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Human behavior learning for robot in joint space

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ABSTRACT

Many robots, such as human guide robots and service robots, need to learn the human behavior such that the robots can merge into human society. This learning process is in task space. However, the desired trajectories should be in joint space such that each joint can be moved like human. This needs inverse kinematics. In most of cases, the inverse kinematics do not have analytical solutions. Few training methods work in joint space directly, because they need dynamic time warping to remove speed influence. Both inverse kinematics and dynamic time warping destroy the accuracy of the learning.

In this paper, the desired trajectory is trained in joint space without the dynamic time warping. In order to learn the demonstrations in joint space, we use two techniques, Lloyd's algorithm and modified hidden Markov model, to solve the problems in joint space learning. Since the desired trajectories are the joint angles, they can be applied directly without inverse kinematics. Experimental results show that the proposed algorithm works well for human behavior learning.

1. Introduction

Human guide robots, such as robot exoskeleton, humanoid robot, and surgical robot, need three basic operations: joint angle tracking, trajectory planning, and path planning, see Fig. 1. The path planning is in task space.[1] It generates a path from a starting-point to an ending-point with respect to some restrictions. The trajectory planning is in joint space.[2] It gives desired joint angles. The joint angle tracking usually uses some controllers to force the joints follow the desired joint angles. The object of this paper is to generate desired joint angles in joint space which correspond to the human behavior in task space, i.e., we want to transfer human skill to the robot through human demonstrations [1].

Human behavior learning for robot is also called programming by demonstration(PbD) or learning from demonstration (LfD) [2]. Trajectory generation can be broadly divided into two trends: (1) Symbolic-numeric level: human skill is decomposed into a sequence of action-perception units, then a statistical model is used to deal with the demonstrations [3,4]. (2) Trajectories level: a nonlinear mapping is used to model the sensor/motor information. The trajectories level method is robust to the environment changes [5]. The symbolic level method is suitable to model complex motions. In this paper we use the symbolic-numeric level method.

Although the trajectory planning in joint space can avoid the calculation of the inverse kinematics,[3] the demonstrations in joint space are time-dependent. Fig. 2 shows the trajectories of a broken line in task space (right). The three lines overlap in task space. However, they are complete different in joint space (left), because the drawing speeds are different. The trajectories in task space cannot be applied to the robot directly. We need to solve inverse kinematics, which requires complete knowledge of the robot, and the inverse kinematics do not have analytical solutions for most robots. Although time variable can be integrated into the task space variables, some additional techniques, such as time normalization, are needed to deal with this four dimension variables. Usually training in task space is easier than in joint space [6–9], because the trajectories in task space only give space relation, and we do not need to pay so much attention on the time relation of human behavior.

There are few training methods in joint space [10,11]. Because the joint space methods are sensitive to speed, time scale methods should be applied. Dynamic time warping (DTW) is an effective tool to deal with the time-dependent problem. It measures similarity between two temporal sequences which may vary in time or speed, and calculates an optimal match between two given time series. The time series classification is a popular sequence alignment method for DTW. Computation time for one-dimensional signals, such as time series, is

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[1] Task space (or Cartesian space) is defined by the position and orientation of the end effector of a robot.

[2] Joint space is defined by a vector whose components are the translational and angular displacements of each joint of a robotic link.

[3] Inverse kinematics determines the joint parameters of a robot by a desired position of the end-effector. It transforms the end-effector motion into joint actuator trajectories.

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in polynomial. The extension of DTW for more than two-dimension, like robots, becomes NP-complete. The accuracy of the high dimension approximation is also very low [12].

There are several methods to generate human trajectories in task space. Spline smoothing technique can deal with the uncertainty in several motion demonstrations [13]. The mean and variance of the collected variables are applied in [14] to generate a model. Ito et al. [15] realizes online imitation by encoding two different motor loops. In [16], the reinforcement learning method is applied for human behavior learning with noises. In [17] and [18], the trajectories are analyzed by the inverse reinforcement learning.

Hidden Markov Model (HMM) is a statistical learning technique, which deals with the high variability inherent in the demonstrations. HMM has been applied in many temporal pattern recognitions, such as speech, handwriting, and gesture recognitions. It is not sensitive to disturbances. Markov models use the state transition probabilities as model parameters. Hidden Markov model has only output, and each state has a probability distribution over the possible output tokens. So the sequence of tokens gives some information about the states. HMM generates a sequence which is called Markov chain [19,20]. It can encode the motion of a robot, and find a highest probability state path by Viterbi algorithm [21]. HMM offers many advantages over the other statistical models for human behavior modeling, such as better compression, variant structures, and training incrementally. There are many successful applications on robot trajectory generation via HMM [20,22].

