# A Comparison of Policy Search in Joint Space and Cartesian Space for Refinement of Skills

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**Abstract.** Imitation learning is a way to teach robots skills that are demonstrated by humans. Transfering skills between these different kinematic structures seems to be straightforward in Cartesian space. Because of the correspondence problem, however, the result will most likely not be identical. This is why refinement is required, for example, by policy search. Policy search in Cartesian space is prone to reachability problems when using conventional inverse kinematic solvers. We propose a configurable approximate inverse kinematic solver and show that it can accelerate the refinement process considerably. We also compare empirically refinement in Cartesian space and refinement in joint space.

**Keywords:** learning from demonstration, imitation learning, reinforcement learning, policy search, inverse kinematics

# 1 Refinement of Demonstrated Skills

Autonomous, mobile robots with manipulators can be benificial in many different environments, for example, deep sea [7] or household and factories [13]. In order to create these robots for real, dynamic environments they have to be able to learn. Skill learning frameworks for robots often combine various approaches to leverage intuitive knowledge from humans [3]. Most of these fall into the categories imitation learning and reinforcement learning (RL). A standard approach to learning skills is to initialize with a demonstrated movement and then refine the skill with policy search [9,2,3]. Both methods are complementary because on the one hand policy search methods are often local optimizers that require good initialization and on the other hand imitation learning usually does not produce a perfect skill from the start because of the correspondence problem [3], that is, different kinematic and dynamic properties of the target system and the demonstrator result in different outcomes. We argue that it is sometimes better to do policy search directly in task space because demonstration and main objectives of the learning problem are given in task space, for example, end-effector poses in Cartesian space. When policy search methods are used to learn end-effector trajectories in task space it often occurs that a trajectory is not completely in the robot's workspace. This results in reward landscapes that are difficult to optimize. We will address this problem with an approximation of inverse kinematics (IK) and investigate when to use it.

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# 2 Related Work

We will present the setting in which our problem is embedded and give a brief overview of inverse kinematics that are related to our work.

Transfering skills from humans to robots is prone to the correspondence problem. Consider, for example, a reaching trajectory that is recorded from a human and transfered to the robot's end-effector. Because the robot probably has a different hand shape, it cannot grasp the object with exactly the same end-effector trajectory. In this case, policy search in Cartesian space can be used to refine the initial trajectory. Transfering trajectories directly in joint space is even more difficult because the segment lengths of a robot arm and the human arm are most likely different. Examples for skills that have been demonstrated in task space and transfered to robots are pancake flipping (learned from kinesthetic teaching; [11]), peg in hole (learned from tele-operation; [15]), and serving water (kinesthetic teaching with a similar arm; [18]). There are several reasons for learning trajectories in task space. Learning in Cartesian space is often easier when the main objectives are defined in Cartesian space. For example, learning to grasp an object in joint space might result in complicated Cartesian trajectories. When we want to transfer a skill from one robot to another it is easier to go over end-effector poses instead of joint angles because of different kinematic structures [18] because part of the correspondence problem is solved by forward and inverse kinematics. All of the mentioned works use dynamic movement primitives (DMP) as underlying trajectory representation. In our work, we will use a DMP based on quaternions [23] to generate end-effector poses.

Let  $\boldsymbol{q}_t$  be the joint angles of a kinematic chain at time t. The forward kinematics of the chain is given by  $f(\boldsymbol{q}_t) = \boldsymbol{p}_t$ , where  $\boldsymbol{p}_t$  denotes the end-effector's pose. An exact solution to the inverse kinematics (IK) problem would be  $f^{-1}(\boldsymbol{p}_t) = \boldsymbol{q}_t$ . However,  $f^{-1}$  is usually not a function. Many joint configurations might result in the same end-effector pose. Numerical solutions to inverse kinematics handle redundant kinematic chains that can have many solutions or complex analytical solutions efficiently. Widely used approaches are based on the Jacobian pseudo-inverse or Jacobian transpose [17]. However, sequential quadratic programming has been shown to outperform these in terms of joint limit handling and computation time [1]. Indirect formulations of the form

$$\arg\min_{\boldsymbol{q}_t \in \mathbb{R}^n} (\boldsymbol{q}_{t-1} - \boldsymbol{q}_t)^T (\boldsymbol{q}_{t-1} - \boldsymbol{q}_t), \quad \text{s.t. } g_i(\boldsymbol{q}_t) \le b_i, \quad i = 1, \dots, m$$

