A NEURAL NETWORK BASED FAST STARTING METHOD FOR SERVO SYSTEMS

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This paper introduces a fast starting motion control method for servo systems. The method consists of two phases. In the first phase, a time-optimal controller is used to accelerate the servo system. The second phase adopts a neural network based approach for speed regulation. It also achieves robustness to payload variation by estimating the payload uncertainty from the motion characteristics of the first phase. Experimental results demonstrate the effectiveness of the proposed approach.

1. INTRODUCTION

In many control applications, a servo system is required to reach a target speed from rest. In such applications, an ideal servo system controller should meet the following demands. First, the servo system should reach the target speed as fast as possible. Second, after reaching the target speed, the controller should regulate the servo system such that speed variation is minimized. Third, the controller should provide sufficient robustness to make the stability and performance of the servo system insensitive to payload variation.

The first objective can be satisfied by adopting a time-optimal (or near time-optimal) control strategy. To meet the second requirement, a regulator-type controller can be designed given appropriate performance specifications. However, due to their conflicting nature, designing a single controller to simultaneously satisfy both control objectives does not seem to be possible. As a result, conventional controller design methods often involve a trial-and-error parameter tuning process so that a balance between time-optimal and regulator-oriented control methods can be obtained. Inevitably, this design strategy comprises control system performance.

A possible solution is to design separate time-optimal and regulator-oriented controllers. An on-line control process can then be used to switch from the time-optimal controller to the regulator-oriented controller at an appropriate time. For example, Rubo and Araci (1997) rely first on a deadbeat controller to rapidly accelerate a servo system and then switch to an LQR/LTR based controller to perform speed regulation when the speed of the servo system is sufficiently close to the target speed. This controller switching method seemingly combines the advantages of time-optimal and regulator-oriented controllers. However, a drawback of this method is that it is not adaptive to payload variations. A more flexible approach would be to tailor an LQR/LTR based controller offering sufficient robustness to account for payload uncertainty. However, providing robustness comprises the regulation performance of an LQR/LTR based controller. The goal of this work is to develop a more general control method to resolve this difficulty.

The remainder of this paper is organized as follows. Section 2 describes the method in detail, Section 3 presents experimental results, and Section 4 offers conclusions.

2. METHODOLOGY

2.1 The Predictive Control Method

The dynamics of the system considered in this paper can be represented by the following discrete-time transfer function model

$$y(k) = \frac{q^{-d} B(q^{-1})}{A(q^{-1})} u(k) + x(k) \quad (1)$$

Note that y is the output variable, u is the control variable, q^{-1} is the backward shift operator, d is the time delay of the process (in samples), x is the disturbance and

$$A(q^{-1}) = 1 + a_1 q^{-1} + \cdots + a_n q^{-n} \quad (2)$$

$$B(q^{-1}) = b_0 + b_1 q^{-1} + \cdots + b_m q^{-m} \quad (3)$$

where n and m are the degrees of the polynomials A and B, respectively. With $e(k)$ denoting a discrete white noise sequence with zero mean and unit variance, the disturbance is modeled as

$$x(k) = \frac{T}{D} e(k) \quad (4)$$

with T and D being monic polynomials in q^{-1}.

Many methods have been proposed to design the closed-loop control law for systems that can be represented by equation (1). In this study, the unified predictive control method (Soeterboek, 1992) is adopted. Specifically, the control law is obtained by minimizing the following criterion function

$$J = J_1 + J_2 \quad (5)$$

With y^* and w denoting the predicted and desired output of the process, respectively, the first part of the criterion function characterizes the tracking output error and is defined as

$$J_1 = \sum_{i=1}^{H} \left[P y^*(k+i) - P(1) w(k+i) \right]^2 \quad (6)$$

where P is a monic polynomial in q^{-1}. The second part of the criterion function represents the controller output weighting and is defined as

$$J_2 = r \sum_{i=1}^{H} \left[\frac{Q_n}{Q_d} u(k+i-1) \right]^2 \quad (7)$$

Note that Q_n and Q_d are monic polynomials with no common factor. In the predictive control framework, the control law is obtained by minimizing the criterion function of equation (4) under the following constraint

$$f P u(k+i-1) = 0 \quad 1 \le H_c \le H - d \quad (8)$$

Hence, the design parameters include H, H_c, P, f, Q_n and Q_d. In addition, the polynomials T and D of the disturbance model are also used as design parameters.

