Robust Self-Learning Fuzzy Logic Servo Control With Neural Network-Based Load Compensator

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Abstract: - In this paper, a fuzzy-neural control scheme composed of a sensitivity model-based self-learning fuzzy logic controller (SLFLC) and a neural network-based (NN) load estimator consisting of two off-line trained feedforward neural networks is described. The outputs of the NN estimator have been used to generate a compensation signal whose aim is to increase robustness and to widen the operational range of the SLFLC.

Accuracy of NN compensation depends on the correct value of a load compensation gain, but this gain varies with operating point transitions and consequent variations of gain coefficients in the feedforward control path (e.g. a power amplifier gain varies much). A composition of NN-based estimator and the SLFLC has resolved this problem, as a potential inaccuracy of estimation has been accomodated by the learning adaptability of the SLFLC.

Experiments performed on the laboratory positioning servo system characterized by the presence of a gravitation-dependent load and fairly high friction have shown that upon applying the NN compensation signal to the output of the SLFLC, position responses have been significantly improved during start of learning and duration of learning has been much shorter than in case without NN compensation.

Key-Words: - Self-learning fuzzy logic control, neural networks, nonlinear load compensation, intelligent control, servo systems. *IMACS/IEEE CSCC'99 Proceedings,* Pages: 3351-3356

1 Introduction

Friction, backlash, deadzone, nonlinear loads, torsion and shaft flexibility are most common nonlinearities in practical motion control systems. If robotic mechanisms are considered, then in the vicinity of the given position (where velocity is close to zero) aforementioned non-linearities may cause a noticeable discrepance between a desired and actual tool tip position. Another problem coming with non-smooth non-linearities is that they bring parameter uncertainties and time-dependent parameter variations in the system which cannot be easily handled with traditional control methods. Possible ways to solve such problems are to apply adaptive control [1, 2, 3, 4] or intelligent control techniques using fuzzy logic (FL) and neural networks (NN), as described in [5, 6, 7, 8, 9].

In this paper, a fuzzy-neural control scheme composed of a sensitivity model-based self-learning fuzzy logic controller (SLFLC) and two off-line trained feedforward neural networks performing as friction and gravitation-dependent load estimators is described. The SLFLC contains a learning algorithm that utilizes a second-order reference model and a sensitivity model related to the fuzzy controller parameters [5]. This algorithm is capable to learn and produce a nonlinear control surface (mapping function) which incorporates and compensates those nonlinearities that were present during learning (e.g. gravitation-dependent load, backlash and friction, as described in [5, 6, 10]). The outputs of NN-based load estimators have been used to generate a compensation signal, which is added to the SLFLC output. Its aim is to increase robustness and to widen the operational range of the SLFLC. The compensation signal must always have the opposite sign of the load influence and its magnitude must compensate the load influence [11], which is achieved by setting an adequate compensation gain value.

Continuous operating point transitions causing variations of gain coefficients in the feedforward control path (e.g. of a power amplifier gain), will inevitably hurt the precision of compensation and make it more or less inaccurate. When the NN-based load compensator is attached to the SLFLC, then problems with an ambiguity of the compensation gain disappear thanks to the learning adaptability of the SLFLC. This means that a whole design can start with a fairly rough approximation of the compensation gain.

Experiments performed on the laboratory

positioning servo system affected by the presence of a highly nonlinear gravitation-dependent load and friction have shown that the proposed control scheme has enforced position responses that are especially improved during start of learning and which has significantly shortened a duration of learning in comparison with the case without NN compensation.

The paper is organized as follows. Section 2 presents a description of the servo system affected by friction and gravity-dependent load nonlinearities. Section 3 presents a concise description of the self-learning fuzzy logic control scheme. Section 4 is focused on the design and off-line training of the neural network-based estimators of friction and nonlinear load. Section 5 shows the experimental results obtained in a laboratory dc servo system. Final conclusions are presented in Section 6.

2 Description of the Servo System

The system under consideration is a chopper-fed dc servo positioning system affected by impact of friction and gravitation-dependent shaft load (a bar and a weight), as shown in Fig. 1. The implementation of a SLFLC controller and NN-based estimators has been conducted on the personal computer running at 120 MHz with a 12-bit A/D and D/A converter board.

