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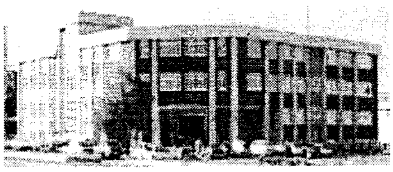

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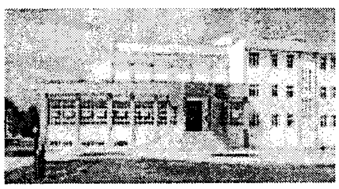

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NEURO-GENETIC BASED FUZZY SLIDING MODE CONTROLLER AND PMDC MOTOR CONTROL APPLICATION

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ABSTRACT

In this paper we propose a new method for determining architecture of a Sliding-mode fuzzy controller. The method uses the power of genetic algorithm (GA) for searching the optimal values of these parameters. For the computation of the fitness function, GA uses the neural network model of the system. To demonstrate the efficiency of the proposed control, a real-time PMDC servo motor speed control application is given at the end.

KEY WORDS

Sliding Mode Control, Genetic Algorithms, ANN, PMDC Motor Control

1. INTRODUCTION

Sliding mode control (SMC) is a powerful method for controlling the nonlinear systems where the system has lots of uncertainties and disturbances. The power of the method lies under its independency to parameter variations and model free architecture except the bounds of parameters.

In the last decade, many attempts have been made to design the Fuzzy Logic Controller (FLC) based on the SMC laws [1], [2], [3]. In [4] it's proposed that an FLC can be handled as an extension of the conventional variable structure controller with a boundary layer. Hwang *et al.* proposed a fuzzy sliding mode controller for high order nonlinear processes [5].

During the design process of a sliding mode controller, it is a real problem to determine the optimal topology of the sliding surface and the boundary layer thickness. In this paper we propose a new method for determining these parameters. The method uses the power of genetic algorithm (GA) for searching the optimal values of these parameters. For the computation of the fitness function, GA uses the neural network model of the system. To demonstrate the efficiency of the proposed control, a real-time PMDC servo motor speed control application is given at the end. Also the performance comparisons of the proposed controller and the conventional PI and fuzzy PI controllers are given. All the algorithms, including the Genetic and Neural-Network Model are programmed by C++ and applied to the system. The controlled process includes 3 DC servo-motors (each 3000 rpm, 52V, 90W), which are coupled to each other. One of the motors is used as a controlled process, whereas the others are used as load and taco-generator, respectively.

The rest of the paper is organized as follows. Section 2 reviews the sliding mode theory, Section 3 presents the proposed algorithm, Section 4 presents the experimental results of the proposed control system with discussions and finally Section 5 concludes the paper.

2. SLIDING MODE CONTROL

Let (1) be a general n. order differential equation expressing a nonlinear system where f is an unknown function which is not exactly known, but the uncertainty of f is bounded by a known function of $\vec{x}$ as in (2) and (3), $u \in \Re$ and $y \in \Re$ are the input and output of the plant, respectively, and $\vec{x} = (x_1, x_2, ..., x_n)^T = (x, \dot{x}, ..., x^{(n-1)})^T \in \Re^n$ is the state vector of the system that is assumed to be measurable for the system.

$$\begin{aligned} x^{(n)} &= f(x, \dot{x}, ..., x^{(n-1)}) + u \\ y &= x \end{aligned} \tag{1}$$

$$f(\vec{x}) = \hat{f}(\vec{x}) + \Delta f(\vec{x}), \tag{2}$$

$$|\,\Delta f(\vec{x})\,| \leq F(\vec{x}) \tag{3}$$

In (3) $\Delta f(\vec{x})$ is unknown but $\hat{f}(\vec{x})$ and $F(\vec{x})$ are known. The control objective is to determine a feedback control $u = u(\vec{x})$ such that the state vector $\vec{x}$ of the closed-loop system will follow the desired state $\vec{x}_d = (x_d, \dot{x}_d, ..., x_d^{(n-1)})^T$. In other words, the tracking error

$$\vec{e} = \vec{x} - \vec{x}_d = (e, \dot{e}, ..., e^{(n-1)})^T, \tag{4}$$

should converge to zero. The basic idea of SMC is as follows. Define a scalar function

$$s(\vec{x},t) = (\tfrac{d}{dt} + \lambda)^{n-1}\vec{e}\,, \quad (5)$$

where λ is positive constant. Then, $s(\vec{x},t) = 0$ defines a time-varying sliding surface. Specially for $\Re^2$ (5) can be rewritten as,

$$s(\vec{x},t) = \dot{e} + \lambda e = \dot{x} + \lambda x - \dot{x}_d - \lambda x_d = 0\,, \quad (6)$$

which is a straight line in $x - \dot{x}$ phase plane. Indeed, $s(\vec{x},t) = 0$ represents a linear differential equation whose unique solution is $\vec{e}(t) = \vec{0}$. In order to achieve the objective, which is defined above, the control signal u should satisfy,

$$\frac{1}{2}\frac{d}{dt}s^2 \le -\eta\,|\,s\,| \quad (7)$$

where η is positive constant. Let n=2, then (7) becomes

$$s[f(\vec{x}) + u - \ddot{x}_d + \lambda\dot{e}] \le -\eta\,|\,s\,|. \quad (8)$$

