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SINGLE MULTIPLICATIVE NEURON MODEL AS AN ALTERNATIVE TO MULTI-LAYER PERCEPTRON NEURAL NETWORK

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ABSTRACT. The paper presents an approach to nonlinear control of complex dynamic systems using artificial neural networks (ANN). A novel form of ANN, namely, single multiplicative neuron (SMN) model is proposed in place of more traditional multi-layer perceptron (MLP). SMN derives its inspiration from the single neuron computation model in neuroscience. SMN model is trained off-line, to estimate the network weights and biases, using a population based stochastic optimization technique, namely, particle swarm optimization (PSO). On-line learning of SMN based on gradient-descent has been presented. The development of the control algorithms is illustrated through the hardware-in-the-loop (HIL) implementation of magnetic levitation and a cart position control system in LabVIEW environment. SMN structure was much simpler than the MLP for similar performance. The simple structure and faster computation of SMN have the potential to make it a preferred candidate for controller implementation for real-life complex dynamic systems.

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1. INTRODUCTION

Artificial neural networks (ANN) have been proposed for control of nonlinear systems since early nineties (Narendra and Parthsarathy, 1990; Hunt et. al, 1992; Sartori and Antsaklis, 1992). ANN based controllers have been used for systems that are otherwise difficult to control with traditional controllers. Among the different forms of ANN, multi-layer perceptron (MLP) are most commonly used (Hunt et. al, 1992; Hagan and Menhaj, 1994; Haykin, 2009). In a general structure of MLP, between input and output layers, one or more hidden layers with a varying number of neurons are used. In each of the hidden and the output neurons of the MLP, the inputs, modified with weights and biases, are summed up and the resulting sum is processed through a nonlinear activation function. In MLP based controllers, the structure of the ANN, mainly the number of hidden layers and the number of neurons in each hidden layer, needs careful consideration for the success of the algorithm (Haykin, 2009; Turner and Samanta, 2012). The complexity of computation algorithm

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increases with the number of hidden layers and the number of neurons in each hidden layer.

Recently, single neuron computation model is generating a lot of interest in computational neuroscience (Koch, 1997; Koch and Segev, 2000). Inspired by this development, a single multiplicative neuron (SMN) model has been proposed as an alternative to the general multi-layer perceptron (MLP) type artificial neural network (ANN) (Zhao and Yang, 2009; Samanta, 2011). In SMN, there is only one neuron in the hidden layer where all the inputs, modified with weights and biases, are multiplied. The resulting intermediate variable is processed subsequently through a nonlinear activation function to map the inputs with the output. The SMN model is much simpler in structure than the more conventional MLP type ANN and can offer better performances, if properly trained. However, like MLP, its success depends on estimating the model parameters in the off-line training and on-line learning stage.

In this work, off-line training of SMN is done using a variation of particle swarm optimization (PSO) that is derived from the social nature of bird flocking (Kennedy, Eberhart and Shi, 2001; Poli, Kennedy and Blackwell, 2007). Training a SMN requires determination of the weight and the bias for each input node. An optimized set of these parameters minimizes the mean square error (MSE) between the desired and the computed network output. To find this set of network parameters, a cooperative form of PSO (COPSO) has been used in this paper. COPSO has been shown to find optimized solutions more quickly than the traditional single swarm PSO (Zhao and Yang, 2009; Samanta, 2011). On-learning of SMN model parameters are essential in control of complex, nonlinear dynamic systems to account for changed system characteristics and interactions with the environment. In this work, gradient-descent based approach is proposed for on-line learning of SMN model parameters (Turner and Samanta, 2012; Hall and Samanta, 2013).

In this paper, the application of SMN based control system has been illustrated using two examples- a lab-scale magnetic levitation setup and a cart position control system (Turner and Samanta, 2012; Hall and Samanta, 2013). For cart position control system, a controlled based on adaptive dynamic programming (ADP) (Werbos, 1992; Prokhorov and D. Wunsch, 2007; Lendaris, 2008) using SMN has been used. The control structure includes a PI controller in a feedback loop for system stabilization and an ANN in a feed-forward path to compensate for any changes in the system dynamics or the presence of un-modeled higher order dynamics. For both systems, the designed ANN based controllers have been implemented in real-time in LabVIEW environment (National Instruments, 2015). Three versions of ANN controllers have been used: (i) an off-line trained MLP, (ii) an off-line trained SMN, and (iii) an on-line learning SMN.