Genetic Algorithm Based Fuzzy Controller for Nonlinear Process

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Abstract — A Genetic Algorithm (GA) based fuzzy approach for on-line process control is proposed in this paper. In this approach, a T-S fuzzy controller is used to control the system. To reduce the fuzzy system design effort and to find the optimum fuzzy controller parameters, GA has been employed. It is also possible to emphasize on the system response specification by changing the fitness function and then finding the best controller parameters. The simulation results indicate that the proposed approach works well.

Keywords: Genetic Algorithm, Fuzzy controller, fitness function,

I. INTRODUCTION

The development of control systems to nonlinear processes is an active research area. Classic control theory handles linear processes very well but has several limitations facing with nonlinear problems. The standard procedure is first linearize the system around an equilibrium point, and then use a linear controller for that point. Due to the difficulty in modeling of nonlinear systems, the evolving approach is to use control algorithms that do not require an accurate mathematical model. These types of controllers are “intelligent control” that incorporates some heuristical knowledge of how to control the system. These control techniques are the Artificial Neural Networks [1], the Fuzzy Control [2], and the GAs [3].

Nowadays, many researchers have been combined the above control techniques to improve the efficiency of the optimization. These combined systems are called hybrid systems and have been widely used in different areas such as function approximation, control algorithms and so on.

In this paper a T-S type fuzzy system has been used for control of a nonlinear system. The performance of fuzzy control system highly depends on the system parameters. To find the global optimal parameters, a GA has been employed due to its capabilities of direct random search.

This paper is organized as follows: Section 2 presents a summary of T-S fuzzy system approach. In section 3 a brief description of GA is presented. Implementation of the proposed approach to a nonlinear system as a case study is presented in section 4. Section 5 presents the conclusions.

II. T-S FUZZY APPROACH

T-S type fuzzy approach is proposed by Takagi and Sugeno [4]. The main contribution of T-S fuzzy model is that the stability can be guaranteed [5]. Figure 1 illustrates T-S fuzzy model structure.

![Fig. 1 – Structure of T-S fuzzy model](image)

In control applications, generally $x_1$ and $x_2$ are the controlled parameter and its derivative and $y$ is the control signal. The fuzzy controller performance depends highly on its parameters. To find the best parameters of the fuzzy model, some techniques have been proposed. One of the most popular techniques is ANFIS [6] which is based on the gradient method and attempting to find the parameters to minimize the MSE between the desired and real output. The main drawback of this method is due to the possibility of falling into the local minimums. This problem
depends highly on the start position. Another problem of ANFIS is the fact that the desired output is needed while generally in control application it is not available. Of course, some methods have been proposed to overcome this problem, however they need the exact model of the plant.

Another technique is GA which can be used to find the global optimal parameters. This technique prevents falling into the local minimum and does not need the plant model in control applications.

III. GENETIC ALGORITHM

GA originated from the studies of cellular automata, conducted by Holland and his colleagues at University of Michigan [7]. It is a stochastic global search method that mimics the metaphor of natural biological evolution. GA operates on a population of potential solutions applying the principle of survival of the fittest solution.

At each generation, a new set of potential solution is created by the process of selecting individuals according to their fitness in the problem domain and manipulating them like natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the prior individuals, just as in natural adaptation. This technique is especially useful for complex optimization problems with a large number of parameters that make global analytical solutions difficult to obtain.

The main operations of GA are initialization, fitness evaluation, selection, mutation and crossover. Figure 2 shows the procedure of GA.

A. Initialization

Each population consists of a number of individual or chromosomes and each chromosome consists of a number of elements or genes. Generally, the number of chromosomes in a population is between 20 and 100, and the size of chromosomes is equal to the number of unknown parameters in the system which is desired to be optimum. In initialization, all the chromosomes in the population shall be initiated with random or predefined values.

B. Fitness evaluation

To select the best suited solution, a criterion is needed. This criterion is fitness function [8]. In control applications, the fitness function is generally referred to minimization of the error between the desired and real output.

C. Selection

The most popular selection technique which is mainly used in GA is “roulette wheel” mechanism [9]. In this study the basic “roulette wheel” mechanism with a little change has been employed.

D. Crossover (recombination)

The basic operator for producing new chromosomes in GA is crossover. Like its counterpart in nature, crossover produces new individuals that have some parts of both parent’s genetic material. Single-point crossover, multi-point crossover, uniform crossover, line recombination and intermediate recombination are various crossover techniques [10]. In this Study, intermediate recombination has been employed.

E. Mutation

In natural evolution, mutation is a random process where one allele of a gene is replaced by another to produce a new genetic structure. In GA, mutation modifies elements in the chromosomes randomly with low probability. The main role of mutation is providing a guarantee that the probability of searching any individual will never be zero and to recover good genetic material that may be lost through the action of selection and crossover [9].

F. Reinsertion

Once a new population has been produced by selection and recombination of chromosomes from the old population, the fitness of the chromosomes in the new and old population should be evaluated together to extract the next
This is called reinsertion and the chromosomes choosing method is like the selection stage.

IV. SIMULATION RESULTS

Many simulation tests have been performed in order to verify the performances of the proposed approach. In this section a cart and pole system simulation has been considered as a sample nonlinear system and the performance of the proposed genetic fuzzy algorithm is compared with the best manually tuned fuzzy controller.

Figure 3 depicts the simplified schematic of a cart and pole system.