where the constraints include the Euclidean distance error, the angular distance error, and joint limits (e.g. [12,14]), have a lower success rate than direct formulations of the form

$$\arg\min_{\boldsymbol{q}_t \in \mathbb{R}^n} d(f(\boldsymbol{q}_t), \boldsymbol{p}_t^{\text{des}})) \tag{1}$$

s.t. 
$$g_i(\boldsymbol{q}_t) \le b_i, \quad i = 1, \dots, m$$
 (2)

where d is a pose distance metric,  $p_t^{\text{des}}$  is the desired end-effector pose, and the inequality constraints only consist of the joint limits [1]. Few works investigate

approximate IK solutions. However, in cases where the desired end-effector pose cannot be reached exactly, we would like to have at least the closest possible solution. Unreachable poses might be a problem of robots that have a low number of joints [6] or at the borders of workspaces as this can be seen for example in visualizations of capability maps [24]. Traditional methods based on the Jacobian pseudoinverse tend to be instable and run into local minima [17,6].

### **3** Configurable Approximate Inverse Kinematics

A disadvantage of previous approaches is that they do not allow to configure the approximation. In the domain of robot skill learning it is often not required to reach each pose in a trajectory exactly. Consider the problem of learning to grasp an object. At the beginning of a reaching movement orientation of the endeffector is not relevant. It only becomes important at the end. That is the reason why we develop a configurable IK solver based on [1]. In the IK formulation in Equations 1 and 2 we can use a weighted distance metric of the form

$$\begin{aligned} d(\boldsymbol{p}_{1},\boldsymbol{p}_{2}) &= w_{\text{pos}} || \boldsymbol{p}_{1,1:3} - \boldsymbol{p}_{2,1:3} ||_{2}^{2} \\ &+ w_{\text{rot}} \left[ \min(||\log(\boldsymbol{p}_{1,3:7} * \overline{\boldsymbol{p}}_{2,3:7})||_{2}, 2\pi - ||\log(\boldsymbol{p}_{1,3:7} * \overline{\boldsymbol{p}}_{2,3:7})||_{2}) \right]^{2}, \end{aligned}$$

where  $p_{1:3}$  represents the position of the end-effector and  $p_{3:7}$  is a quaternion that represents the orientation of the end-effector. It consists of a position distance metric and a rotation distance metric. There are other distance metrics for rotations that we could use [8]. This allows us to set different weights on position and rotation because it is often much more important to reach a desired position than the desired rotation. We could extend this pose metric so that we can weight each of the six degrees of freedom individually.

# 4 Experiments

### 4.1 Methods

We use DMPs as policies because they are well known and stable trajectory representations that can be used for imitation and RL. In the following experiments we will only learn the weights of the DMPs. Metaparameters are constant. Many policy search algorithms [5,10,16,19,21,22] are based on similar principles: a Gaussian distribution is learned from which we sample policy parameters. We will use Covariance Matrix Adaption Evolution Strategy (CMA-ES; [4]) to learn the policy because it has few critical hyperparameters. Even when those are not set perfectly CMA-ES is still reliable. The most important hyperparameter is the initial step size  $\sigma$ . It determines the width of the initial search distribution. If it is not large enough, the algorithm will first have to increase the step size for several generations before it can converge. If it is set too large, convergence will take longer. For our comparison it is important to select the correct step size ratio between joint space and Cartesian space so that the results will not be

