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ORIGINAL ARTICLE

Position error compensation of semi-closed loop servo system using support vector regression and fuzzy PID control

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Abstract This paper discusses how to improve the position precision of a semi-closed loop servo system. A support vector regression algorithm is chosen to model and predict position error. The predicted error is then fed back to the input entry to compensate the error. Fuzzy PID control is introduced to adjust the controlling rule of the PID controller in the semi-closed loop servo system so as to improve the dynamic response characteristics of the servo system and reach a high degree of position precision. A case study is implemented. The simulation and experimental results show that combining the improved fuzzy control with predicted position error feedback ensures a high degree of position precision and a high degree of dynamic response characteristics.

Keywords Semi-closed loop servo system · Position error · Support vector regression · Fuzzy control

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1 Introduction

Servo systems of CNC machine tools are generally classified into three types, that is, open loop system, semi-closed loop system, and closed loop system. Semi-closed loop systems have a higher control precision compared with the open loop systems and are much cheaper than the closed loop systems [1]. For this reason, semi-closed loop systems have been widely adopted in CNC machines tools, especially in P. R. China. However, the errors of the mechanical transmission system in CNC machine tools, possibly resulting from wear, are unable to be fed back by the semi-closed loop servo system. This seriously affects the machining precision and stability of CNC machine tools. Therefore, a position error compensation of semi-closed loop systems has been paid special attention to.

It is known that error compensation basically involves a study of methods to compensate for the various sources of errors in machine tools. The errors in the machine tools are measured and suitably compensated for in various ways. Ramesh et al. [2] reviewed the works done in reducing the errors of machine tools, which were divided into two categories, namely error avoidance and error compensation. Therein error compensation was considered the primary method of error elimination. It could further be divided into two categories namely precalibrated error compensation and active error compensation. Artificial neural network method was adopted in [3–5] to compute the mapping of position errors, and the errors were reduced by introducing suitable compensation into the control loop. However, a large number of training sets required by this method is very difficult to be obtained in industry. A general approach for real-time error compensation technique was proposed by Yuan and Ni [6] to compensate for volumetric errors caused by geometric, thermal, and cutting force-induced errors. However, robust error models used in the error compensation technique have still some major obstacles for better application of the technique. A new sliding model was proposed by Xie et al. [7] to improve the tracking precision of a laser beam positioning system. Compared with a conventional control method, the control model had higher tracking precision when it tracked different shapes of parts. An adaptive fuzzy logic controller for precision contour machining was proposed by Jee and Koren [8] to improve the contouring accuracy by simultaneously adjusting both input and output membership functions based on the performance of each control rule. The combination of fuzzy Proportion Integration Differentiation (PID) control and simplified BP neural network brought self-adaptive control of electric motor into effect [9–13]. Compared to the conventional controllers, the fuzzy PID controllers can improve the performance of machines tools which have variable friction in the guideway, large variations in load, and deflection of the lead screw. In addition, the contour errors especially the nonlinear contours that can also be improved for the fuzzy PID controllers are not sensitive to feedrate changes. For semi-closed loop servo system, the dynamic characteristics of the mechanical structure and servo motor obviously affected the position accuracy. So there have been many researches on the servo parameters tuning in order to match the changes. A novel initial value compensation was implemented by Hirose et al. [14] using an additional input for semi-closed control systems. A feedforward-compensator design technique was presented by Goto and Nakamura [15] to improve dynamic characteristics of servo system by modifying the input signals. To sum up, there is a shortage of effective methods to deal with the error compensation of the semi-closed loop servo system considering the time-varying tendency of position errors and the dynamic response characteristics of servo system, although a considerable volume of research work has been reported in the area.

The objective of this research is to develop new error compensation methods for improving the position accuracy of semi-closed loop servo systems. In order to obtain the required compensation value in advance, the authors propose the position error prediction method using support vector regression algorithm. According to the predicted variation tendency of the position error, the compensation value is fed back to the input dictate of the servo system. Furthermore, fuzzy PID control is adopted to adjust the controlling rule in the servo system in order to compensate the position error caused by the debasement of the dynamic characteristics of the servo system.

The details of our work are presented as follows. The principle and method of the position error compensation for a semi-closed loop servo system is briefly described in Sect. 2. The position error prediction based on the support vector regression algorithm is discussed in Sect. 3. The position error compensation based on the fuzzy PID control is presented in Sect. 4. A case study is implemented in Sect. 5. Finally, the conclusions are given in Sect. 6.

2 Position error compensation of a semi-closed loop servo system

The semi-closed loop servo system studied in this paper mainly contains a servo driving device, servo motor, angular rotation monitor, mechanical transmission system (including couplings, bearings, ball screw, and nuts), and an executive component such as a workbench. Its structure is described in Fig. 1. The semi-closed loop servo system has the complicated controlling principle with two control loops, a position control loop and a velocity control loop, as shown in Fig. 2. The mechanical transmission system is not included in the control loops. The rotating angle of the ball screw is measured by the rotary encoder and then is fed back to the input dictate. Many factors such as vibration, friction, heat distortion from the transmission system, as well as wear from the screw nut pairs will increase the transmission error and hence decrease the dynamic response properties. Moreover, it is known that the position error is a comprehensive precision index of the CNC machine tool. The position error can reflect different errors such as location error, dynamic error, and dead zone error when the machine tool is no load running. Therefore, position error compensation is one of the ways to improve the position precision and the machining performance of the machine tool in engineering practice. A two-step position error compensation method is proposed in this paper through using support vector regression and fuzzy PID control.

As shown in Fig. 3, the first step of the position error compensation is to predict the position error according to the

