IMPROVEMENT OF NEURO-PREDICTIVE CONTROL USING A NEW SCHEME FOR TRAINING

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ABSTRACT

In this paper a new method for improving the training of neural network is presented and its effect on neuro-predictive control is shown. The improvement of training is accomplished with ordering of training data set based on a criterion function and using linear interpolation between different training sets. The result is compared with other neuro-predictive control methods. It is shown that the proposed scheme can improve other neuro-predictive control methods, especially when the dynamic system is highly nonlinear.

KEY WORDS

Neuro-predictive control, receding horizon control, neural networks, nonlinear systems.

I. INTRODUCTION

Using neural networks to model and control nonlinear systems are attracting more and more attentions [1-4]. The structure of neural networks is made of uniformly distributed Computation units and synaptic connections between them. In order to model a dynamic system, first a proper structure is selected for the neural network, and then the parameters of this network are computed in such a way that can approximate the input-output behavior of the system. This method provides considerable reduction in mathematical complexity arising from physical modeling laws of dynamic systems.

The predictive control has gained many industrial applications. This is mainly due to its robustness against model uncertainties, especially against system order, time delays, and the effects of non-minimum phase [5]. The predictive control an optimal approach based on receding horizon theory. The optimal control vector, in this method, is obtained by optimizing a performance index, which minimizes the error between the future output of the system and a reference path. But, according to receding horizon theory, only the first element of this vector is applied to process and the entire computations are repeated in the next step. Therefore in order to predict the future output of the system, we must use a model in this control scheme.

Although the linear predictive control has found numerous industrial applications, in contrast the nonlinear predictive control has limited applications due to nonlinear model [6]. Utilizing neural networks, due to their ability of system modeling, results in reduction of this problem and development of predictive control. The neural network, in this method, is trained in such a way that represents a proper approximation of the system based on the input-output behavior. Then, based on this model and utilizing the future outputs of the system, in predictive-control performance index, the optimized control is achieved.

In this paper, the neuro-predictive control is introduced in section II. Then, in section III, the proposed training scheme for neural network is presented, and the results are compared with reference [1]. In section IV we show the effect of this training on improvement of the neuro-predictive control, and the conclusion is presented in section V. The dynamic system and the utilized neural model is shown in appendix.

II. NEURO-PREDICTIVE CONTROL

The neuro-predictive control takes advantage of a neural network, based on the input-output behavior of the dynamic system, to model the system. The most common neural networks for system modeling are multi-layer perceptron (MLP) and radial-basis function(RBF) networks. The training time of the MLPs is relatively more than that of RBF network. On the other hand, the MLPs usually require less number of neurons. Because of more neurons in RBF networks [7], the required computational time is more compared to that of MLPs [1], [8] and [9]. This is the main reason for using the later network in most of the neuro-control methods.

The future outputs of the systems, in neuro-predictive control, are obtained based on the present data of the system and cascading the trained neural networks, corresponding to the required number of predictive horizon. Using these predicted outputs in performance index, the optimal control vector is obtained so as the error between these outputs and a desired path is minimized. Now, according to the receding horizon theory, only the first element of this vector is applied to the system and the entire computations are repeated in the next step. The most important advantage of this method is the feasibility of obtaining an analytical control law. This is due to the use of neural model and the abilities of this model in reduction of mathematical complexities of the physical systems.

III. IMPROVING THE TRAINING METHODS OF THE NEURO-PREDICTIVE CONTOL

The neural network is trained with a set of input-output data, which are obtained by exciting the dynamic system with rich inputs. In all neuro-predictive control methods, there is no specific order for applying the data. We show in this paper that with certain ordering of the training data, one can achieve better training quality. In this method, using a certain error criterion function, the sets of training data are ordered in such a way that the distance between the last data of a set and the first data of the next set is minimized. The other improving method, which have been used in this paper, is linear interpolation, and taking advantage of extra data between difference training sets.