The rated parameter values are: k_p=1.5 V/V (P controller gain), K_s=0.318 V/rad (position feedback gain), K=0.191 Nm/A (torque coefficient), K_a=0.106 V/A (armature gain), J_T=2.7E^{-4} kgm^2 (reduced load weight), J_T=1.27E^{-3} kgm^2 (full load weight), N=4 (gear ratio). The structure of a nonlinear position control loop is shown in Fig. 2.

Fig. 1. Experimental setup of a chopper-fed dc servo drive.

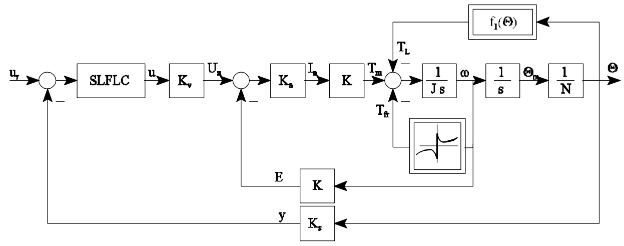

Fig. 2. The structure of a position control loop.

The gravitation-dependent shaft load is described with the following expression:

$$t_L = f_1(q) = t_{L0}\sin(q) \qquad (1)$$

where: q - current load shaft position,

t_{L0} - maximal load torque (0.17626 Nm).

Friction is modeled according to the velocity-dependent Tustin's static model:

$$t_f(w) = t_f^v w + \operatorname{sgn}(w)\left[t_f^d + (t_f^s - t_f^d)\exp\left(\frac{-|w|}{e}\right)\right] \qquad (2)$$

where: t_f^v - viscous friction coefficient, t_f^d - dynamic friction, t_f^s - static friction, e - Stribeck velocity.

Static friction has been measured during open-loop operation at idle speed: t_f^s = 0.02 Nm. Dynamic friction has an order of magnitude smaller value: t_f^d = 0.002 Nm. The viscous friction coefficient has been measured during open-loop operation at several different velocities: t_f^v = 1.3825*10^{-4} Nms. The Stribeck velocity has been set arbitrarily to the small value e = 0.01 s^{-1}. According to observations of the Tustin's model in various practical situations, such a setting of å is justified [1, 2].

3 Self-learning Fuzzy Logic Controller

A self-learning fuzzy logic controller (SLFLC), whose structure is shown in Fig. 3, is self-organized by means of a model reference-based and a sensitivity model-based learning mechanism. In the presence of a P controller in parallel to the SLFLC, learning starts from a blank fuzzy rule-table, and proceeds after each run of the system by adding centroid increments to fuzzy output subsets of the activated fuzzy control rules. The usage of the SLFLC prevails the need for heuristic determination of a knowledge base substituting it with a completely automatic procedure. An in depth description of the SLFLC design and performance can be found in [5].

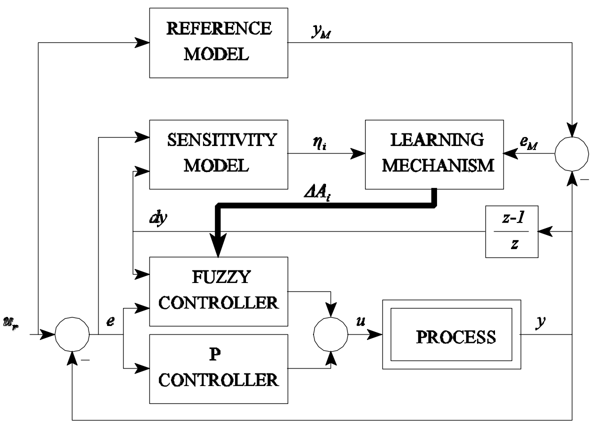

Fig. 3. The structure of the SLFLC scheme.

4 NN-based load compensation

Neural networks have been adopted for estimation of nonlinearities as universal nonlinear approximators [12]. Best results of friction and gravitation-dependent load estimation have been obtained with two feedforward neural networks, one estimating friction and the other estimating a nonlinear load. Namely, a single neural network cannot estimate well both nonlinearities at the same time. Both networks have been trained by using a Levenberg-Marquardt algorithm. Data needed for training of the first network have been provided from the simulation model based on a fairly well identified parameters of the friction model (2). The second network has been trained a regular sine function and data for this purpose have been provided. After some experimenting with a number of layers and neurons in these layers, we have finished with three-layer network structures, as shown in Fig. 4.