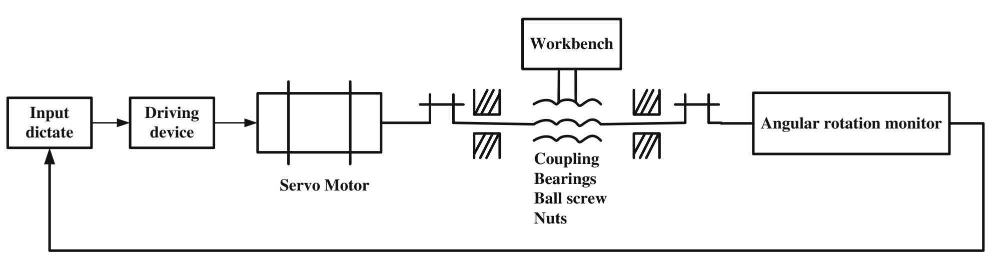

Fig. 1 Structure of a semi-closed loop servo system

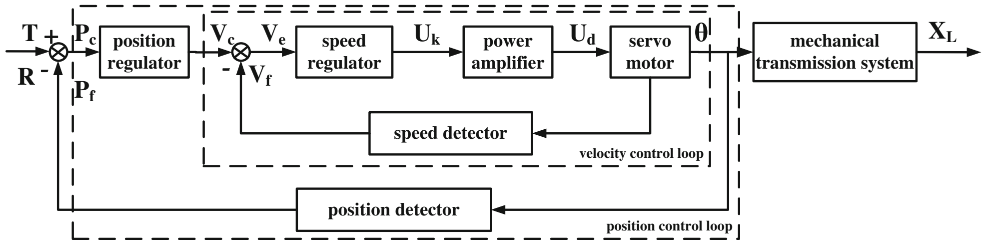

Fig. 2 Controlling principle of the semi-closed loop servo system

collected error data and then feedback the compensated error into the position control loop. Thus, it can be seen that error measurement is the premise for the position error compensation. Once error values at a period of time are obtained, a support vector regression algorithm will be adopted to build the degradation model of the position error. This is because the support vector regression algorithm has very excellent learning capacity and generalization capability with a small amount of samples. The degradation level and tendency of the position error will be reduced by the training and prediction of the degradation model. The required compensated values will be counted and fed back to the input dictate of the servo system in order to compensate the position error. This is called feedback position error compensation.

The second step of the position error compensation is to adjust the controlling rule of PID in the servo system. It is known that the decrease of the position accuracy is followed by the falling-off of the dynamic characteristics of the servo system when performance degradation happens. The debasement of the dynamic characteristics will further cause the increment of the position error in the servo system. Therefore, the main goal of the second step of the position error compensation is to improve the dynamic characteristics of the servo system. However, the servo system has nonlinear and time-varying characteristics. Outside perturbation and control parameter variety have a strong effect on the performance of the servo system. Although fuzzy control may efficiently diminish the influence from the nonlinear and time-varying characteristics of the servo system, it is not able to eliminate the steady-state error. It is found that PID control may efficiently decrease the steady-state error of the servo system. So the combination of fuzzy control and PID control is adopted to change the controlling rule of PID. A fuzzy PID controller is designed to compensate the position error.

3 Position error prediction based on support vector regression algorithm

Position error prediction needs plenty of error data if traditional methods such as neural networks are used. However, the number of the measuring points of the servo system is usually less than ten, and there is a relatively slow degradation rate among servo systems. Thus, the obtained degradation sample data of the positioning error is often rare in engineering practice.

Support vector regression originally proposed by Vapnik and his co-workers is a new machine learning algorithm based on the statistical learning theory [16–18]. It implements the rule of structural risk minimization to obtain a very good generalization on a limited number of learning patterns. For this reason, support vector regression algorithm is introduced in this paper to model position error regression and predict the tendency of the position error.

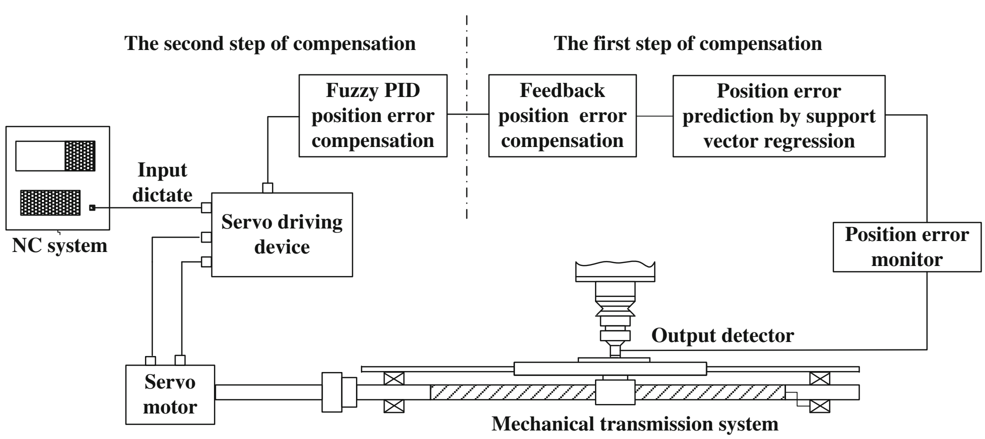

Fig. 3 The two-step position error compensation

3.1 Support vector regression algorithm

Given a measurement dataset $\{(x_i, y_i) | x_i \in R^n, y_i \in R, i=1, 2, \cdots, l\}$ with input data x_i and output data y_i, which, respectively, indicate measurement time point and position error, and l is the number of samples. The goal of the support vector regression algorithm is to identify the following nonlinear representation in a so-called high-dimensional feature space:

$$y_i = w \cdot \psi(x_i) + b + e_i \tag{1}$$

where w is the weight vector and b is the bias term. $\psi(\bullet)$: $R^n \rightarrow R$ is the nonlinear mapping function by which a nonlinear regression in input space is converted into linear regression in high-dimensional feature space. e_i is the vector of error terms which is assumed to have random distributions with zero mean and constant variance. According to the theory of support vector machines [19], the nonlinear representation can be identified via minimizing the following cost function:

$$\begin{cases} \min\limits_{w,\xi_i,\xi_i^*} & \frac{1}{2} w^T w + C\left(\varepsilon + \frac{1}{l}\sum\limits_{i=1}^{l}\left(\xi_i + \xi_i^*\right)\right) \\ \text{subject to} & -\varepsilon - \xi_i^* \leq (w \cdot \psi(x_i)) - b - y_i \leq \varepsilon + \xi_i \\ & \xi_i,\ \xi_i^* \geq 0,\ i = 1, 2, \cdots, l \end{cases} \tag{2}$$

where C is the regularization parameter determining the tradeoff between minimizing the training error and the model complexity. ξ_i and ξ_i^* are penalty terms to measure the cost of errors on the upper and lower constrains of the training points. By applying the Lagrange multiplier method and Wolfe dual, the solution to the nonlinear representation is transformed to the following dual optimization problem:

$$\begin{cases} \max\limits_{\alpha,\alpha^*} & \frac{1}{2}\sum\limits_{i=1}^{l}\sum\limits_{j=1}^{l}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right)K\left(x_i, x_j\right) - \sum\limits_{i=1}^{l} y_i\left(\alpha_i - \alpha_i^*\right) + \sum\limits_{i=1}^{l}\varepsilon\left(\alpha_i + \alpha_i^*\right) \\ \text{subject to} & \sum\limits_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right) = 0, 0 \leq \alpha_i, \alpha_i^* \leq C \end{cases} \tag{3}$$

