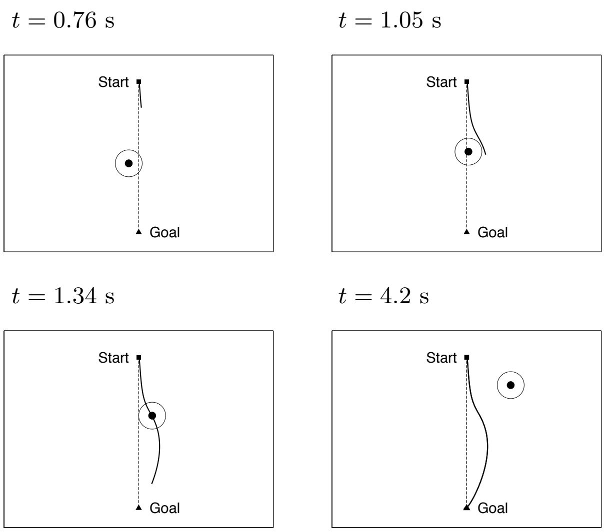

Fig. 2: Movement generation with potential field and moving obstacle. Different time steps of the movement are shown. The obstacle moves from bottom left to top right of the workspace.

Robot experiment

We tested our framework on the Sarcos Master robot arm. Since the workspace of the robot is very limited, we extended the end-effector with a stick and a ball attached to it (Fig. 3). The DMP describes the end-effector movement, and we use inverse kinematics and dynamics to compute the joint torques. Link collisions are avoided with a null-space control that maximizes the distance between obstacle and links. In the demonstration, first, the Sarcos arm reproduced a given movement; second, we added an obstacle into the path of the end-effector. Using the potential field (5) around the obstacle, the robot could smoothly avoid the obstacle (Fig. 3).

Conclusions

We combined the dynamic movement primitive framework with potential fields for online obstacle avoidance. DMP provided us with a framework to reproduce a movement from demonstration while being flexible to react to perturbances.

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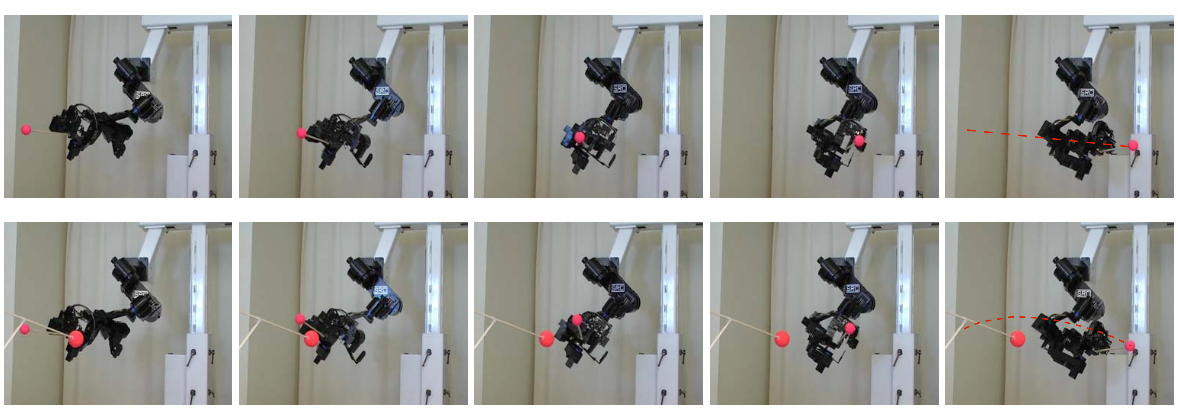

Fig. 3: Obstacle avoidance with Sarcos Master Arm. The first row shows the reproduction of a demonstrated movement, and the second row shows the result of obstacle avoidance with the potential field.