If we choose

$$u = -\hat{f}(\vec{x}) + \ddot{x}_d - \lambda\dot{e} - K(x,\dot{x})\,\mathrm{sgn}(s) \quad (9)$$

then (8) becomes

$$\mathrm{sgn}(s)[f(\vec{x}) - \hat{f}(\vec{x}) - K(x,\dot{x})\,\mathrm{sgn}(s)] \le -\eta \quad (10)$$

where sgn(s) = 1 if s >0 and sgn(s) = -1 if s < 0. one can rewrite (10) as,

$$K(x,\dot{x}) \ge \eta + \mathrm{sgn}(s)[\Delta f(\vec{x})]. \quad (11)$$

Therefore choosing $K(x,\dot{x}) = \eta + F(\vec{x})$ will satisfy (11). It is obvious that using (9) as a controller will result discontinuous state movement across the sliding surface $s(t)$. This phenomenon is known as *chattering*. Chattering is undesirable since it may excite high-frequency dynamics in the system. A way to eliminate chattering is to introduce a thin boundary layer neighboring the sliding surface:

$$B(t) = \{\vec{x} : |\,s(\vec{x},t)\,| \le \phi/2\}\;, \quad (12)$$

such that the control signal changes continuously within this boundary layer. Here $\phi/2$ is called the *thickness* of the boundary layer. Specifically, for the second order system, we change the control law (9) to

$$u = -\hat{f}(\vec{x}) + \ddot{x}_d - \lambda\dot{e} - K(x,\dot{x})sat(2s/\phi) \quad (13)$$

where the saturation function $sat(2s/\phi)$ is defined as

$$sat(2s/\phi) = \begin{cases} -1 & \text{if } 2s/\phi \le -1 \\ 2s/\phi & \text{if } -1 < 2s/\phi \le 1 \\ 1 & \text{if } 2s/\phi > 1 \end{cases} \quad (14)$$

Generally, if the system is in the form (15) where the control gain is unknown but of known bounds as in (16), by using (17) as a control signal and (18) as the amplitude of discontinuous part of the control signal one can easily show that (5) is satisfied [6].

$$\ddot{x} = f + bu \quad (15)$$

$$\begin{aligned} &0 < b_{\min} \le b \le b_{\max} \\ &\hat{b} = (b_{\min} b_{\max})^{1/2} \\ &\beta^{-1} \le \frac{\hat{b}}{b} \le \beta \\ &\beta = (b_{\max}/b_{\min})^{1/2} \end{aligned} \;, \quad (16)$$

$$u = \hat{b}^{-1}[-\hat{f} + \ddot{x}_d - \lambda\dot{e} - K(x,\dot{x})\mathrm{sgn}(s)] \quad (17)$$

$$K \ge \hat{b}b^{-1}F + \eta\hat{b}b^{-1} + |\,\hat{b}b^{-1} - 1\,|\cdot|\,\hat{f} - \ddot{x}_d + \lambda\dot{e}\,| \quad (18)$$

3. NEURAL-GENETIC BASED SLIDING FUZZY CONTROL

From Section 2, we can conclude that the performance of the Sliding Mode Controller highly depends on choosing the correct values of K and λ. There is a restriction for choosing K, which is given in (18), whereas there is no restriction for choosing λ. In this work we propose a new method for choosing the correct and near-optimal values for these parameters. Our method is based on Genetic Algorithms (GAs). In this work GA searches the 2 dimensional plane composed of K and λ to minimize the performance measure, which is given in (19);

$$F = \frac{100}{0.001 + 10 * IAE + 20 * \%OS + 10 * ITAE} \quad (19)$$

where IAE (Integral of Absolute Error) and $ITAE$ (Integral of Time Multiplied Absolute Error) are computed as in (20) and (21), respectively. Also $\%OS$ stands for percentage overshoot.

$$IAE = \sum_{k=0}^{\infty} |e(k)| \quad (20)$$

$$ITAE = \sum_{k=0}^{\infty} k|e(k)| \quad (21)$$

Then the new form of the fuzzy sliding mode controller will be,

$$u = \hat{b}^{-1}[-\hat{f} + \ddot{x}_d - \lambda\dot{e} - K(x,\dot{x})u_{fuzzy}(2s/\phi)] \quad (22)$$

In what follows, we will describe the optimization process steps:

Step 1 The system is which is controlled is operated for the different set of values of K and λ and the Fitness function given in (19) is computed. All the values including the Fitness are stored. During this process the values of K and λ are chosen in an interval which is determined by trail and error. During the determination of this domain of interval (18) must be taken into consideration.