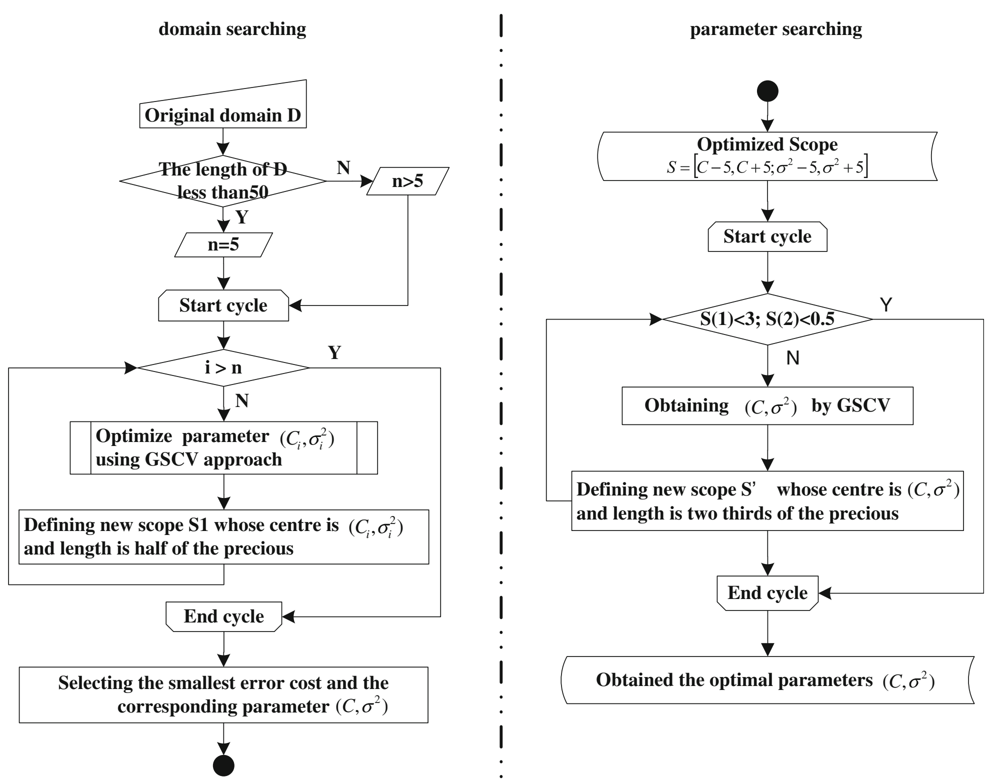

Fig. 4 Model parameter selection based on the two-stage searching method

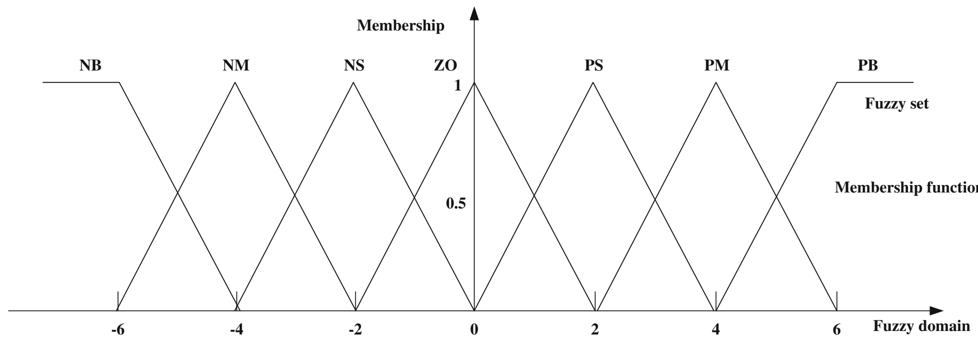

Fig. 5 Membership functions of normalized fuzzy variables

Here, the sequential minimal optimization algorithm is used to solve the dual optimization problem [20], and the Lagrange multipliers α_i and α_i^* will be obtained. Furthermore, the bias term b is reduced according to the following equation: $b = y_i - \varepsilon - \sum_{i=1}^{l} \left(\alpha_i^{*} - \alpha_i\right) K\left(x_i, x_j\right)$. Finally, the optimal nonlinear regression function is acquired for curve fitting and prediction of the position error, which is expressed as follows:

$$y(x) = \sum_{i=1}^{l} \left(\alpha_i^* - \alpha_i\right) K(x_i, x) + b \tag{4}$$

where $K(x_i, x)$ is a nonlinear kernel function satisfying the Mercer's condition. The selection of kernel function is a vital problem to minimize the generalization error of the support vector regression algorithm. Compared with other feasible kernel functions, the radial basis function (RBF) kernel can reduce computational complexity of the training process and improve generalization performance of the support vector regression algorithm. Therefore, RBF kernel is selected as the kernel function in the paper, which is formulated as follows:

$$K(x, x_i) = \exp\left[-(x - x_i)^2 / \sigma^2\right] \tag{5}$$

where σ^2 is the scale factor for tuning.

3.2 Model parameter selection for position error prediction

The regularization parameter C and RBF kernel parameter σ^2 play an important role in the results of the position error prediction. So these parameters in the regression algorithm have to be tuned before being applied to fuzzy PID position error compensation. There are different parameter optimization methods such as the grid-search and cross-validation arithmetic to search for optimal parameters [21–23]. Most current researchers try to balance searching speed and accuracy. However, it is revealed in our research that the error between the forecasted value and the true value was much bigger when using the optimal parameters to train the remaining dataset. By analyzing the parameter optimization process, it was found that the selection of original scope of parameters and the sample step in the support vector regression algorithm depend very much on experience. The obvious limitation is that if the scope and step are too small or too big, the optimal parameters may either be missed or need too much time to be found. Due to the limitations of the current parameter-searching methods, the performance of the support vector regression algorithm is still unsatisfactory. For this reason, a novel two-stage searching method is proposed in the paper to improve the parameter optimization process. The method includes a domain searching stage and a parameter searching stage. The detailed steps involved are illustrated in Fig. 4.