Figure 8 in appendix shows the dynamic system of reference [1]. In this system r, θ ,and η_3 are the outputs (η_3 and η_4 represent the elastic deformation part of the system) and f (applied force to the second arm) and τ (applied tourqe to the first arm) are the inputs to this dynamic system. Song et al. [1] have used a feedforward neural network to model this system. They have used the following equations to generate the input-output data:

$$\begin{aligned} \theta_d(t) &= \theta_{.} + \sum_{k=1}^{5} \left(\frac{a_k^\theta}{k\omega_f}\sin k\omega_f t - \frac{b_k^\theta}{k\omega_f}\cos k\omega_f t\right) \\ r_d(t) &= r_{.} + \sum_{k=1}^{5} \left(\frac{a_k^r}{k\omega_f}\sin k\omega_f t - \frac{b_k^r}{k\omega_f}\cos k\omega_f t\right) \\ \eta_3(t) &= \eta_4(t) = 0 \\ \theta_{.} &= 0.0883 \qquad r_{.} = 0.2934 \end{aligned} \tag{1}$$

Where $a_k^\theta, a_k^r, b_k^\theta$, and b_k^r are uniformly distributed random numbers.

Control inputs $f(t)$ and $\tau(t)$ have been applied for 1 second with sampling period of 0.02 second in order to create desired outputs. Hence, there are 50 vectors in the form of $[\theta_d, r_d, \eta_3, f, \tau]^T$, which form the first set of data. Reference [1] has generated 19 more sets with different and random value for $a_k^\theta, a_k^r, b_k^\theta$ and b_r^k. Therefore, 20 sets of data, each with 50 points, establish the training data. The training performance of reference [1] is shown in Fig. 1.

In this paper, first the twenty training data sets are ordered so that the distance between the last point in a set and the next point in the next set is minimized. For this, we introduce the following error criterion function:

$$\begin{aligned} E &= \sum_{i=1}^{20} e(i) \\ e(i) &= [M_\theta(\theta(i)-\theta(i+1))]^2 + [M_r(r(i)-r(i+1))]^2 \\ &\quad + [M_\tau(\tau(i)-\tau(i+1))]^2 + [M_f(f(i)-f(i+1))]^2 \end{aligned} \tag{2}$$

The term $[M_{\eta_3}(\eta_3(i)-\eta_3(i+1))]^2$ has not been included in here, since it has been assumed that $\eta_3(i) = \eta_4(i) = 0$ during generation of data. The coefficients $M_f, M_\tau, M_r, M_\theta$ are chosen somehow that four parameters f, τ, r, θ have the same value in criterion function. Fig. 5 illustrates one of the training data sets.

Fig. 2 shows the training performance for the case where the training data sets are ordered according to the above proposition. It is clear that the result is better than the result of reference [1] and the steady-state error has been reduced by 33%. Next, by using extra data between two consecutive data sets and performing interpolation, we could still improve the training performance of neuro-predictive controller. This process reduces the distance when going from one data set to the next. The number of extra points between two consecutive data sets can be achieved with trial and error. For the simplest case, that is using only one extra point between two data sets and utilizing linear interpolation, the training performance is shown in Fig. 3. The steady-state error is 78% less than that of reference [1]. The training performance for the case of three extra points and third order nonlinear interpolation is also shown in Fig. 4. As this curve shows, using more points may not necessarily improve the training performance.

IV. THE EFFECT OF THE PROPOSED SCHEME IN NEURO-PREDICTIVE CONTROL

Although the neuro-predictive control is robust against model uncertainty, but its performance deteriorates for controlling highly nonlinear dynamic systems, specially when encountering disturbances from environment. Fig. 6 illustrates the response of the predictive control, for the system in Fig. 8, for the path $\theta_d(t) = 0.3708 - 1.427t$, $r_d(t) = 0.3656$, $\eta_{3d}(t) = 0$, and $\eta_{4d}(t) = 0$ for transition from position $[\theta \;\; r \;\; \eta_3 \;\; \eta_4]^T = [0.3708 \;\; 0.3656 \;\; 0 \;\; 0]^T$ to position

$[-0.2 \quad 0.3656 \quad 0 \quad 0]^T$, for the case of reference [1], as well as the proposed method in this paper. In this example, a disturbing tourqe with the value of 100 Nm has been applied to the manipulator at time 1 sec. According to this Fig., the predictive controller in reference [1] is able to control the system very well. But, after exertion of disturbing tourqe, it could not cancel out the effect of the disturbance completely and the output θ has converged from the desired value of 0.2 rad to almost zero rad. On the other hand, the employed method (representing the data in ordered fashion), with extra points between data sets, can control the system, before and after the 100 N.m disturbance, better than reference [1]. Fig.7 shows the applied inputs f and τ . The profile of f and τ of the proposed method is smoother, specially after the disturbance, compared to those of reference [1].