2.2 The Payload Estimation Method

Payload uncertainty often degrades the performance of a servo system. A possible solution to this problem is to use neural networks to estimate the payload. For example, by dividing the payload into a finite number of classes and by training neural networks to recognize a payload variation associated with degradation in tracking performance, Leahy et al. (1991) provided a method that adapted the feedforward dynamic compensation torques to payload variation. However, the effectiveness of this approach remains to be investigated when the payload does not belong to any of the predefined classes.

This paper adopts a neural network based method to make the controller adaptive to payload variations. It relies on the fact that with the same control law, the response of the servo system varies with the payload. Sharing the common property of using neural networks to estimate the payload uncertainty, the proposed approach differs from the approach proposed by Leahy et al. (1991) in several aspects. First, the proposed control method divides the control process into two phases. A time-optimal control strategy is used to bring the servo system to the vicinity of the target. Based on the performance of the time-optimal controller, a neural network estimates the payload at the end of the first phase of the control process.

As shown in Fig.1, the motion of the first phase of the control process is divided into three subphases that have equal speed increments. (In Fig.1 S_p denotes the target speed.) The means and variances of the speed of these three subphases as well as those of the entire first phase of the control process are used as feature variables. As such, the neural network is used only once in the control process. In contrast, Leahy's method estimates the payload in each sampling period, imposing a computational burden on the controller.

A second difference between the proposed work and Leahy's method is in the application of the neural networks. During the control process, Leahy et al. used the neural network to determine which of the predefined payload classes the payload uncertainty belongs to. However, in training the neural network, Leahy et al. formulated the neural network learning task as a function approximation problem. Since the minimization of the function approximation error does not necessarily lead to the minimization of classification error, the trained neural network often has room for further improvement. In view of this problem, this work uses a hyperspherical classifier (Telfer and Casasent, 1993) to learn to recognize the payload uncertainty. One reason for choosing the hyperspherical classifier is the existence of an effective training method (Yen and Liu, 1997). The other reason is

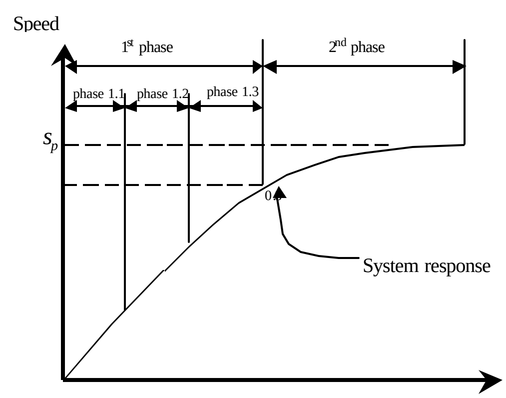

Fig. 1 The feature variable extraction strategy

that this neural network, once successfully trained, is computationally very efficient in performing classifications allowing for on-line control.

The following steps illustrate the neural network training process of the proposed method.

Step 1: Based on their weights, payloads are divided into a number of classes. For example, in the experiments the payload is divided into light, medium, and heavy weight levels.

Step 2: With a given payload, a time-optimal controller is used to bring the servo system to the target speed and the resulting rise time is determined. The mean and standard deviation of the servo system speed in the rise time period are computed. This time period is divided equally into three time subintervals and the mean and standard deviation of the servo system speed in each subinterval are computed. In this study, these eight feature variables are used to characterize the response of the servo system.