Table 1 Control effects of PID parameters

Parameter	Effects	Increase parameter	Decrease parameter
K_p	Accelerate response speed; improve adjusting accuracy	Fast response speed; high adjusting accuracy; overshoots and instability	Low response speed; decrease adjusting accuracy; long regulation time
K_i	Eliminate steady-state deviation	Eliminate deviation quickly; integral saturation in initial stage of response and a high overshoots	Can not eliminate deviation and reduce the adjusting accuracy
K_d	Improve dynamic property; prevent deviation from happening.	Brake the response advanced; a long adjusting time and a bad anti-disturbance	Cause a large error and a low dynamic property

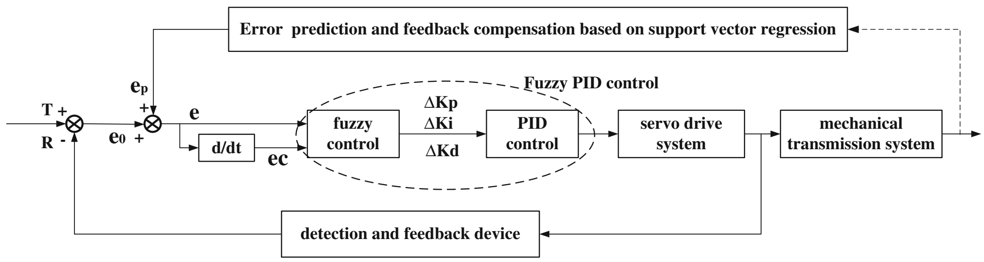

Fig. 6 Error compensation based on fuzzy PID control

First of all, the measurement dataset should be normalized to limit numeric ranges and numerical difficulties during the calculation. An original domain of parameters such as $C \in [10^0, 10^{20}]$ and $\sigma^2 \in [10^{-10}, 10^{10}]$ is confined, and the domain should be as large as possible in order that the optimal parameters may not be missed. Then, the cycle index n is defined. The center and scope of the optimization in each cycle are changed according to the result of the last cycle. The smaller the scope is, the more satisfactory the result is. After the n cycles are run, n sets of the parameters will be obtained. And the parameters (C, σ^2) with the smallest error are selected.

In the parameter searching stage, parameters are tuned automatically to identify optimal parameters. The center of the optimization is defined by the parameters (C, σ^2) obtained in the domain searching stage, and the scope of the optimization is defined as [C−5, C+5; σ^2−5, σ^2+5]. Meanwhile, the threshold values of the optimization precision are confined. Once the threshold values are overrun, the cycle will end. The optimal parameters are finally found.

4 Position error compensation based on fuzzy PID control

4.1 Fuzzy PID control

Fuzzy control is a specific type of knowledge-based control method having roots in the fuzzy set theory, where the experience and knowledge available from experts such as process operators may be captured and implemented. Fuzzy PID control, combines the traditional PID and the fuzzy control algorithm, and has shown excellent control effects on many engineering problems such as position control of slider crank mechanism and speed control for high-performance brushless servo drives [24–33].

A fuzzy PID controller usually includes fuzzification, control rules, fuzzy logic inference, and defuzzification procedure. It has two input variables: the control error e and the error change rate ec, and has one output variable U. They are defined using the fuzzy sets. Here, the linguistic labels used to describe the fuzzy sets are as follows: negative big (NB), negative medium (NM), negative small (NS), nearly zero (ZO), positive small (PS), positive medium (PM), and positive big (PB). In Fig. 5, triangular-shaped membership functions are chosen to make the fuzzy sets.

According to the control conditions and operations, fuzzy PID control will use control error and the error change rate to set the PID parameters automatically. K_p, K_i, and K_d are the control parameters of PID. The servo system would have a good dynamic response property if the values of those three parameters are appropriate. The control effects of PID parameters are shown in Table 1.

4.2 Position error compensation and fuzzy control improvement

As shown in Fig. 6, a position error compensation based on fuzzy PID control is proposed in this paper. The original

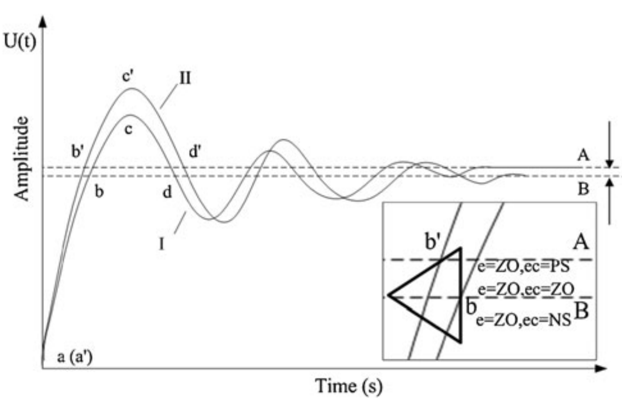

Fig. 7 Step response of the servo system

Table 2 Fuzzy control rule matrix of ΔK_p

e	ec						
	NB	NM	NS	ZO	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PS	PS	ZO	NS
NS	PM	PM	PM	PS	ZO	NS	NS
ZO	PM	PM	PS	ZO	NS	NM	NM
PS	PS	PS	ZO	NS	NS	NM	NM
PM	PS	ZO	NS	NM	NM	NM	NB
PB	ZO	ZO	NM	NM	NM	NB	NB

Table 3 Fuzzy control rule matrix of ΔK_i

e	*ec*						
	NB	NM	NS	ZO	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PS	PS	ZO	NS
NS	PM	PM	PM	PS	ZO	NS	NS
ZO	PM	PM	PS	ZO	NS	NM	NM
PS	PS	PS	ZO	NS	NS	NM	NM
PM	PS	ZO	NS	NM	NM	NM	NB
PB	ZO	ZO	NM	NM	NM	NB	NB

control error e_0 is expressed as $e_0=T-R$, where T represents the input instruction and R represents the feedback instruction from the detection and feedback device. The control error e is expressed as $e=e_0+e_p$, where e_p represents the predicted position error from the degradation model based on support vector regression algorithm. The control error e and the error change rate ec are input to the fuzzy controller, and the PID control parameters K_p, K_i, and K_d will be adjusted according to the input variables. The fuzzy domain and fuzzy subset of those variables should be designed by rules. Taking the real domain of the variables into consideration, the fuzzy domain of e and ec are designed to be [−3, 3], the fuzzy domain of ΔK_p is [−6, 6], the fuzzy domain of ΔK_i is [−1.5, 1.5], and the fuzzy domain of ΔK_d is [−0.25, 0.25]. The fuzzy subset [NB, NM, NS, ZO, PS, PM, PB] is chosen for all variables.