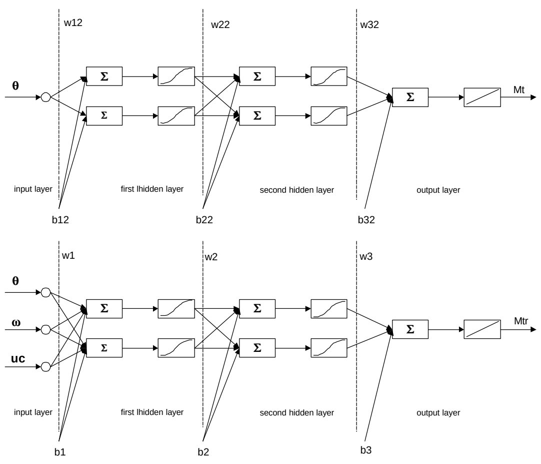

Fig. 4. Structures of neural network-based estimators: shaft load (up), friction (down).

As may be seen, the load torque estimator is a SISO network with a position as an input, two neurons and standard sigmoidal activation functions in the inner layers, and standard linear activation function in the output layer. The friction estimator network has position, speed and controller output as its inputs with the inner structure resembling the structure of the complement neural network (Fig. 4).

The outputs obtained from the NN estimators have been used for generation of the nonlinearities compensation signal. This signal obtained by summing of estimated values must be normalized before adding to the SLFLC output (Fig. 5). The normalization factor should attain the reciprocal value of the gain coefficient of the path between the controller and the torque input (denoted as K_xK_aK, where K_x is the product of chopper and IxR compensation gain coefficients). It must be noted that the velocity control loop was closed by IxR compensation feedback that normally provides less accurate steady state than standard closed loop control.

5 Experimental Results

In this section, the results of closed-loop experiments are presented. The parameters of the positioning system shown in Fig. 5 have been given in Section 2. The parameters of the 2nd-order reference model have been determined according to the selected performance indices: overshoot in response, ó$_m$=0.5%, and time of maximum t_m=0.6s. The reference model is also used for a process approximation in the sensitivity model [5]. Five linguistic subsets have been defined for both FLC inputs (universes of discourse E and DY): LN, MN, Z, MP, LP. A linear distribution of the corresponding membership functions has been selected.

The proposed fuzzy-neural control method has been experimentally tested for a series of step changes of the reference input equal to Äè$_r$=±20° in two intentionally selected operating points, è$_0$=0° and è$_0$=-90°, which correspond to the extremal magnitudes of a position dependent load torque (1). Experiments were conducted in two ways: with and without NN-based estimators.

5.1 SLFLC without NN load compensator

First the performance of the positioning system has been tested at full load (T_{L0}=max) in the operating point è$_0$=0° in case of disabled NN load compensation. Fig. 6a shows the reference model and the measured position responses obtained after several starting runs of the system (in both directions). Impact of nonlinearities is seen in different dynamics for each direction and in the presence of a steady state error. Fig. 6b shows the model tracking error, which in the beginning exceeds 40 % of the imposed change of the