Step 2 The set of values of K and λ which are obtained in Step 1, are used in this step for training the Artificial Neural Network (ANN) model of the system. The ANN model of the system is shown in Figure 1.

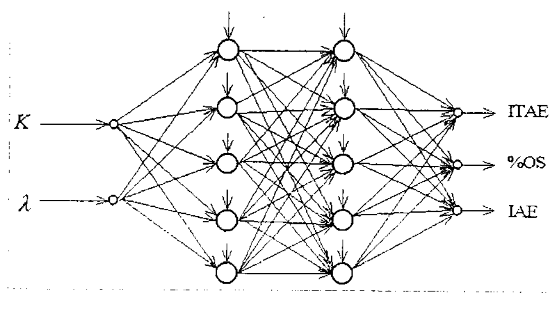

Figure 1. ANN model of the optimization process

Step 3 GA is used in order to find the near-optimal values of K and λ. During the GA process, the chromosomes which include the binary codes that do not satisfy (18) are assigned to 0 fitness.

The proposed controller fuzzifies the distance to the Sliding Surface and smoothes the undesirable discontinuous control action as shown in Figure 2. The architecture of the controller is shown in Figure 3. The proposed controller uses triangular member-ship functions for input (Figure 2) and output. The width of the output universe is equal to K. The rule base is shown in Table 1. Here **NB** stands for Negative Big, **NM** stands for Negative Medium, **NS** stands for Negative Small, **ZE** stands for Zero, **PS** stands for Positive Small, **PM** stands for Positive Medium and finally **PB** stands for Positive Big. As an inference engine, we use; individual-rule based inference with union combination, Mamdani's minimum implication, *min* for all t-norm operators and *max* for all s-norm operators. As a defuzzifier, center of average defuzzifier is used.

In this work, in order to model the dynamic system, a multiplayer feed-forward neural network is used. As a training algorithm, error back-propagation method is used. The ANN, which is used for the model of the system, has 2 hidden layers with 5 neurons in each layer. The ANN has 2 inputs and 3 outputs. The learning coefficient and momentum constant is selected as 0.7 and 0.9, respectively.

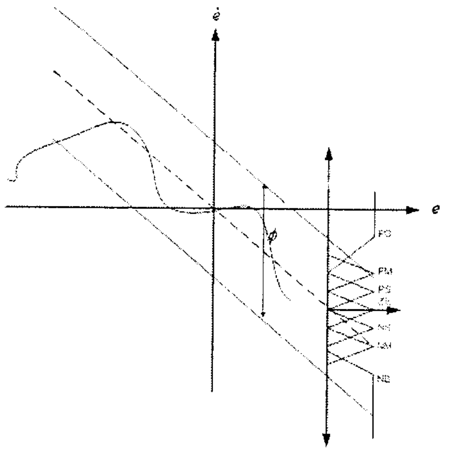

Figure 2 Fuzzy Smoothing of the proposed controller

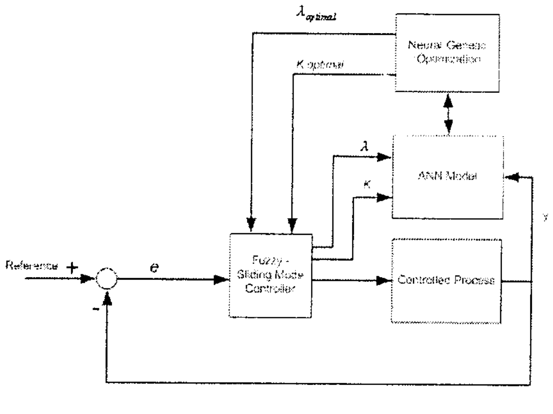

Figure 3. Block diagram of the proposed controller

Table 1. Rule Base for Fuzzy Smoothing

	$2S/\Phi$						
U_{FUZZY}	**NB**	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
	NB	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**

4. RESULTS AND DISCUSSION

In this section, we show the real time performance comparison results of the proposed Fuzzy Sliding Mode controller and the conventional Fuzzy-PI Controller. The controller performances are compared on a permanent magnet DC servo motor mechanism with a nonlinear load increasing with the speed of the system. The amount of the load increases exponentially with the increasing speed of the rotor.

The sampling period is chosen as 2kHz. All the software is coded with C++ and applied to the system via Pentium 200Mhz PC. The process has three DC motors, which are 90W each, and are coupled to each other on the same rotor axis. One of them is used for feedback generation and the others are used as plant and load, respectively. The feedback signal is eliminated from disturbances by a passive filter and a digital moving average type 20^{th} order filter by software.