The typical step response of the servo system is shown in Fig. 7. Curved line I is the system step response line without position error and curved line II is the system step response line with position error. The line A represents the theoretical steady state of system response without position error, and the line B represents real steady state of system response. The range Δ between the line A and B is the position error of the system. The rectangle part described at the lower right of Fig. 7 is the enlarged view of the response line around point

Table 4 Fuzzy control rule matrix of ΔK_d

e	*ec*						
	NB	NM	NS	ZO	PS	PM	PB
NB	PS	NS	NB	NB	NB	NM	PS
NM	PS	NS	NB	NM	NM	NS	ZO
NS	ZO	NS	NM	NM	NS	NS	ZO
ZO	ZO	NS	NS	NS	NS	NS	ZO
PS	ZO	ZO	ZO	ZO	ZO	ZO	ZO
PM	PB	NS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PM	PS	PS	PB

Table 5 Improved fuzzy control rules

e	*ec*	ΔK_p	ΔK_i	ΔK_d
ZO	NS	PS	NS	NS
	ZO	ZO	PS	NS
	PS	NS	NS	PS

b. In the enlarged view, the triangular symbol represents the fuzzy set of $e=ZO$. According to the error change rate, there are $e=ZO$, $ec=PS$ in the upper half of the triangular, $e=ZO$, $ec=ZO$ around the midline, and $e=ZO$, $ec=NS$ in the lower half. It is found from Fig. 7 that both the position precision and dynamic response property have declined after degradation. Without the position error, the fuzzy control rules of ΔK_p, ΔK_i, and ΔK_d can be designed according to Table 1 and the simulated fuzzy control rules are shown in Tables 2, 3, and 4. For example, at point a, the fuzzy control should be $e=NB$, $ec=ZO$. In order to reach higher response speed, the system should have a larger K_p, smaller K_i and K_d. So the control rules around point a should be $\Delta K_p=PM$, $\Delta K_i=NM$, $\Delta K_d=NB$.

In order to improve the dynamic response and reduce the range between the line A and B, the fuzzy control rules should be modified as follows: (a) when e and ec, respectively, is equal to ZO and NS, the response line does not reach the line A. So K_p should be increased, K_i and K_d should be decreased. The control rule has no need to be changed. (b) When e and ec, respectively, is equal to ZO and ZO, K_i should be increased and K_d should be reduced to stabilize the response line around the line A. So the control rule should be changed from $\Delta K_p=ZO$, $\Delta K_i=ZO$, $\Delta K_d=NS$ to $\Delta K_p=ZO$, $\Delta K_i=PS$, $\Delta K_d=NS$. (c) When e and ec, respectively, is equal to ZO and PS, K_d should be increased and K_p and K_i should be decreased to stabilize response line around the line A. So the control rules should be changed from $\Delta K_p=NS$, $\Delta K_i=PS$, $\Delta K_d=NS$ to $\Delta K_p=NS$, $\Delta K_i=NS$, $\Delta K_d=PS$. According to the above analysis, the improved fuzzy control rules are shown in Table 5.

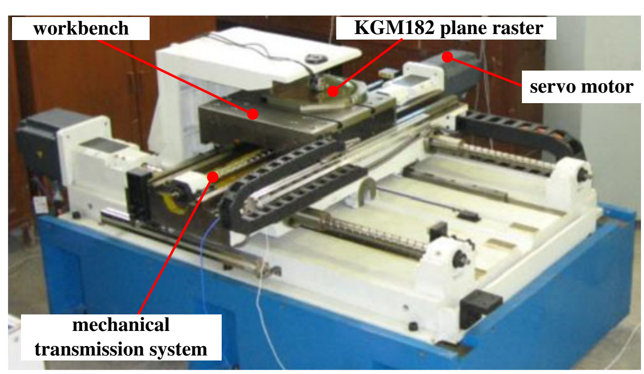

Fig. 8 The feed servo system worktable

Table 6 Measured and fitted data of the position error

Serial	Position (mm)							
	40		160		280		400	
	Measured value	Fitted value	Measured value	Fitted value	Measured value	Fitted value	Measured value	Fitted value
1	0.0031	0.0030	0.0307	0.0306	0.0464	0.0464	0.0544	0.0543
2	0.0038	0.0038	0.0316	0.0316	0.0475	0.0476	0.0558	0.0558
3	0.0047	0.0046	0.0326	0.0326	0.0487	0.0488	0.0573	0.0573
4	0.0057	0.0055	0.0338	0.0337	0.0501	0.0501	0.0590	0.0589
5	0.0068	0.0066	0.0350	0.0350	0.0515	0.0516	0.0607	0.0607
6	0.0079	0.0076	0.0363	0.0362	0.0529	0.0530	0.0625	0.0624
7	0.0091	0.0088	0.0376	0.0376	0.0545	0.0546	0.0643	0.0643
8	0.0104	0.0100	0.0390	0.0390	0.0560	0.0562	0.0662	0.0662
9	0.0117	0.0113	0.0405	0.0405	0.0577	0.0579	0.0682	0.0682
10	0.0130	0.0127	0.0420	0.0420	0.0594	0.0596	0.0702	0.0702
11	0.0144	0.0140	0.0435	0.0436	0.0611	0.0614	0.0723	0.0723
12	0.0159	0.0154	0.0451	0.0452	0.0629	0.0632	0.0744	0.0744
13	0.0174	0.0169	0.0468	0.0469	0.0647	0.0651	0.0765	0.0766
14	0.0189	0.0184	0.0485	0.0486	0.0666	0.0670	0.0788	0.0788
15	0.0205	0.0200	0.0503	0.0504	0.0686	0.0690	0.0810	0.0810

5 Case study

An experiment about position error compensation was carried out on a feed servo worktable made by Huazhong Numerical Control Corporation. As shown in Fig. 8, the GK6081-6AF61 servo motor was a power supply to drive the worktable. And the ball screw was a mechanical actuator to translate the rotational motion of the servo motor to the linear motion of the worktable with little friction. The maximum motion distance of the worktable was designed to be 750 mm. The positioning accuracy of the worktable was required to be ±0.05 mm. Ten points of the measurement which were evenly located on the x-axis were selected as x=40, 80, 120, 160, 200, 240, 280, 320, 360, and 400 mm. Each position error was obtained using precise measuring system-KGM182 planar grid encoder made by Heidenhain. The worktable continuously operated 400 h, and the measurement was executed at 20-h intervals. The 20 group of the test data at these measurement points were eventually acquired, of which four measurement points shown in Table 6 were picked up. At the same time, the simulation on the worktable was carried out to evaluate the effect of the position error compensation and fuzzy control improvement. The SIMULINK tools and ADAMS software were used to build the simulation model of the worktable [34]. In the simulation model, the back-emf coefficient, viscous damping coefficient, and rotary inertia of the servo motor are, respectively, 0.0386 V s/rad, 380 N s/m, and 1.35 kg m^2. The viscous damping coefficient, rotary inertia,

