Design of a Fuzzy Controller Using Random Signal-Based Learning Employing Simulated Annealing

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Abstract

This paper describes the application of simulated annealing to a random signal-based learning. Simulated annealing is used to generate the reinforcement signal of the random signal-based learning. The validity of the proposed algorithm is confirmed by applying it to the control of the inverted pendulum using fuzzy controller and finding the minimum of the nonlinear function.

1. Introduction

In spite of theoretical developments and many practical successes since Mamdani's pioneer work, the process for fine tuning of fuzzy control rules in order to get the desired performance is time-consuming and tedious task even though linguistic control rules are extracted from experts' knowledge. To overcome these difficulties, the self-organizing fuzzy controller was proposed by Mamdani[1] and extended by others.

This paper describes the application of simulated annealing to a random signal-based learning[2]. Simulated annealing is used to generate the reinforcement signal of the random signal-based learning. The validity of the proposed algorithm is confirmed by applying it to the control of the inverted pendulum using fuzzy controller and finding the minimum of the nonlinear function.

2. Random signal-based learning

The synapse strength of the proposed learning is adjusted as following form:

$$m(t+1) = m(t) + \eta r(t) f(n(t) - \theta) \quad (1)$$

where, η : learning rate, f : activation function

n : discrete random process with values between 0 and 1, θ : bias (=0.5)

and the reinforcement signal $r(t)$ is defined as follows:

$$r(t) = u(J(t) - J(t-1)) \quad (2)$$

where, $u(x) = \begin{cases} 1, & \text{if } x \le 0 \\ 0, & \text{otherwise} \end{cases}$

In this learning law, synapses learn when only a performance index(eq. (4)) defined as a sum of squared-error and derivatives of error is decreased after the learning. In other words, $r(t)$ of eq. (1) is set by 1. Otherwise, the learning is rejected, that is, $r(t)$ of eq. (1) is set by 0. The activation function f is a bipolar sigmoid function as following form:

$$f(x) = 2/(1 + e^{-\lambda x}) - 1 \quad (3)$$

In eq. (3), it lowers the slope of the nonlinear function that λ is decreased in constant rate during the learning

The learning algorithm is to adjust both the width and center of membership functions of the initially given fuzzy control rules so that the performance index is minimized. The following performance index is introduced:

$$J = \sum_{j=0}^{k} [e_j^2 + \dot{e}_j^2] \quad (4)$$

where e is error, $\dot{e}$ is derivative of error.

3. Simulated annealing and its application

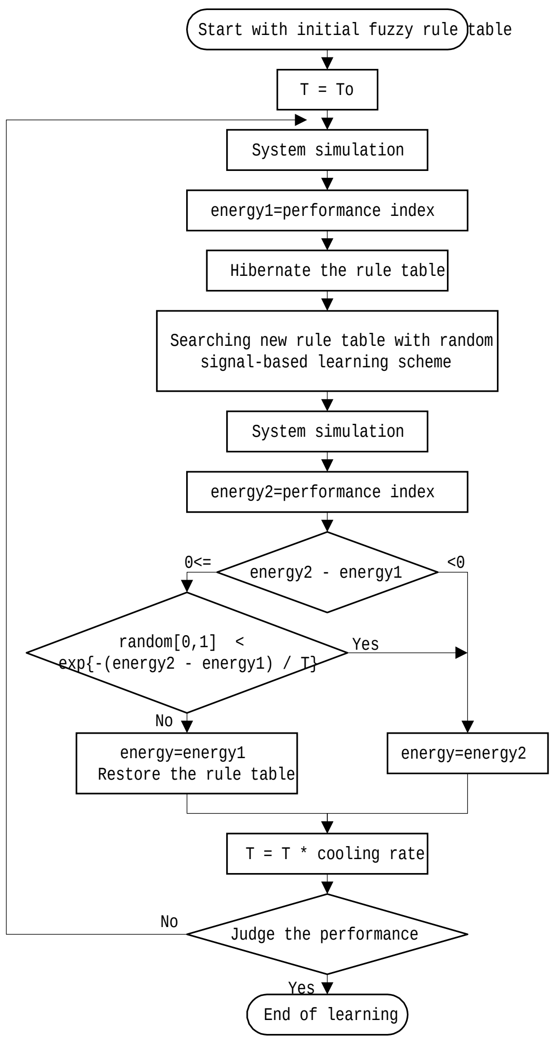

Fig. 1. Proposed algorithm

Simulated annealing allows a system to change its state to a higher energy state occasionally such that it has a chance to jump out of local minima and seek the global minimum. Downhill moves are always accepted, whereas uphill moves are accepted with the probability that is a function of temperature. The acceptance probability is usually given by the Boltzmann distribution,

$$p = \exp(-\Delta E / T) \qquad (5)$$

where ΔE is the change in the objective function and T is the temperature.