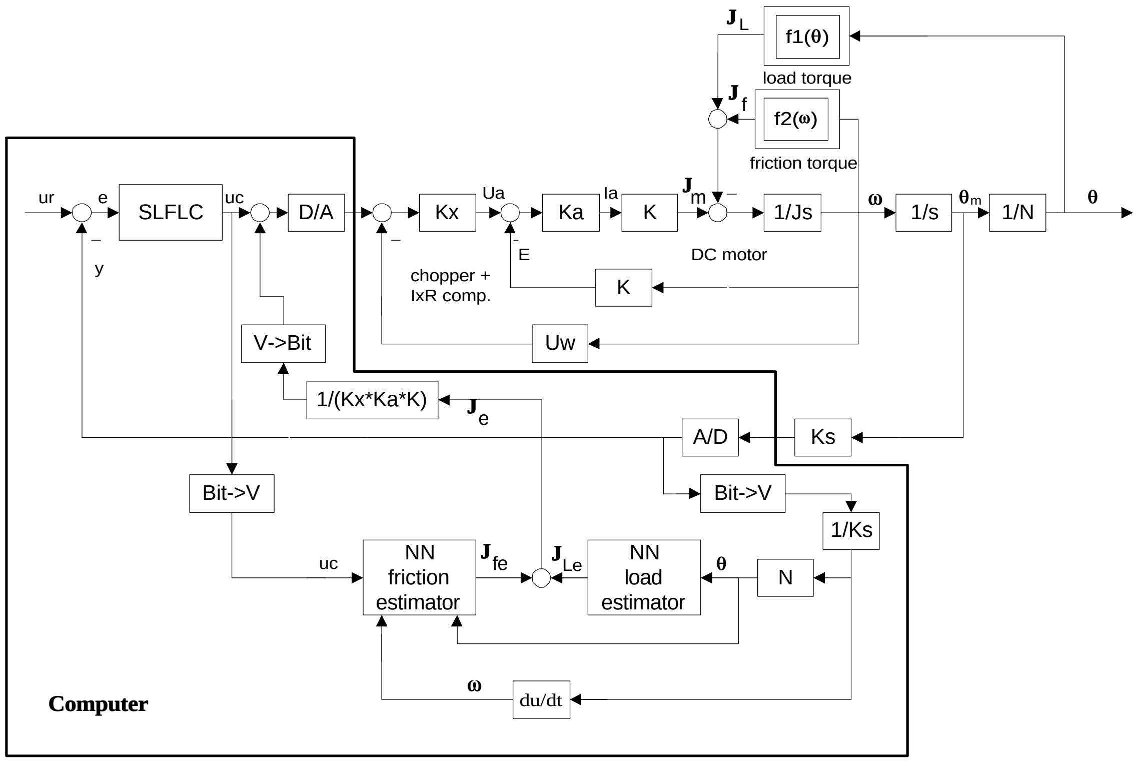

Fig. 5. The structure of a self-learning fuzzy logic controlled dc servo system with NN compensators.

reference input (only P controller is acting as depicted in Fig. 3) and then constantly decreases as learning is going on. Figs 6c and 6d show the reference model and the measured position responses and the tracking error, respectively, obtained after completion of learning (i.e. after fulfilment of the selected mean square error criterium shown in Fig. 6e). Now the system follows the reference model very closely and the maximum tracking error value is kept within 5%, thus illustrating the effectiveness of the SLFLC. Fig. 6f shows a very acceptable nonoscillatory form of the controller output.