Step 3: The experiments are repeated for a sufficient number of payloads such that the entire range of payload variations is effectively covered.

Step 4: With the eight feature variables obtained in the previous steps as inputs and the class of the corresponding payload as output, a neural network is trained to relate the servo system response with the payload class.

3. EXPERIMENTS

3.1 Experimental System

To test its effectiveness, the proposed control method was implemented for speed control of an AC servomotor (NIKKI DENSO, model number NA50-40NA). Using an 80486 PC to perform the I/O actions, analog inputs and outputs were calculated with 16-bit resolution. The motor driver was set to a torque mode so that PC generated commands were proportional to the output torque of the motor. In this study, the target speed was chosen as 1800 rpm and the sampling frequency was chosen as 100 Hz. The hyperspherical classifier was chosen as the neural network model and was trained by a method proposed by Yen and Liu (1997).

3.2 Experimental method

In the experiments, the payload was varied from 4 to 20 times the inertia of the rotor. In the remaining part of this paper the term "payload parameter" will be used to characterize the weight of the payload. In particular, a payload parameter of *m* signifies that the payload is *m* times the inertia of the rotor. The payload was divided into three classes: low (payload parameter of 4 to 8), medium (payload parameter of 9 to 14) and high (payload parameter of 15 to 20). A nominal payload was chosen for each class. In particular, payload parameters of 6, 9 and 15 were selected as nominal values for the low, medium and high classes, respectively. For each of these nominal payloads, a first order difference equation was determined experimentally to characterize the motor dynamics from input voltage to speed. With these models and the predictive controller parameters of H=5, H_c = 1, P=1, T=1, D=$A(1-q^{-1})$, ϕ=$1-q^{-1}$, Q_n =1 and Q_d =1, three predictive controllers were designed independently for the three payload classes. In specifying these control parameters, the goal was to achieve regulation. The speed of response of the adopted predictive controllers was between the speeds of response of deadbeat and mean-level controllers.

Payloads with integer payload parameters (in the range of 4 to 20) were used to generate training and testing samples for the neural network. For each of the payload parameters, 100 sets of PC generated command versus speed data were collected. Half of the data was used to train the neural network. The other half was used to test the generalization error of the neural network. It was found that that the hyperspherical classifier achieved perfect classification results in performing the generalization tests.

In the first phase of the control process, a deadbeat

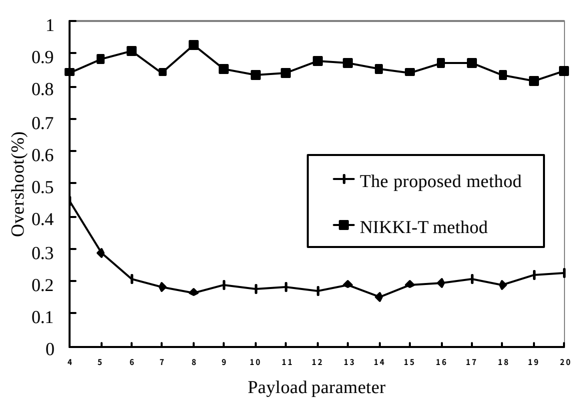

Fig. 2 Overshoot of tested control methods

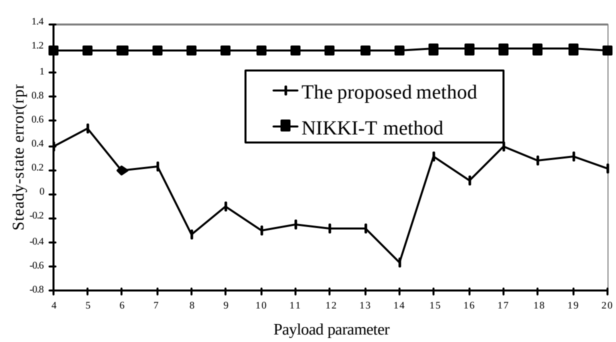

Fig. 3 Steady state error of tested control methods

controller was used to accelerate the AC servomotor. The deadbeat control strategy was selected due to its ripple free time optimal nature.