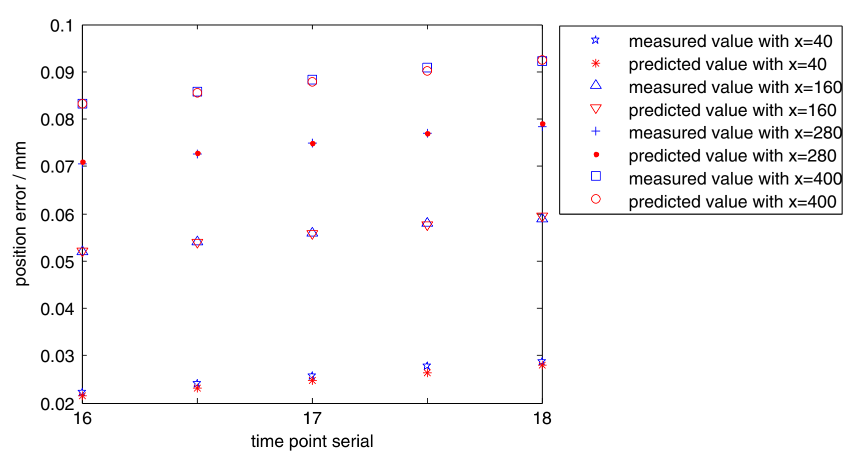

Fig. 9 Measured curve and predicted curve of the position error

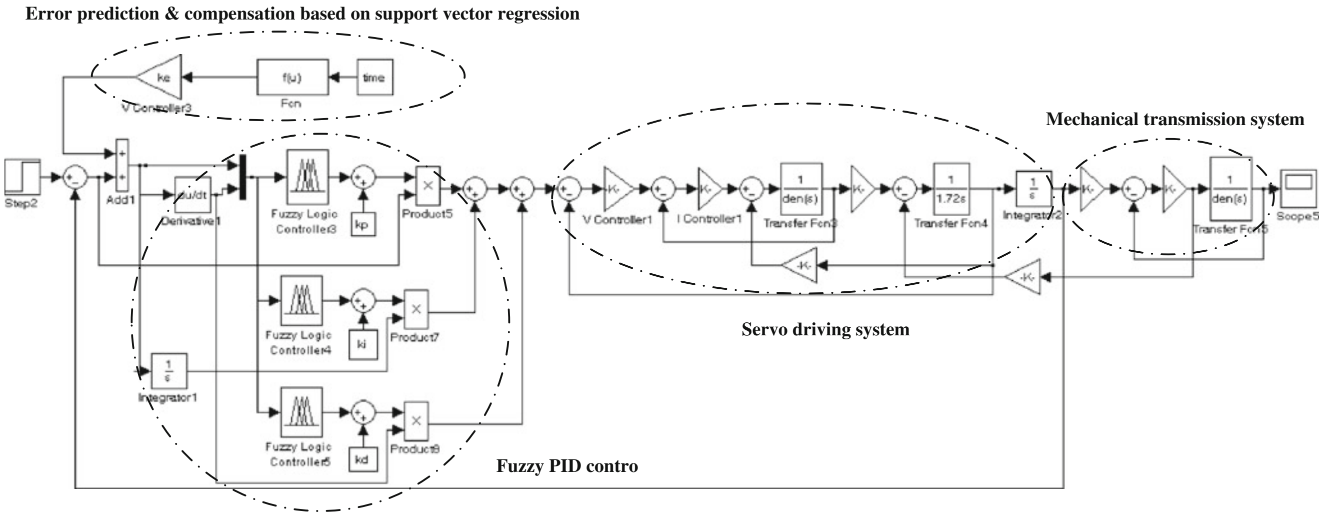

Fig. 10 Simulation model of position error compensation method based on fuzzy control

and screw lead of the ball screw are, respectively, 380 N s/m, 0.37 kg m^2, and 5 mm/rad.

As shown in Table 6, the measured position errors of the 1 to 15 time points from the selected four measurement locations were used to train the position error regression model based on the support vector regression algorithm. Then, these fitted values were deduced from the obtained position error regression model. It was found that the maximum of the relative deviation between the measured values and fitted values is 0.03797. So the position error regression model was satisfactory.

Now, the position error of the next five time points could be predicted using the position error regression model. The measured values and predicted values are shown in Fig. 9 with the four points as follows: x=40, 160, 280, and 400 mm. It was found from Fig. 9 that the deviations between the measured and prediction values of the position errors were very small, and the built position error regression model is feasible.

As shown in Fig. 10, the simulation model of the position error compensation method based on fuzzy PID control is built using the SIMULINK tools. Given the compensation position point x=400 mm and the compensation time point t=16. Step signal is the signal source while the step value is 80. Theoretical output value is 80*L=80*5=400 mm, where L is screw lead. The initial PID control parameters are given as follows: K_p=50, K_i=−0.0105, and K_d=−0.0026. By simulation, the simulated position error is 0.083321 mm and the measured position error is 0.083323 mm. So it means that the simulation model is reasonable to simulate the dynamic performance of the feed servo worktable. There are three modes to compensate the position error of the servo system, that is, error compensation with support vector regression, error compensation combined support vector regression with fuzzy control, and error compensation combined support vector regression with improved fuzzy PID control. Figure 11 shows the step response with the original system. In the original system, there has no error compensation for the worktable. Figures 12, 13, and 14 show the system step response under the three modes.

The dynamic response index in different compensation modes are given in Table 7. It can be concluded from these

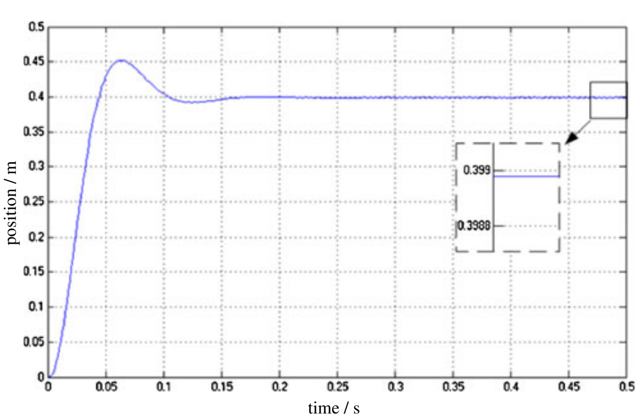

Fig. 11 Original system

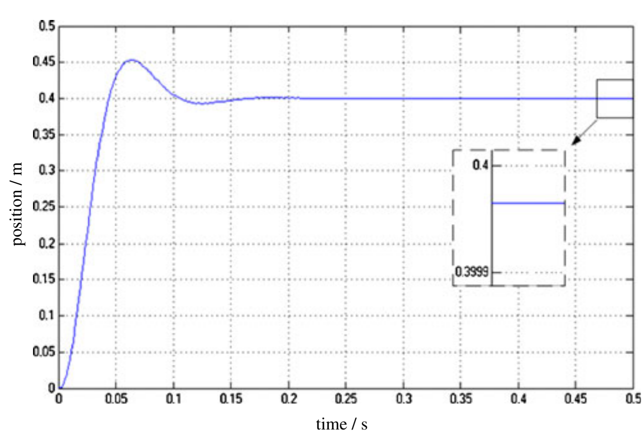

Fig. 12 System error compensation with support vector regression

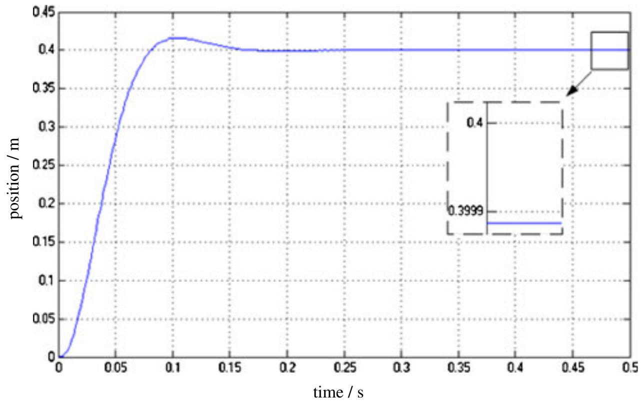

Fig. 13 System error compensation with support vector regression and fuzzy PID control