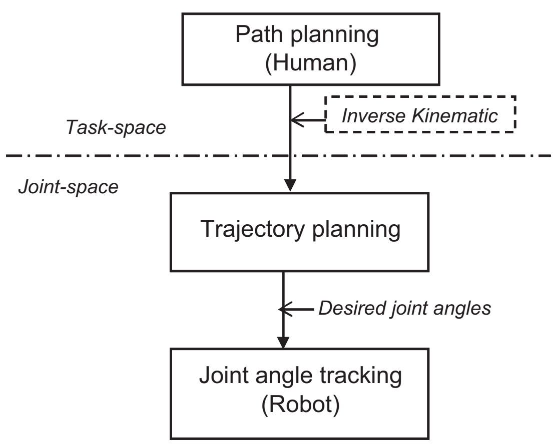

Fig. 1. Control structure of a human guide robot.

Gaussian mixture model (GMM) can also encode a set of trajectories [2]. GMM is a probabilistic model to represents the statistical inferences of observations. It can be regarded as types of unsupervised learning or clustering procedures. A time series can be modeled by GMM with its prior distribution, while the parameters are the mixture weights [4]. One weakness of GMM is the emission and the transition probabilities only use current state. In some cases, GMM cannot map well for time-dependent domains, such as joint space [23].

In order to train HMM in joint space, it is necessary to map continuous trajectories into discrete values. In some cases, such as non-stationary, it is impossible to use all sampled data to train HMM. We need to sample some important points, which can shape the trajectory. These points can be obtained by positions evaluation [20], position/velocity evaluation [6], or Linde–Buzo–Gray algorithm [24], which is a very popular method for vector quantization. The above methods only use the shape information [25]. They do not consider data density. K-means clustering algorithm is an effective tool to partition the input according to data distributions. However, k-means clustering cannot work in a continuous geometric region.

Lloyd's algorithm partitions data into well-shaped and uniformly sized convex cells according to their Gaussian distributions [26]. It repeatedly finds the centroid of each set in the partition using Voronoi diagrams. In this paper, we use Lloyd's algorithm for human behavior learning to avoid the following two problems: the calculation problem of the dynamic time warping in joint space, the key point selection problem of the demonstrations in joint space.

In order to generate desired trajectories of human guide robots, this paper proposes a different method from the previous works like inverse kinematics and dynamic time warping. Since the demonstrations in joint space are time-dependent (see Fig. 2), HMM cannot model them directly. The contributions of the paper include three parts: (1) The classical HMM is modified such that it

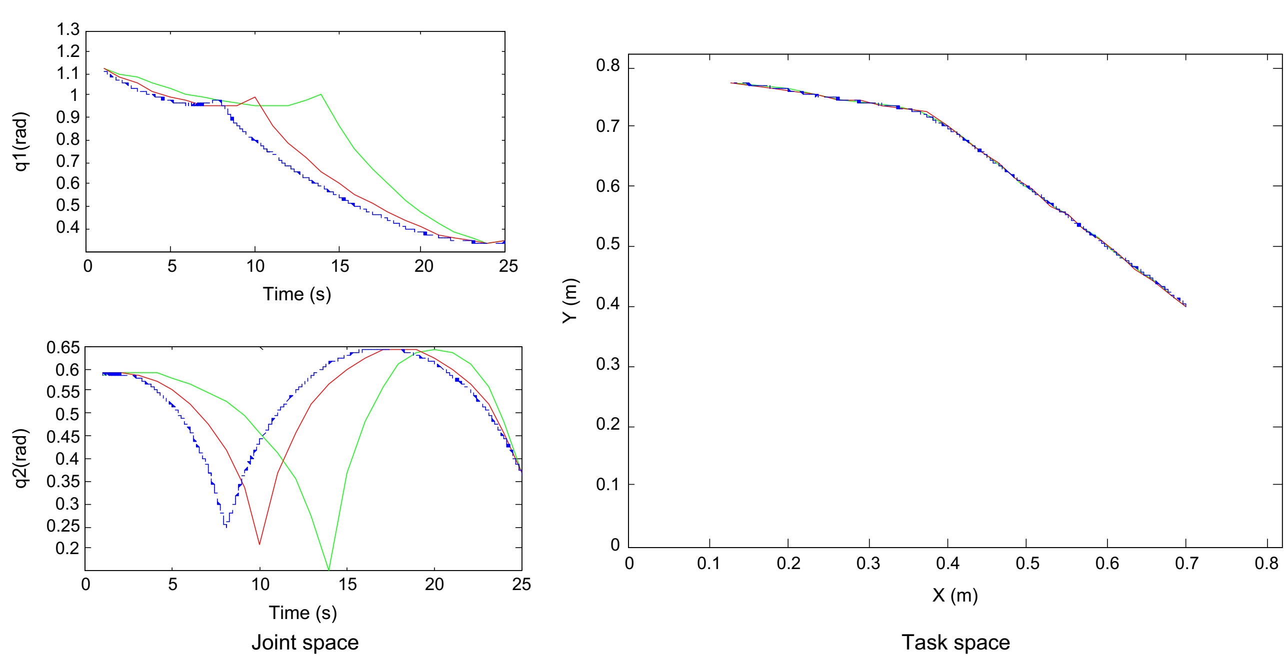

Fig. 2. A two-link planar robot draws a broken line: (1) left is in joint space, (2) right is in task space.