V. CONCLUSION

It has been shown in this paper that the order of training data set in neuro-predictive control of nonlinear dynamic systems can play important roll, specially when the system encounters disturbances. Furthermore, smoothing the consecutive training data sets can greatly affect the error reduction for training of the neural network. A linear interpolation for a manipulator with flexible forearm yielded good results.

APPENDIX

Figure 8 shows the arrangement of the dynamic system which have been used in reference [1] and in this paper. The mathematical model of this system is as follows [1]:

$$M\ddot{U} + C\dot{U} + KU = Q$$

$$M = \begin{bmatrix} M_{rr} & M_{rf} \\ M_{fr} & M_{ff} \end{bmatrix} \qquad \text{(A1)}$$

$$C = \begin{bmatrix} C_{rr} & C_{rf} \\ C_{fr} & 0 \end{bmatrix} \quad K = \begin{bmatrix} 0 & 0 \\ 0 & K_{ff} \end{bmatrix}$$

where in this equation:

$$M_{rr} = \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & M_1 + m_2 \end{bmatrix}$$

$$M_{ff} = \begin{bmatrix} m_p + \frac{13}{35}\rho L & -\frac{11}{210}\rho L^2 \\ -\frac{11}{210}\rho L^2 & \frac{1}{105}\rho L^3 \end{bmatrix}$$

$$M_{rf} = \begin{bmatrix} m_p + \frac{7}{20}\rho L^2 + M_2 r & -\frac{1}{20}\rho L^3 - \frac{1}{12}\rho L^2 r \\ 0 & 0 \end{bmatrix}$$

$$M_{fr} = M_{rf}^T \quad C_{rr} = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & 0 \end{bmatrix}$$

$$C_{rf} = \begin{bmatrix} M_2\dot{r} + M_2 d\dot{\theta} & -\frac{1}{12}\rho L^2\dot{r} - \frac{1}{12}\rho L^2 d\dot{\theta} \\ M_2\dot{\theta} & -\frac{1}{12}\rho L^2\dot{\theta} \end{bmatrix}$$

$$C_{fr} = \begin{bmatrix} -M_2 d\dot{\theta} & -M_2\dot{\theta} \\ \frac{1}{12}\rho L^2 d\dot{\theta} & -\frac{1}{12}\rho L^2\dot{\theta} \end{bmatrix}$$

$$K_{ff} = \begin{bmatrix} 12\frac{EI}{L^3} & -6\frac{EI}{L^2} \\ -6\frac{EI}{L^2} & 4\frac{EI}{L} \end{bmatrix}$$

$$M_1 = m_p + \rho L, \quad M_2 = m_p + \frac{1}{2}\rho L, \quad M_3 = m_p + \frac{1}{3}\rho L$$

$$m_{11} = I_0 + (M_1 + m_2)(d^2 + r^2) + M_3 L^2 + \frac{1}{3}m_2 a^2 + (2M_2 L - m_2 a)r - 2M_2 d\eta_3 + \frac{1}{6}\rho L^2 d\eta_4$$

$$m_{12} = (M_1 + m_2)d - M_2\eta_3 + \frac{1}{12}\rho L^2\eta_4$$

$$c_{11} = (M_1 r + M_2 L)\dot{r} + m_2(r - (a/2))\dot{r} - M_2 d\dot{\eta}_3 + \frac{1}{12}\rho L^2\dot{\eta}_4$$

$$c_{12} = -(M_1 + m_2)r\dot{\theta} + (\frac{1}{2}m_2 a - M_2 L)\dot{\theta} - M_2\dot{\eta}_3 + \frac{1}{12}\rho L^2\dot{\eta}_4$$