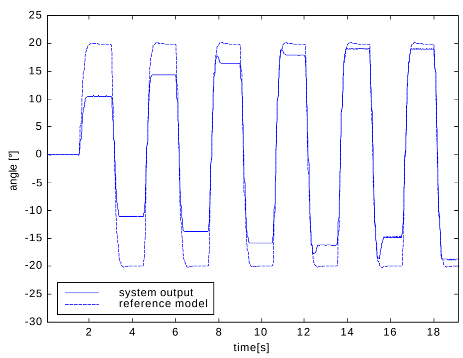

Fig. 6a

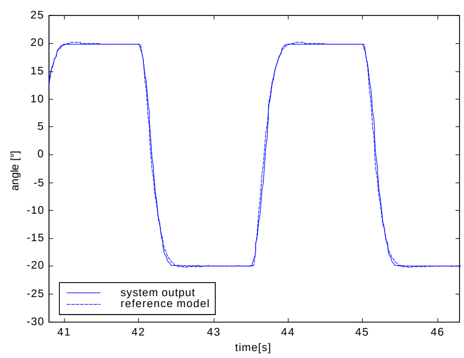

Fig. 6c

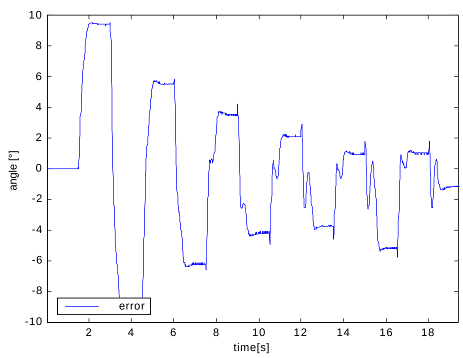

Fig. 6b

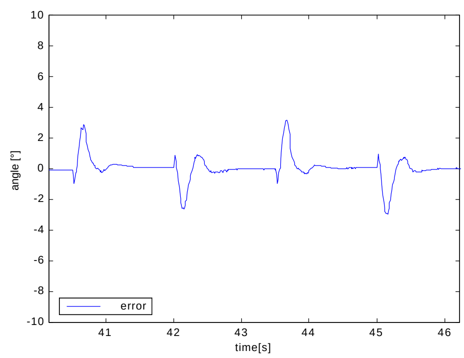

Fig. 6d

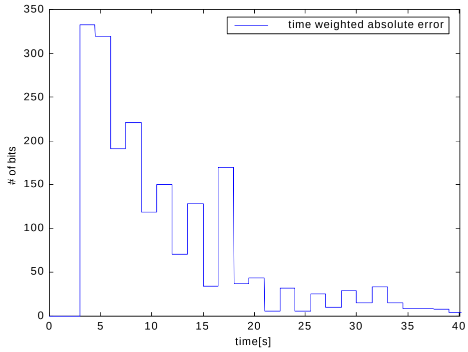

Fig. 6e

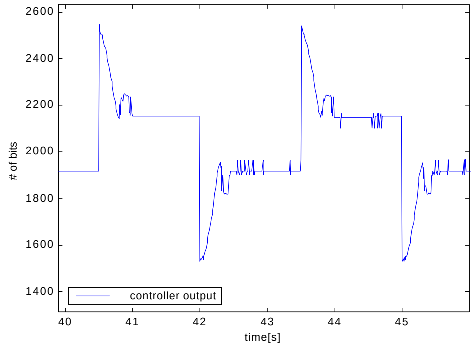

Fig. 6f

5.2 SLFLC with NN load compensator

Fig. 7 shows the same group of responses obtained with activation of a NN-based load compensator. The performance of the system is considerably improved in the initial phase of learning, as shown in Figs. 7a (reference model and system output) and 7b (model tracking error), respectively. After completion of learning, as expected, the system closely follows the reference model (Fig. 7c), and the tracking error (Fig. 7d), although slightly higher, never exceeds 10% of the imposed change of the reference input. The controller output (Fig. 7f) retains its acceptable form and the steady-state system error is kept at zero as required.

The most important effect of adding the NN-based load compensator is in considerably faster convergence of learning. As depicted in Fig 7e (mean square error), the learning criterium has been reached in two times shorter time (20s w.r.t. 40s) and the maximum mean square error has been also considerably reduced (200 w.r.t. 330). Figs. 7g and 7h show the outputs of NN compensator in the start of learning and after the end of learning, respectively. A discontinuity of friction is manifested in the oscillatory waveform of the compensation signal.

Experiments have also been carried out under full load condition in the operating point è$_0$=-90°, which is the most difficult operating point for starting with positioning. By adding the NN load compensator, learning has finished four times earlier than without compensation (25s w.r.t. 100s) while the maximum mean square error has been reduced from 1050 to 700. The output of the fuzzy-neural controller has retained a very acceptable form keeping the state state error at zero level.