The proposed controller is compared with the GA based optimal pure FLC and GA based PI controller in terms of *IAE*, *ITAE* and *%OS*. The *IAE* gives idea about the process ability for tracking the reference whereas, the *ITAE* gives idea about the steady state errors between the reference and system output.

To search an optimal solution, a population of 30 chromosomes is selected. Each chromosome is constructed to include K and λ. The mutation rate P_m and the crossover rate P_c are chosen as 0.01 and 0.95, respectively. For crossover operation, fixed-point crossover mechanism is used. As selection mechanism roulette wheel selection is used. On the other hand, in order to guarantee the survival of the best chromosome; worst chromosome is replaced with the best chromosome in each generation. The number of generations is chosen as 300. The change of total fitness with respect to generation obtained during the optimization process is shown in Figure 4.

In general, speed control of a PMDC motor system can be modeled by a second order differential equation as,

$$\frac{\omega(s)}{U(s)} = \frac{\lambda_0 K / JL}{s^2 + \frac{\beta_0 L + JR}{JL} s + \frac{\beta_0 R + K^2}{JL}}, \quad (23)$$

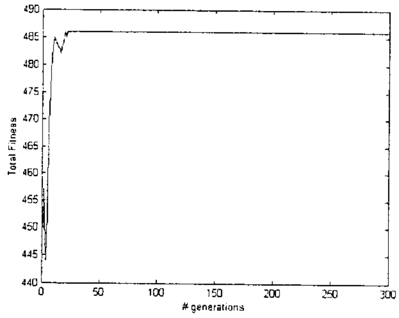

Figure 4. Total Fitness in each generation

where $\lambda_0 =$ 600 denotes the controller gain, K denotes the motor constant, J denotes total inertia of motor and load, L denotes armature inductance, R denotes armature resistance, β_0 denotes the total friction coefficients of load and motor, ω denotes the angular velocity of rotor and finally U denotes the applied voltage to motor.

If we represent ω by x and $\dot{\omega}$ by $\dot{x}$ then (23) can be rewritten as

$$\ddot{x} = -\dot{x}a - xb + cu \quad (24)$$

where a stands for $\frac{\beta_0 L + JR}{JL}$, b stands for $\frac{\beta_0 R + K^2}{JL}$ and finally c stands for $\frac{\lambda_0 K}{JL}$.

The characteristics of the controlled motor are listed in Table 2.

Table 2. Parameters of PMDC Motor used in experiment

$U_{nominal}$	52V
P	92W
$I_{nominal}$	2.2A
$n_{nominal}$	3000rpm.
L	0.0015H
K	0.14Vsec.rad^{-1}
β_0	0.00011NmSecRad^{-1}
J	0.0000421kgm^2
R	2.9Ω

As a result of Neural-Genetic optimization process, near optimal values of K = 0.17 and λ=17 are obtained. To demonstrate the validity of the proposed controller, the tracking performance of the proposed and conventional fuzzy-PI controllers are compared. The comparison results (Figure 5, Table 3) show that there is a significant improvement in the tracking performance in terms of overshoots and $ITAE$.

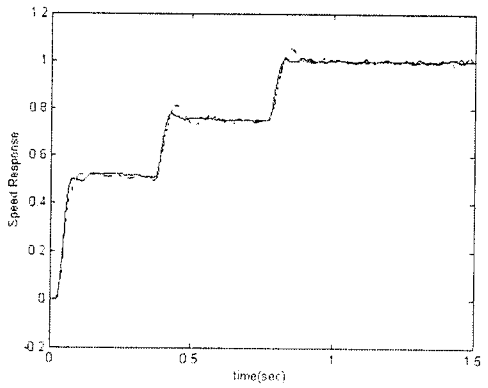

Figure 5. Response of the proposed controller (—) and the conventional fuzzy –PI controller (—·)

Table 3. Performance analyses of the controllers

	IAE	ITAE	t_r (sec.)
Proposed Cont.	90506	9114	0.1
Conv. Fuzzy PI	92846	9748	0.125

5. CONCLUSION

In this work, we have proposed a systematic method to find out the near optimal architecture of a sliding fuzzy controller. As an optimization method GA is used. During the optimization procedure ANN model of the system provided the parameters of the fitness function. Instead of using the exact system during fitness computation in each cycle, the wasted time is shortened by using ANN model.

On the other hand, undesirable discontinuous control signal effect is eliminated by using a fuzzy boundary layer. In order to show the validity of the proposed controller, the algorithm is applied to a speed control of a servo system. The experimental results demonstrated that the proposed controller shows satisfactory improvement in trajectory following when it is compared with conventional fuzzy-PI controller.

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