$$c_{21} = (M_1 r + M_2 L)\dot{\theta} + m_2(r - (a/2))\dot{\theta}$$

$$d = 0.15m \quad a = 1.5m \quad I_0 = 0.075\,kgm^2$$

$$m_p = 0\,kg \quad m_2 = 20\,kg$$

$$\rho = 0.07706\,kg/m \quad L = 1.4m$$

$$EI = 26.94486\,Nm^2$$

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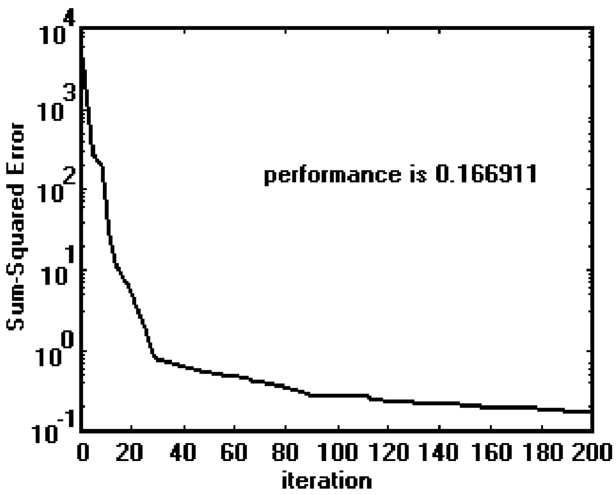

Fig 1. The training performance of neural network of reference [1]

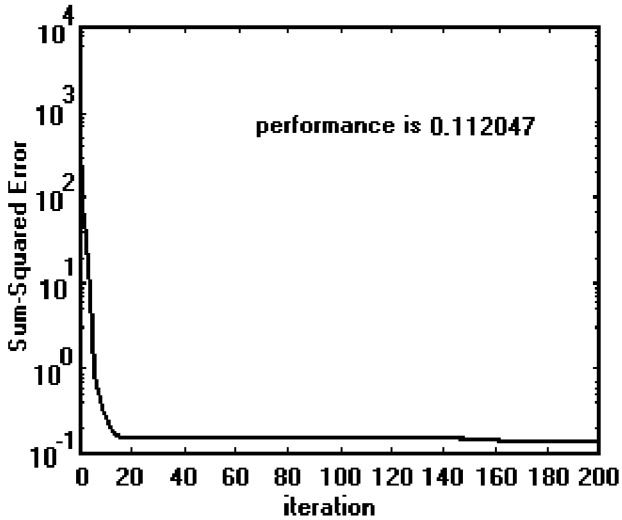

Fig 2. The training performance of neural network when training data has been ordered.

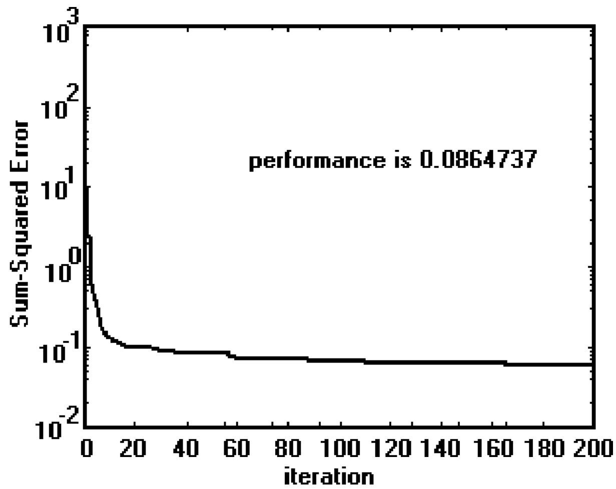

Fig 3. The training performance of neural network base on ordered data and linear interpolation when only one interpolated data has been used in every interpolation.

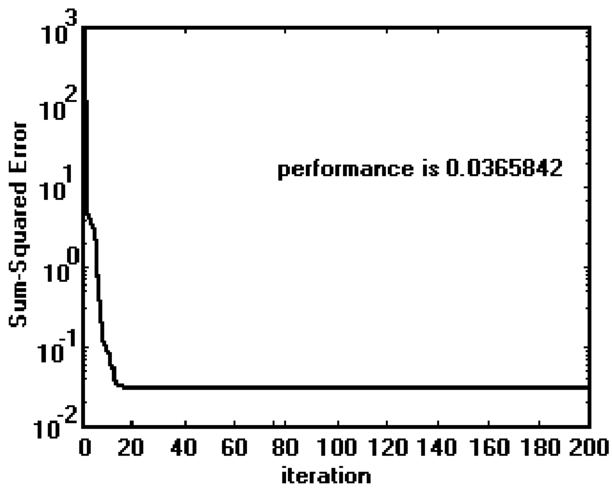

Fig 4. The training performance of neural network base on ordered data and linear interpolation when three interpolated data have been used.