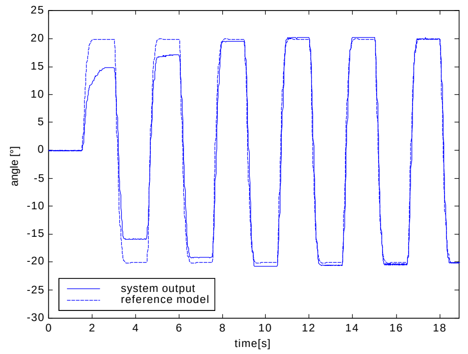

Fig. 7a

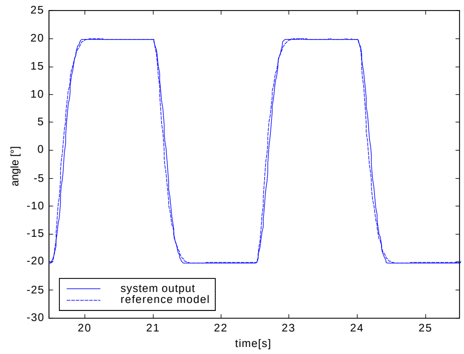

Fig. 7c

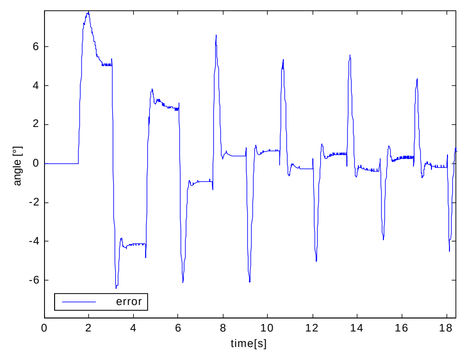

Fig. 7b

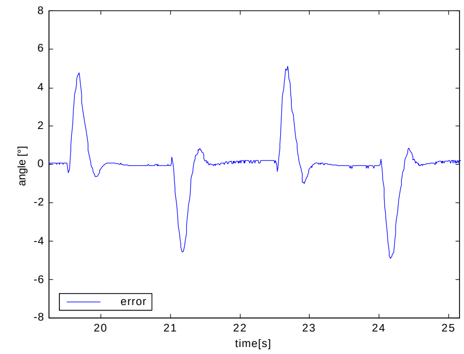

Fig. 7d

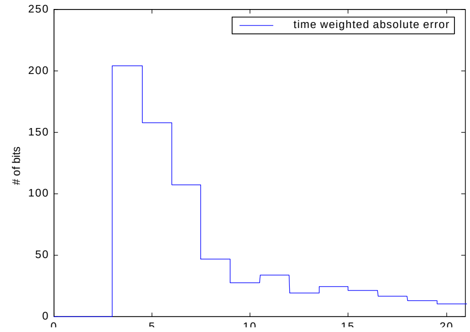

Fig. 7e

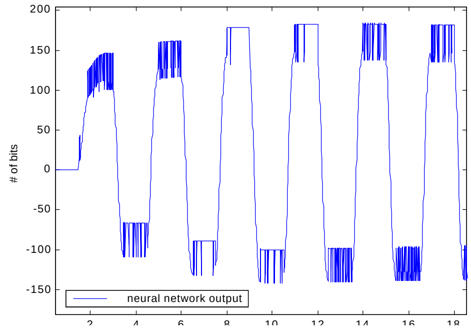

Fig. 7g

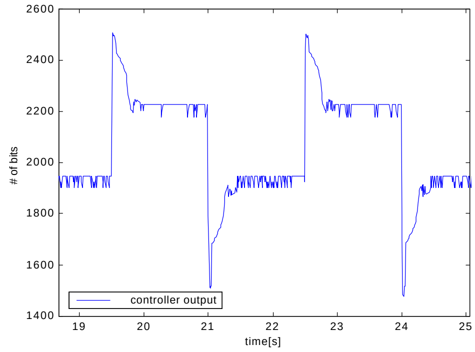

Fig. 7f

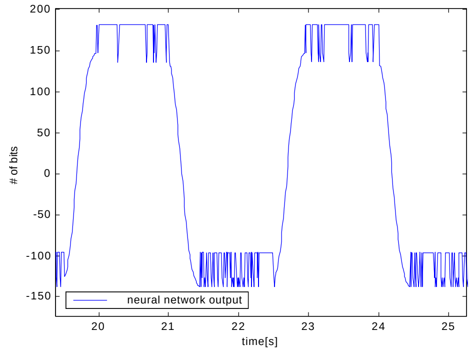

Fig. 7h

6 Conclusion

In this paper we present an experimental study which has had a goal to test the performance of the NN-based estimators of friction and gravitation-dependent shaft load in the dc servo system controlled by a self-learning fuzzy logic controller. For this purpose, two off-line trained feedforward NNs have been designed and implemented, one for friction and the other for gravitation-dependent load estimation. The experimental results obtained have shown that addition of NN-based estimators may considerably increase the performance of the servo system, raise the speed of learning and reduce the reference model tracking error.

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