Novel Leaning Feed-Forward Controller for Accurate Robot Trajectory Tracking

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Abstract. This paper presents a novel learning feed-forward controller design approach for accurate robotics trajectory tracking. Based on the joint nonlinear dynamics characteristics, a model-free learning algorithm based on Support Vector Machine (SVM) is implemented for friction model identification. The experimental results verified that SVM based learning feed-forward controller is a good approach for high performance industrial robot trajectory tracking. It can achieve low tracking error comparing with traditional trajectory tracking control method.

1 Introduction

The industrial robot manipulator is, in general, a highly nonlinear coupled dynamic system and, therefore, achieving high performance in trajectory tracking control is a very challenging task. To be able to track a motion with small errors, a feed-forward controller can be used. The feed-forward controller generates the control signal from the reference (the desired motion). Instead of computing the required feed-forward compensation mathematically, it can also be learnt from the feedback signal using a function approximator. The usually used function approximator is the B-spline neural network [1], which often suffers from curse dimensionality and over fitting problem.

Recently Support Vector Machine (SVM) [2] has aroused research interests in data classification and regression. An SVM for regression, like regularization networks, proves to be a potential tool for constructing the approximation of a function from sparse training data. The approximation of a function using SVM offers some attractive properties. An SVM for regression does not suffer from the over-fitting problem and it has good generalization ability. The feasibility of applying an SVM for learning feed-forward control signals has been investigated in [3], but only with simulation studies. Up to now, using SVM based learning feed-forward control for accurate trajectory tracking has not been exploited much experimentally.

2 SVM Based Learning Feed-Forward Controller

A typical industrial robot trajectory tracking with SVM based learning feed-forward controller is described in [3]. One reason for choosing the feed-forward loop is that,

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for reproducible disturbances such as unmodeled dynamics, feed-forward compensation is principally faster than feedback compensation. In other words, we get the best performance if we try to learn the inverse process in the feed-forward path.

The approximation of a function using SVM offers some attractive properties. For example, it does not suffer from the over-fitting problem and it has good generalization ability. These features suggest that it may be a good candidate for constructing approximations for unknown nonlinear functions needed in learning feed-forward control system designs. So the nonlinear dynamics can be first learned offline by SVM, then model can be implemented in the learning feed-forward control.

3 Support Vector Machines for Model Learning

This section presents SVM [2] for dynamics modeling. The SVM algorithm has its origin in the theory of statistical learning and it has found many applications in pattern recognition [4].

Given l training data (x_i, y_i), where x_i is the input, y_i is the output, SVM based nonlinear dynamics identification algorithm can be derived by preprocessing the training points by a mapping $\phi : x \to F$ into a very high dimensional feature space F. The dynamics model in high dimensional space F is:

$$f(x) = \pi \cdot \phi(x) + m \tag{1}$$

With ε-insensitive loss function [2], we have the following convex optimization problem:

$$\text{Minimize: } \|\pi\|^2 + c\sum_{i=1}^{l}\left(\zeta_i + \zeta_i^*\right) \tag{2}$$

Subject to:

$$\begin{cases} y_i - \langle \pi, \phi(x_i) \rangle - m \le \varepsilon + \zeta_i \\ \langle \pi, \phi(x_i) \rangle + m - y_i \le \varepsilon + \zeta_i^* \\ \zeta_i, \zeta_i^* \ge 0 \end{cases} \tag{3}$$

Where $c \succ 0$ is a constant that determines the tradeoff between the empirical risk minimization (ERM) error and the bound of $\|\pi\|^2$ value.

To solve the convex optimal problem, we need to construct a Lagrange function from both the objective function and the corresponding constraints. It can be shown that this function has a saddle point with respect to the primal and dual variables at the optimal solution [5]. Solving this optimization problem by using kernel property [2], the identified function is:

$$f(x) = \sum_{i=1}^{l}\left(\alpha_{Fi} - \alpha_{Fi}^*\right)k(x, x_i) + \overline{m}_F \tag{4}$$

where $\alpha_{Fi}, \alpha_{Fi}^*, \overline{m}_F$ are constant values obtained by solving the optimization problem.

4 Experimental Results

The learning feed-forward controller designed for one DOF robot can be extended to multi-degree-of-freedom robotics device with no technical difficulty. So in the following, we use a simple one horizontal DOF device to illustrate our SVM based learning feed-forward control strategy. This device consists of a mechanical link driven by a DC motor through a gearbox with a ratio of 1:80.

As the link is horizontal, the gravity torque can be ignored when the robotic device is in motion. So the dynamics of this robotic device can be described by the following equation:

$$\tau_{motor} = \tau_{friction}(\dot{q}) + I\ddot{q} \tag{5}$$

where τ_{motor} is the motor torque, $\tau_{friction}$ is the frictional torque, I is the mass moment of inertia, q is the angular position. According to the dynamics model (equation (5)), the inertia has been designed known, so the unknown nonlinear friction model can be identified through the training data points. As the first step toward off-line learning of the friction model, a number of experiments were performed to obtain the training data sets. The tests included two different directions of motions of the link. The corresponding friction torques were recorded to give two groups of angular velocity-friction torque training data sets for the two cases with the angular velocity $\dot{q} > 0$ and $\dot{q} < 0$ respectively. The zero velocity friction value (at $\dot{q} = 0$) was measured by conducting "break-away" experiments in the two directions, as suggested by Armstrong [6].

After obtain the 54 data points in each data sets with the angular velocity $\dot{q} > 0$ and $\dot{q} < 0$ respectively, the optimal results found for implementing the SVM algorithm were: for $\dot{q} \geq 0$, C=0.25, ε=0.00025 with 10 Support Vectors, and for $\dot{q} \leq 0$, C=0.05, ε=0.0003 with 9 Support Vectors.

For the evaluation of the performance of the considered controller, the experiments are conducted with reference trajectory tracking as described in Fig. 1. When applying a traditional PD based controller, the proportional parameters $k_p = 5$, the derivate parameters $k_d = 0.01$; when applying the learning feed-forward control, the

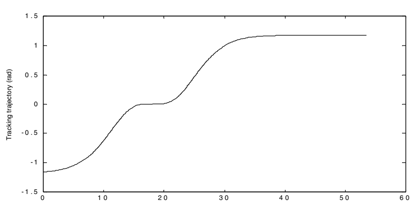

Fig. 1. Reference trajectory

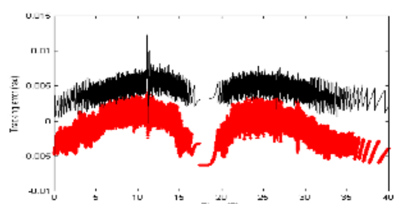

Fig. 2. Tracking error comparison: solid line: PD control; Dotted line: SVM based

proportional parameters $k_p = 5$, the derivate parameters $k_d = 0.01$; Fig.2 shows the trajectory tracking error comparison of these two control methods. We can see that the tracking accuracy of the SVM based learning feed-forward controller has improved compared with that of the traditional PD based controller.

5 Conclusions and Discussion

The experimental results verified that the SVM based learning feed-forward controller is a good approach for high performance industrial robot trajectory tracking. It can achieve low tracking error comparing with traditional trajectory tracking control method. These results suggest that SVM method may be a good candidate for constructing approximations for unknown nonlinear functions needed in learning feed-forward control system designs.

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