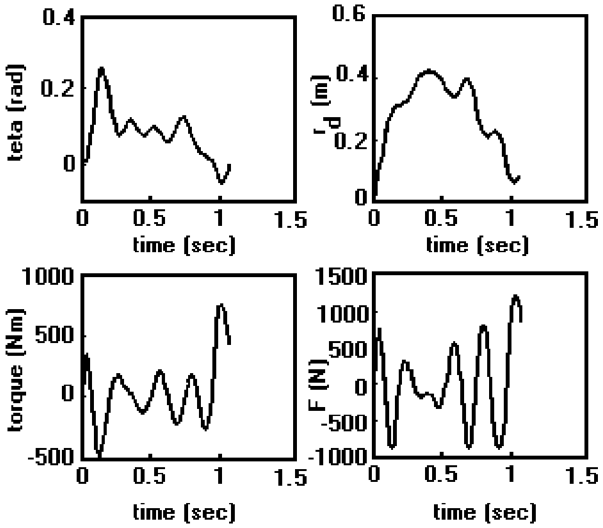

Fig 5. One set of training data sets

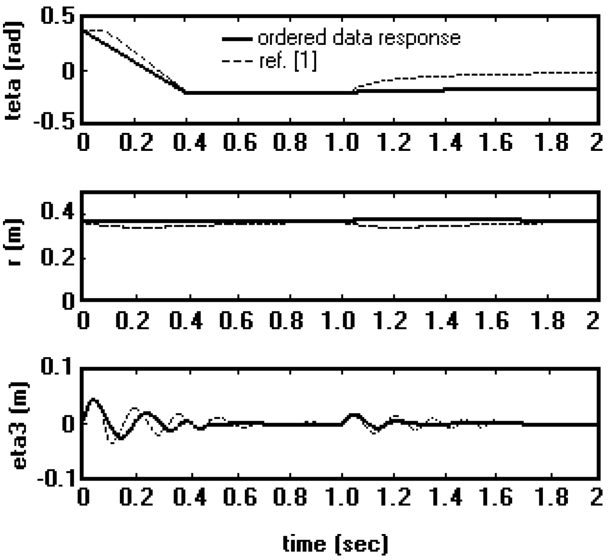

Fig 6. The comparison of the responses of the neuro-predictive controls.

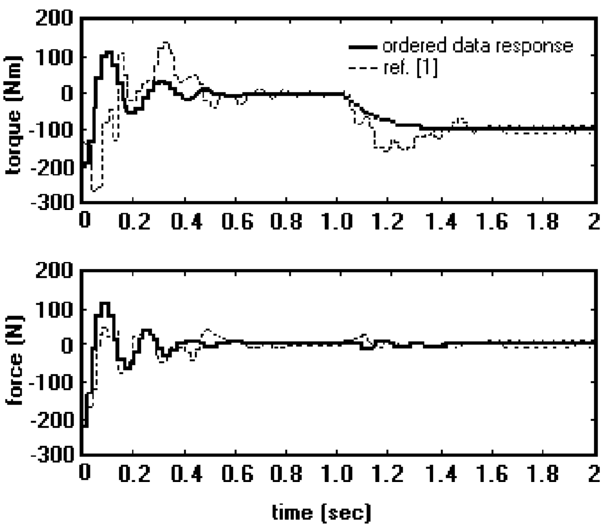

Fig 7. The inputs to the neuro-predictive control.

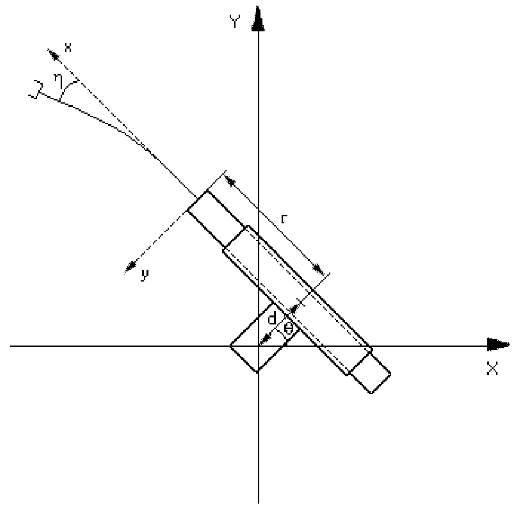

Fig 8. Manipulator with flexible arm. The first joint is rotary and the second joint is prismatic.