![Fig. 3 – Simplified schematic of a cart and pole system](image)

The dynamic equation of the cart and pole system is as follows:

\[
g \sin \theta - \frac{1}{m_p + m_c} \cos \theta \cdot (f + 0.5m_p \cdot \dot{\theta}^2 \sin \theta) \]

\[
\dot{\theta} = \frac{0.5l \cdot \left( \frac{4}{3} \frac{m_c \cos^2 \theta}{m_p} \right)}{m_p + m_c}
\]

(1)

\[
\dot{x} = \frac{f + 0.5m_p \cdot \dot{\theta} \cdot \sin \theta - \dot{\theta} \cdot \cos \theta}{m_p + m_c}
\]

(2)

where \(f\) is the control signal, \(\theta\) is the pole angle, \(x\) is the cart position, \(l\) is the pole length and \(m_p, m_c\) are the pole and cart weights respectively.

A T-S fuzzy controller has been employed to control the cart and pole nonlinear system. The inputs of the fuzzy controller are \(e, \dot{e}, \theta, \dot{\theta}\), where \(e\) is the cart position error:

\[
e = x_d - x
\]

and \(x_d\) is the cart desired position. The output of fuzzy controller is \(f\). The goal of controller is manipulating the control signal \(f\) such that the cart position error and pole angle tend to zero as soon as possible.

The membership function (MF) of the inputs is Gaussian with 3 MFs for each input. To find the best parameters of the controller, a GA has been used. These parameters are the inputs and output MFs parameters and their number is 39. This number can be calculated as follows:

\[
N = N_i \cdot N_{mf} \cdot N_{mp} + N_{mf} \cdot (N_i + 1)
\]

(4)

where \(N_i, N_{mf}, N_{mp}\) are number of fuzzy controller inputs, number of MFs for each input and number of MF parameters respectively. \(N_{mp}\) depends on the MF type, for ex for Gaussian is 2 and for triangular is 3. Of course it is possible to not fix the type of MF at first and let the GA change them dynamically during training procedure and finally find the best. In this case, \(N_{mp}\) is equal to 4; 3 for MF parameters and one for the type of MF. It should be noted that in this case for all types of MFs 3 parameters is needed, however for some of them the third one is not used.

For the GA, a population with 40 chromosomes has been assumed. The chromosome size is equal to the fuzzy controller parameters. It is 39 for the fixed Gaussian type of MFs and 51 for the dynamic type of MFs. It is clear that the genes of the parameters are real-valued. Since the chromosomes size of the second one is larger, its simulation time is more. Generally the performance of the dynamic MF is more, however for this case study the difference is not very significant. The initial values of the chromosomes can be either random or predefined, however the predefined values take less time to converge to the final values. It is maybe due to this fact that in fuzzy control systems the human knowledge is very important and determinant. For this case study, the following predefined values have been chosen as initial values:

\[\begin{bmatrix}
1 & -1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 0 & \ldots
\end{bmatrix}\]

where each 6 values are for one input, 2 values for each MF, and the last 15 zeros are for the output MFs.

The desired cart position, \(x_d\), is a 0.05 Hz square wave and the controller sampling time is 0.1 second. The fitness function for each chromosome is defined as follows:
\[ f(x) = \sum_{i=1}^{n} e_i^2 \]  \hspace{1cm} (5)

where \( n \) is the number of calculations in one period for each chromosome and \( e_i \) is the cart position error in each sampling time. The above fitness function is good if we are looking for the best response time, but if the minimum steady state error is desired, it is better to use the following fitness function:

\[ f(x) = \sum_{i=1}^{n} \sqrt{|e_i|} \]  \hspace{1cm} (6)

In general, we can use the following combined fitness function:

\[ f(x) = \sum_{i=1}^{n} (k1 \cdot e_i^2 + k2 \cdot \sqrt{|e_i|}) \]  \hspace{1cm} (7)

where \( k1 \) and \( k2 \) are the weighting coefficients which can be manipulated to get the best response according to problem definition.

The well known “roulette wheel” mechanism has been used for selection.

Intermediate recombination method has been used as crossover technique. The new chromosomes are produced according to the rule,

\[ O1 = P1 \cdot \alpha \cdot (P2 - P1) \]  \hspace{1cm} (8)

where \( \alpha \) is a scaling factor chosen uniformly at random over some interval, typically [-0.25, 1.25] and \( P1 \) and \( P2 \) are the parent chromosomes.

In mutation, one gene of the chromosome is randomly selected and is added with a random value. This random value is small and typically in the range [-0.1, 0.1]. Of course if the selected gene for mutation is a gene that determines the type of mf, the random value is an integer between 1 and \( N \), where \( N \) is the number of allowed MFs.

After recombination and mutation a new population, offspring population, is generated. In reinsertion, the next population with the same size is extracted using the old and new or the parent and offspring population. The main operator in reinsertion is again the “roulette wheel” mechanism. The best fitted chromosome is directly selected at this stage to keep it in the next population.

The MATLAB simulink has been used for this simulation. The model is shown in figure 4.

As depicted in the figure, all the inputs at first normalized and then are used by the fuzzy genetic controller. Using this model, it is possible to view the system output on-line which gives a better sense to designer.

The used cart and pole dynamics in this study has been used by MATLAB to demonstrate the ability of fuzzy controller for nonlinear systems. The response of this manually tuned fuzzy controller is shown in figure 5.

The response of genetic fuzzy controller is shown in figure 6. This genetic fuzzy controller has been obtained after 4000 generations.

![Fig. 4- the control system model](image1)

![Fig. 5- the response of manually tuned fuzzy controller](image2)

![Fig. 6- the response of genetic fuzzy controller](image3)
As it is shown in figure 6, the response is better than in figure 5. This improvement of the system response is due to the better parameters of the controller thanks to GA global search technique.

V. CONCLUSION

In this paper a GA has been employed to tune the parameters of a T-S type fuzzy controller. The results of this genetic fuzzy controller have been compared with a manually tuned fuzzy controller. The results show that the proposed system performance is good enough. Some changes in fitness function give the better results.

REFERENCES