simulation results that the system error compensation module with support vector regression can reduce position error (from 0.083321 to 0.017755 mm) and increase position precision, but the dynamic response property (from 12.97296 to 13.24606) has a little decline. One of the reasons is that the servo system is in the degradation phase, the position error is increasing, and position accuracy is decreasing. And the decline of dynamic response characteristics makes position error increasing. Another reason is that the predicted position error feeding back to the system input is superimposed with the

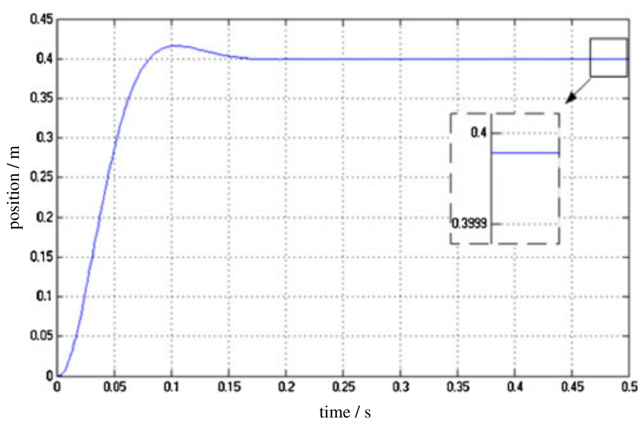

Fig. 14 System error compensation with support vector and improved fuzzy PID control

original error. They control the servo control system directly, which cause the control quantity increasing, overshoot increasing, and regulating time longer.

Comparing to system error compensation, the system error compensation module combining support vector regression and fuzzy PID control can improve the dynamic response property (from 12.97296 to 4.02482) but enlarge position error (from 0.083321 to 0.050682). The fuzzy control rules is based on the steady-state current system response value of zero position, therefore the fuzzy rules in traditional fuzzy control make the dynamic response characteristics improving. On the other hand, the position error causes the difference between the value and the ideal value (at zero position) of the steady-state response. The fuzzy control let the position accuracy decline.

The system error compensation module, combining the support vector regression and improved fuzzy PID control, has good control effectiveness in both position precision (from 0.083321 to 0.011208) and dynamic response property (from 12.97296 to 4.02481), even better than the system error compensation module with support vector regression, of which the position error is 0.01775. Therefore, by comparing with the other compensation model, the combination model of the support vector regression and improved fuzzy PID control makes the position error minimum. It means that the position precision is the highest after the two-step position error compensation.

Finally, let the compensation time point $t=20$. Using the method of two-step position error compensation to compensate all the measured ten points located on the x-axis. According to the position error e and the change scope of error change rate ec, the real domain of each variable in fuzzy control was adjusted while compensating, respectively, for each point. The position errors before and after compensation and the dynamic response properties are shown in Table 8. It can be concluded from Table 8 that the position errors and overshoots after the compensation have improved notably. And the peak time and settling time after the compensation have increased compared to those before the compensation.

The result of the position error compensation, shown as Fig. 15, demonstrated that the error compensation module

Table 7 Dynamic response index in the different compensation modes

Mode	Position error (mm)	Overshoots (%)	Peak time (s)	Settling time (s)
Original system	0.083321	12.97296	0.06319	0.09478
System error compensation module with support vector regression	0.017755	13.24606	0.06239	0.09725
System error compensation module combining with support vector regression and fuzzy PID control	0.050682	4.02482	0.10621	0.13322
System error compensation module combining support vector regression and improved fuzzy PID control	0.011208	4.02481	0.10621	0.13322

Table 8 Properties before and after compensation on feed servo system

Point	Position error (mm)		Overshoots (%)		Peak time (s)		Settling time (s)	
	Before compensation	After compensation	Before compensation	After compensation	Before compensation	After compensation	Before compensation	After compensation
x=40	0.0286	−0.0051	13.2778	3.9701	0.0623	0.1075	0.0970	0.1337
x=80	0.0399	−0.0032	13.2002	3.9950	0.0623	0.1060	0.0969	0.1326
x=120	0.0482	0.0109	13.1638	4.0972	0.0618	0.1020	0.0964	0.1322
x=160	0.0591	0.0104	13.1644	4.1407	0.0624	0.1019	0.0974	0.1330
x=200	0.0702	0.0111	13.1565	3.9916	0.0623	0.1064	0.0971	0.1335
x=240	0.0751	0.0129	13.1510	2.8541	0.0622	0.1265	0.0968	0.1476
x=280	0.0783	0.0124	13.1817	4.2131	0.0624	0.1024	0.0973	0.1317
x=320	0.0853	0.0116	13.2119	4.3129	0.0644	0.1008	0.0963	0.1316
x=360	0.0887	0.0103	13.1922	4.0336	0.0628	0.1032	0.0965	0.1322
x=400	0.0923	0.0116	13.1837	3.9942	0.0628	0.1029	0.0965	0.1329

combining the support vector regression and improved fuzzy PID control can improve the position accuracy. The position errors before compensation at points $x=160$, 200, 240, 280, 320, 360, and 400 mm exceed the given positioning accuracy of the worktable. The position errors have dropped to a satisfying range after the errors have been compensated. However, a phenomenon of overcompensation will arise when the point coordinate is small. This is because when the point coordinate is small, the position error of the servo system is also small. After the feedback position error compensation, the position precision is higher, but after the improved position error compensation by fuzzy control, the theoretical steady-state line of system response is upgraded, which results in the phenomenon of overcompensation.

