Fuzzy-Neural Controller and Real-Time Implementation of A Ball Balancing Beam

K. C. Ng and M. M. Trivedi

Computer Vision and Robotics Research Laboratory
Electrical and Computer Engineering Department
The University of Tennessee - Knoxville, TN 37996-2100
kng@falcon.engr.utk.edu

ABSTRACT

Nonlinear dynamic ball balancing beam has been successfully controlled by applying conventional methods, neural networks, and fuzzy logic respectively. Conventional methods necessitate strong mathematical and control background to derive equations. Neural networks learn to balance a ball, but the ball never settles down due to the fact that “discrete resolution of the boxes representation” was used. Fuzzy logic has continuous representation; however, it takes a lot of efforts to incorporate human knowledge into rules. In order to have a continuous representation learning system with less rules and mathematics, a system with blend of neural networks and fuzzy logic is proposed. Fuzzy logic membership functions are utilized to fuzzify input parameters; neural network interpolates the fuzzy rule set; after defuzzification, the output is used to train a smaller size of neural network; the weights of the later neural network can be adjusted to fine tune the controller. This controller balances balls with one third of the required 27 rules. With learning capability, it approaches its goal more frequently in general. In this paper, the design of the fuzzy-neural controller is discussed, the hardware setup is shown, and the performance is evaluated.

1 INTRODUCTION

Many methods have been applied to the ball balancing beam (BBB) problem [1, 2, 3, 4]. Classical control theorists have claimed that they could bring a ball to rest on a beam in approximately 4 seconds [2]; they, however, did not balance the ball at a specific position. In addition, fairly advanced mathematical background and control theory understanding are required to derive merely simple equations [5]. Reinforcement neural controller learned to balance a ball. Nevertheless, the ball never settled down due to the use of “discrete resolution of the boxes representation,” and the ball was not balanced at a specific position either [3]. With this pure neural network alone, it is hard
Figure 11: Control output versus parameters. The controller was trying to keep up with the ball’s speed and directions. The results validate the appropriateness of the rule set used.

5 CONCLUDING REMARKS

This FNC for BBB is successfully designed and implemented using a real-time VME system to balance balls with one third of the conventional FLC rule set. With this fuzzy-neural architecture, the controller possesses the beauty of both fuzzy logic and neural networks. Fuzzy logic provides a continuous representation and human knowledge incorporation into the system. Membership functions make the controller less sensitive to some slight variations in the physical parameters and control goal. With the learning capability of neural networks, less rules are to be created manually and the controller is fine tuned to its original goal. Experimental studies suggest this FNC has the following special performances:

- No detailed mathematical derivation,
- Same model for linear and nonlinear system,
- Learning capability,
- Continuous representation and human knowledge incorporation,
- Ball size and mass are not in the design consideration,
- High noise tolerance.

Fuzzy logic and neural networks are both model free. Therefore, there is no mathematical equation to derive. The controller inherits their high fault tolerance feature and so it can endure noisy signals. In short, the overall performance of this project is robust and reliable.

References