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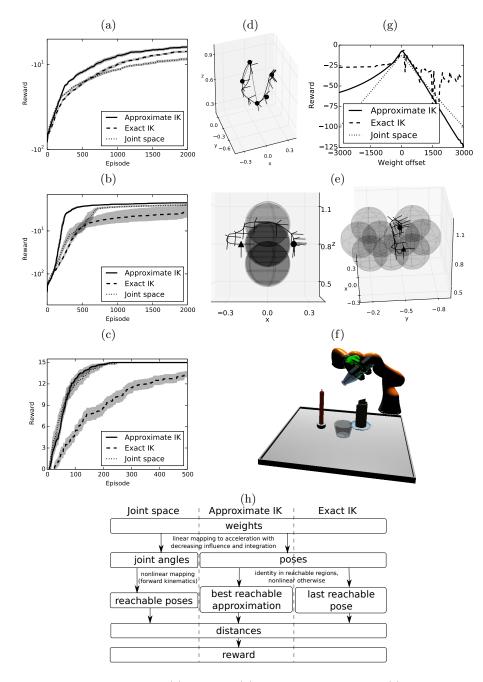
distorted by a wrong choice of this parameter. In our experiments, we use the Kuka LBR IIWA 14 R820 robot arm with 7 DOF. We determined empirically that the initial step size in joint space must be 2 to 3 times higher than in Cartesian space to achieve similar effects on the robot's end-effector. In the first two experiments, the optimum solutions are close to the border of the workspace so that not every orientation can be reached. In all experiments we compare learning weights of DMPs in joint space, in Cartesian space with the proposed approximate IK, and in Cartesian space with an "exact" IK. The term exact throughout this paper means a numerical IK based on the pseudoinverse of the Jacobian that does not move the end-effector if no valid solution has been found. We will execute 30 runs per configuration with different random seeds for CMA-ES. We use the results to plot learning curves with the mean and standard error of the maximum reward obtained so far. Each DMP in our setup has 50 weights per joint space or task space dimension.

#### 4.2 Problems and Results

The following paragraphs will summarize the results obtained for several problems that have different reward surfaces. Implementations for most experiments are available at https://github.com/rock-learning/approxik.

In the viapoint problem, the end-effector should pass through intermediate positions (viapoints). A simpler problem has been used to compare various policy search methods [10,20]. In this version we want the end-effector to pass through five Cartesian points (see Figure 1 (d)) while minimizing joint velocities and accelerations. The reward is  $R = -10 \sum_{(t_{\nu}, \nu)} ||f(q_{t_{\nu}}) - \nu||_2 - 10^{-3} \sum_{t,j} |\dot{q}_{t,j}| - 10^{-3} \sum_{t,j$  $10^{-5} \sum_{t,j} |\ddot{q}_{t,j}|$ , where  $t \in \{1, \ldots, 101\}$  represents the step, j are joint indices and  $(t_{\nu}, \nu)$  represents a position  $\nu$  that has to be reached at time  $t_{\nu}$ . The results are shown in Figure 1 (a). Learning in Cartesian space is more sample-efficient because the primary objective is defined in Cartesian space. The exact IK performs worse because the approximate IK usually generates more smooth trajectories. Viapoint problems belong to the most simple class of problems for policy search methods because there are usually no flat regions or abrupt changes in the reward surface so that it is easy to determine the direction of improvement. We can get a rough impression of the reward surface of the problem from Figure 1 (g). To generate a projection of the reward surface on one DMP weight dimension, we learn a DMP for 1000 episodes, keep the best policy, modify the 50th weight by adding an offset, and measure the corresponding reward. We can see that for both the joint space DMP and the Cartesian DMP with an approximate IK the reward surface is smooth with only one maximum. With the exact IK, the reward surface is rough and abruptly changing in some regions, which makes learning more difficult for CMA-ES. However, learning in joint space is worse than learning in Cartesian space because of the nonlinear mapping from weights to positions in Cartesian space through the forward kinematics of the robot arm. This results in more complex interrelations between parameters.

In the obstacle avoidance problem, the end-effector has to avoid several obstacles represented by spheres. It is an artificial problem because we only consider



**Fig. 1.** Learning curves for (a) viapoint, (b) obstacle avoidance, and (c) pouring problem. Illustrations of environments: (d) Viapoint: 5 viapoints (circles) have to be reached. A line shows the temporal order. An additional line indicates an optimized trajectory (rotations are indicated by small coordinate frames). (e) Obstacle avoidance: ball-shaped obstacles have to be avoided between start (triangle) and goal (circle). An example of an optimized trajectory is displayed. (f) Pouring. (g) Projection of the reward surface of the viapoint problem on one axis. (h) Mapping from weights to corresponding reward in the viapoint problem. For each setup different mappings are involved to compute the reward for a weight vector.