6 Conclusion

A two-step position error compensation method for a semi-closed loop servo system is proposed in this paper. The position error can be well predicted by the position error regression model based on the support vector regression algorithm. The servo system with the error compensation module can compensate for the error well, but lowers the dynamic response property. In order to have a high position precision and a high dynamic response property simultaneously, modified fuzzy PID control is chosen to compensate position error. The simulation results on the case study indicate that comprehensive compensation method which combines support vector regression algorithm with modified fuzzy control cannot only increase position precision but also improve dynamic response property.

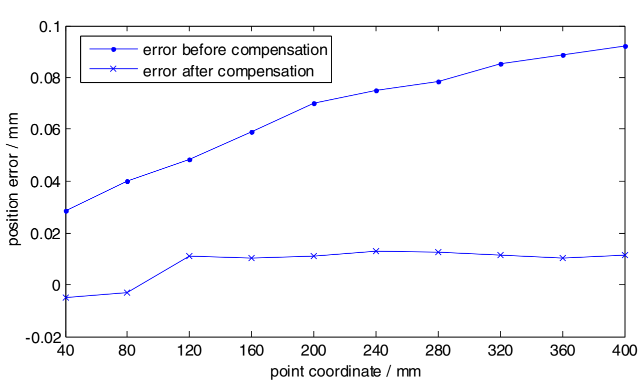

Fig. 15 Position error before and after compensation on the feed servo system

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References

1. Pritschowa G, Bretschneidera J (1999) A self-tuning controller for digitally controlled electromechanical servo drives in machine tools. CIRP Ann Manuf Technol 48(1):307–312
2. Ramesh R, Mannan MA, Poo AN (2000) Error compensation in machine tools—a review part I: geometric, cutting-force induced, and fixture-dependent errors. Int J Mach Tools Manuf 40(9):1235–1256
3. Ziegert JC, Kalle P (1994) Error compensation in machine tools: a neural network approach. J Intell Manuf 5:143–151
4. Ang JH, Goh CK, Teoh EJ, Tan KC (2007) Designing a recurrent neural network-based controller for gyro-mirror line-of-sight stabilization system using an artificial immune algorithm. Stud Comput Intell 66:189–209

5. Yang S, Yuan J, Ni J (1996) The improvement of thermal error modeling and compensation on machine tools by CMAC neural network. Int J Mach Tools Manuf 36(4):527–537
6. Yuan J, Ni J (1998) The real-time error compensation technique for CNC machining systems. Mechatronics 8:359–380
7. Xie SQ, Yu PL, Sheng B, Zhou ZD (2001) An integral sliding model tracking strategy for 3d laser beam position control. Int J Adv Manuf Technol 18:633–640
8. Jee S, Koren Y (2004) Adaptive fuzzy logic controller for feed drives of a CNC machine tool. Mechatronics 14:299–326
9. Lertpiriyasuwat V, Berg MC (2006) Adaptive real-time estimation of end-effector position and orientation using precise measurements of end-effector position. IEEE/ASME Trans Mechatronics 11(3):304–319
10. Yang JZ, Li ZX (2011) A novel contour error estimation for position loop-based cross-coupled control. IEEE/ASME Trans Mechatronics 16(4):643–655
11. Ding F, Qu MC, Lin YQ (2003) Realization of PID control method in AC position servo system. Electro-Mech Eng 19:52–54
12. Veldhuis SC, Elbestawi MA (1995) A strategy for the compensation of error in five-axis machining. Ann CIRP 44(1):373–377
13. Ferreira PM, Liu CR (1986) An analytical quadratic model for the geometric errors of a machine tool. J Manuf Syst 5(1):51–62
14. Hirose N, Iwasaki M, Kawafuku M, Hirai H (2009) Initial value compensation using additional input for semi-closed control systems. IEEE Trans Ind Electron 56(3):635–641
15. Goto S, Nakamura M (2006) Multidimensional feedforward compensator for industrial systems through pole assignment regulator and observer. IEEE Trans Ind Electron 53(3):886–894
16. Vapnike V (1999) The Nature of Statistical Learning Theory. Springer, N. Y
17. Burges JC (2002) A tutorial on support vector machines for pattern recognition. Data Min Knowl Disc 2:121–167
18. Chakguy P, Theodore BT, Raman S (2003) Support vector regression for determination of minimum zone. ASME J Manuf Sci E-T 125(4): 736–739
19. Keerthi SS et al (1999) “A fast iterative nearest point algorithm for support vector machine classifier design.” Indian Institute of Science Bangatolore
20. Stella MC, Jan HG, Timothy WS (2005) Analysis of support vector regression for approximation of complex engineering analyses. J Mech Des 127(6):1076–1087
21. Lin YL, Hsieh JG, Wu HK, Jeng JH (2011) “Three-parameter sequential minimal optimization for support vector machines.” Neurocomputing In Press
22. Suykens JAK, Branbanter JK, Lukas L (2002) Weighted least squares support vector machines: Robustness and spare approximation. Neurocomputing 48(1):85–105
23. Jayadeva, Reshma K, Suresh C (2008) Regularized least squares support vector regression for the simultaneous learning of a function and its derivatives. Inform Sci 178(17):3402–3414
24. Kapoor SG, DeVor RE, Zhu R (1998) Development of mechanistic models for the prediction of machining performance: model building methodology. Mach Sci Technol 2(1):213–238
25. Chinnam RB (2002) Online reliability estimation for individual components using statistical degradation signal models. Qual Reliab Eng Int 18(1):53–73
26. Theodor F, Hu SJ (2002) Impact of machining parameters on machine reliability and system productivity. ASME J Manuf Sci E-T 124(2):296–304
27. Meng S, Yoshiharu F et al (2002) Handwritten numeral recognition using gradient and curvature of gray scale image. Pattern Recogn 35(10):2051–2059
28. Liu CL, Masaki N (2001) Evaluation of prototype learning algorithms for nearest-neighbor classifier in application to handwritten character recognition. Pattern Recogn 34(3):601–615
29. Lee JH, Yang SH (2001) Fault diagnosis and recovery for a CNC machine tool thermal error compensation system. J Manuf Syst 19(6):428–434
30. Donmez A (1986) A general methodology for machine tool accuracy enhancement by error compensation. Precis Eng 8(4):187–196
31. Anjanappa M, Anand DK, Kirk JA (1988) Error correction methodologies and control strategies for numerical control machines. Control Method Manuf Process 7:41–49
32. Islam S, Liu PX (2011) Robust adaptive fuzzy output feedback control system for robot manipulators. IEEE/ASME Trans Mechatronics 16(2):288–296
33. Chen YF, Zhu DM, Zhu GB, Wang HZ (2008) The application of an improved PID control in servo control. Servo Control 1:53–55
34. Zhou Y, Chen JH, Peng FY (2007) Mechatronic integrated system simulation for a high-speed and high-precision CNC feed drive. Mech Sci Technol 26(2):135–139