In the second phase of the control process, the required feature variables were computed in real time from the results of the first phase of the control process. With these feature variables, the neural network determined the class of the payload in real time. Based on this result, one of the three previously designed predictive controllers was selected to regulate the servo system to the target speed.

For comparison, the built-in controller of the motor driver was also used to perform the same control task. With a payload parameter of 9, the experimental procedure given in the motor driver manual was implemented to determine the nominal control parameters for the motor driver. To make fair comparisons between the built-in motor controller and the proposed control method, this set of nominal control parameters was then experimentally tuned. The first tuning method minimized the difference in the rise time and the second tuning approach minimized the difference in the amount of overshoot. The results using these two methods, denoted as NIKKI-T and NIKKI-O, respectively, are described below.

3.3 Experimental Results

For reliability, each experiment was repeated five times and the averages of the experimental results are reported.

The percent overshoot, steady-state error and the standard deviation of the steady-state error of the proposed control method and the NIKKI-T method are plotted in Figs. 2, 3 and 4, respectively, as a function of the payload parameter. As shown in Fig. 2, with the same speed of response, the proposed method yields smaller overshoot.

The percent overshoot generated by the NIKKI-T, NIKKI-O and the proposed control methods are plotted in Fig. 5 as a function of the rise time. As shown in Fig. 5, even with the rise time three times that of the proposed method, the built-in motor controller can not reduce its overshoot to be as small as the proposed method. Generally speaking, the response of built-in motor controller is much slower than that of the proposed control method.

The results depicted in Figs. 3 and 4 demonstrate that the proposed control method yields smaller steady-state error and smaller steady-state error deviation than the built-in motor controller.

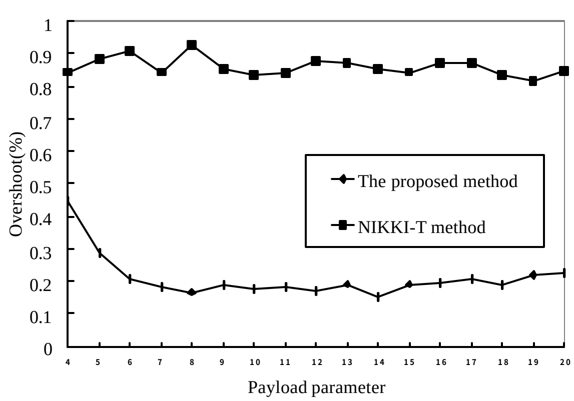

Fig. 4 Standard deviation of steady state error

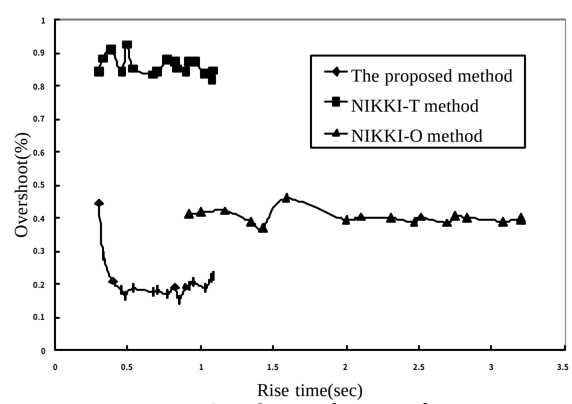

Fig. 5 Overshoot as function of rise time

4. CONCLUSION

This paper presents an intelligent controller switching method for servo systems. A distinct advantage of the proposed approach is that it circumvents the typical tradeoff nature of servo controller design. Compared with other controller switching methods, the approach is capable of estimating the payload uncertainty by observing the characteristics of the servo system motion before making the controller switching decision. As a result, the proposed method can choose an optimal controller for the regulation part of the control process yet remains robust to payload variation. Experimental results demonstrate the effectiveness of the proposed method.

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