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end-effector collisions and not the arm to which it is attached. The environment is displayed in Figure 1 (e). The reward is  $R = -10 \sum_{\rho} p \left( \min_{q_t} ||f(q_t) - \rho||_2 \right) - 100 ||f(q_T) - g||_2 - 10^{-2} \sum_{t,j} |\dot{q}_{t,j}| - 10^{-5} \sum_{t,j} |\ddot{q}_{t,j}|$ , where  $t \in \{1, \ldots, T\}$ , T = 101 represents the step in time, j are the joint indices, g is the desired goal position, and  $p(d) = \max(0, 1 - \frac{d}{0.17})$  is greater than zero when the end-effector is in the vicinity of one of the obstacles. The result is shown in Figure 1 (b). We see that learning in Cartesian space is again more sample-efficient because the primary objective is defined in Cartesian space. The exact IK performs worse because the approximate IK and learning in joint space results in more smooth trajectories. The difficulty of this task and its reward surface are similar to those of the viapoint task. The difference is that it is less smooth because the negative penalty for being in the vicinity of obstacles abruptly vanishes when the end-effector is outside of the radius of the spheres. In this case only the velocity and acceleration penalties guide the search to a better solution.

In the pouring task, the robot fills a glass with 15 marbles from a bottle while avoiding nearby obstacles. The setup is displayed in Figure 1 (f). The reward function is complex. For every marble that is inside of the glass we add 1. For every marble that is outside of the glass but on the table the negative squared distance to the center of the glass is given. For every marble that is still in the bottle we give a reward of -1. For collisions with obstacles we give a reward of -100 and abort the episode. Marbles that fall down the table also finish the episode and a reward of -1000 is given. Results are displayed in Figure 1 (c). Learning in joint space and learning in Cartesian space results in nearly identical learning curves. Using an exact IK is again worse than using an approximate solution. The mapping from weights to reward in this problem is complex, nonlinear, and certainly not smooth. There are abrupt changes in the reward function when a small change of one weight results in a marble falling down the table or the arm touching an obstacle. There are flat regions, for example, when all marbles stay in the bottle because the arm does not turn the bottle upside down, or all marbles miss the table. Therefore, the structure of the reward surface is complex independent of the space in which we describe DMPs, hence, learning in joint space and learning in Cartesian space work similarly well.

#### 4.3 Discussion

The artificial RL problems that we presented vary in difficulty, that is, indirection and smoothness of the reward function. Weights in a DMP are bound to a specific radial basis function. They only influence one specific joint or pose dimension and only affect accelerations of the arm locally in time. They will affect the positions in all following time steps but with a decreasing influence because the weight of the learnable forcing term converges to zero. So it is possible to design a reward function so that the optimization problem becomes partially separable and, hence, easy to solve. For example, in the viapoint and obstacle avoidance problems there is a direct relation between weights of the Cartesian DMP and obtained reward (see Figure 1 (h)). With the approximate IK we use the weights to generate a pose trajectory. An acceleration is computed based on the linear forcing term that includes the weights and decays exponentially over time. The acceleration is integrated to obtain a trajectory of end-effector poses. This trajectory might not be perfectly executable so that in unreachable regions the pose is mapped to the closest reachable pose. For each viapoint we compute the distance to the corresponding poses from the trajectory. Hence, the mapping from specific weights to the reward in the workspace of the robot is straightforward and the reward function is partially separable. Joint space DMPs result in a nonlinear mapping with coupling between dimensions of the weight space because of the forward kinematics of the robot. This results in a difficult optimization problem that is not partially separable any more with probably multiple global and local optima. The more complex the relation between weights and reward becomes, the less significant is the difference between learning in joint space and learning in Cartesian space. An example is the pouring problem. It has an almost flat reward surface where the arm collides with an obstacle or a marble falls down. Small weight changes can make a difference between a marble staying within the glass and falling down, hence, the reward will abruptly change in the corresponding regions of the weight space. The relation between the DMP weights and a successful behavior is complex, highly nonlinear, and non-separable. This eradicates the advantage of learning in Cartesian space.

### 5 Conclusion

We develop a configurable, approximate variation of a state-of-the-art numerical IK solver and show that it accelerates policy search for movement primitives in Cartesian space in comparison to a conventional IK solver. Using inverse kinematics can be regarded as a way to include knowledge about the target system in the learning process. Learning in Cartesian space is not always the best option. It will be advantageous if the main objective has to be solved in Cartesian space and the reward function is almost separable. It is not always obvious when this is the case though. The advantage of learning in Cartesian space vanishes for more complex, nonlinear, non-separable reward functions. Policy search works best in the space in which the primary objectives are defined directly. Generating smooth trajectories is simpler in joint space.

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