The temperature at any stage during the optimization may be expressed as follows:

$$T_k = \alpha^k T_0 \qquad (6)$$

where T_0 is initial temperature that is large enough, α is cooling rate and k is time index.

In this paper, we use simulated annealing to generate the reinforcement signal of the random signal-based learning. Fig. 1 shows a flow chart of the proposed learning algorithm.

4. Simulation results

The validity of the proposed algorithm is confirmed by applying it to two different examples. One is to find the minimum of the nonlinear function $F(x)$, when $-1<x<1$:

$$F(x) = (x+0.9)(x+0.7)(x+0.2)(x-0.4)(x-0.7)(x-0.9)+0.04 \quad (7)$$

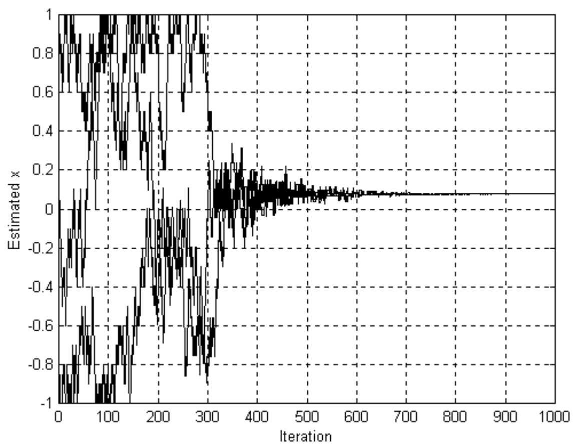

Fig. 2. Estimated x in each iteration

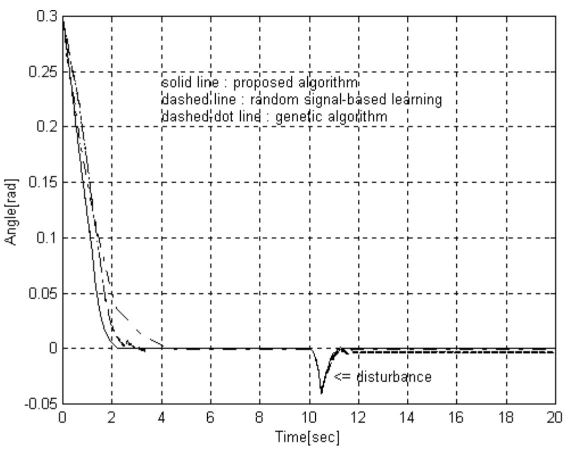

Fig. 3. Simulation result of the proposed algorithm.

Fig.2 shows the estimated x in each iteration for different initial conditions(-0.8, 0.1, 0.9) and eventually converge on global minimum(x=0.0771).

Another example is to control of the inverted pendulum. The mass of cart is 3Kg, the length of pole is 0.6m, the mass of pole is 0.1Kg and only consequent part of the fuzzy control rules are considered to learn for our simplicity.

Fig. 3 shows the controlled output of the inverted pendulum obtained by using the fuzzy control rules after the learning.

The result shows that the control performance of the proposed algorithm is greatly enhanced. Fig. 4. Shows the inverted pendulum energy profile during the learning.

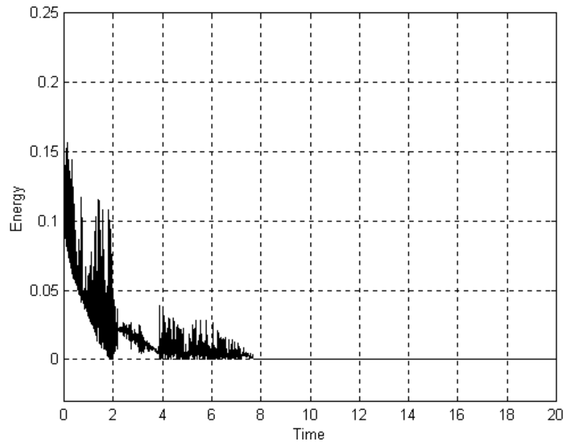

Fig. 4. Energy profile during the learning

5. Conclusions

This paper was described the application of simulated annealing to a random signal-based learning. Simulated annealing was used to generate the reinforcement signal of the random signal-based learning. The validity of the proposed algorithm was confirmed by using two different examples. From the results, we expect that the proposed algorithm can be applied another optimization or control problems.

References

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