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Control of a direct drive robot using fuzzy spiking neural networks with variable structure systems-based learning algorithm

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ABSTRACT

In this work, a sliding mode theory based supervised training algorithm that implements fuzzy reasoning on a spiking neural network has been developed and tested on the trajectory control problem of a two-degrees-of-freedom direct drive robotic manipulator. To describe the generation of a new spike train from the incoming spike trains Spike Response Model has been utilized and the Lyapunov stability method has been adopted in the derivation of the update rules for the neurocontroller parameters. The results of the real-time experiments indicate that stable online tuning and fast learning speed are the prominent characteristics of the proposed algorithm.

1. Introduction

Because of the highly nonlinear and coupled dynamics involved, the trajectory control of robotic manipulators has been usually considered as a challenging engineering problem. Furthermore, the variations in the system parameters with time hamper the development of an accurate model and there are very often uncertainties associated with the load that the gripper carries. Consequently, traditional model-based approaches have become impractical as their performance is directly related to the accuracy of the mathematical model of the system [1,2].

The tracking control of complex nonlinear systems subject to uncertainties has been thoroughly investigated in numerous research works [3–7], and model-free control methodologies based on computational intelligence techniques have been widely utilized in the trajectory control of manipulators to overcome the shortcomings stemming from the lack of modeling information and inaccuracies in the measurements. Artificial neural networks (ANNs) are generally considered among the most common and effective approaches to model-free design. McCulloch–Pitts neurons [8] constitute the first generation of artificial neural networks. In this early model, a neuron fires if the sum of its weighted incoming signals is above a threshold value. In the subsequent generation, the step threshold activation function of the first generation is replaced by a continuous one to promote the use of artificial neural networks in systems with analog inputs and outputs [9]. Hyperbolic tangent and sigmoid functions are typical activation functions of this generation.

Recent research has shown that neurons encode information in the timing of single spikes and not just in their average firing frequency [10]. Unlike the first two generations, in which the outputs of the network can be considered as the normalized firing rates of the neuron within a particular time interval, the third generation of ANNs consisting of spiking neurons (SNs) further improves the level of biological realism by attempting to make direct use of the temporal information of the individual spikes. In this new generation, similar to their biological counterparts, neurons encode the information in the exact timing of the spikes rather than the magnitude of the spikes [11].

In one of the leading works on the spiking neural networks (SNNs) [12], it is stated that SNNs can be applied to any problem that is solvable by the first two generations and this network has at least the same computational power as the neural networks consisting of perceptrons or sigmoidal neurons. Furthermore, it has been shown that these networks are capable of processing a considerable amount of data with a relatively small number of spikes [13]. The above-mentioned advantages and an increasing interest in temporal computation promote the use of SNNs in a

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wide variety of applications, including classification [14–17], image processing [18,19] and control [20–23].

Regarding the fact that every intelligent control technique has some advantages and disadvantages making them suitable for specific applications, hybrid systems combining fuzzy logic and neural networks have been widely used in a variety of classification and control applications. Neural networks are very effective in determining a mapping between the inputs and the outputs of a system, but they have a ”black box” nature. This gives rise to the lack of knowledge about the causal relationships between these inputs and outputs. The parameters that have the most impact on a particular output cannot be distinguished among others, and thus neural networks fail to provide an insight into the system dynamics. On the other hand, fuzzy logic systems are good at explaining how they reach their decisions but they require expert knowledge to form the rules and the membership functions they use to make these decisions. However, if the related knowledge is deficient, erroneous or inexact fuzzy systems may require the adjustment of their membership functions in order to be able to provide the proper output. The tuning of the parameters is generally conducted in a heuristic way due to the lack of any formal approach for it. This heuristic approach might be very time consuming and error-prone. One of the most effective remedies to overcome this shortcoming is the use of a hybrid structure in which the learning ability of neural networks can be utilized to automate the parameter update process and reduce development time and cost substantially while improving performance.

The common learning algorithms employed in the neuro-fuzzy systems can be considered in two groups: those relying on the methods based on gradient evaluation and those using evolutionary methods [24]. The gradient descent-based algorithms of the first group require the computation of partial derivatives of some cost function with respect to the parameters to be updated, which may give rise to the entrapment of the algorithm into a local minimum of the nonlinear objective function. Some other concerns about these learning algorithms can be stated as their sluggish learning speed and the difficulty to obtain analytical results concerning the convergence and stability of the learning schemes [25]. On the other hand, evolutionary algorithms are capable of finding a global optimal solution in most cases, as they do not employ any derivatives. Nevertheless, the stability of such approaches is still questionable and the optimal values for the stochastic operators are difficult to derive. Additionally, the evolutionary process is very time-consuming and this makes these algorithms unsuitable for online learning of SNNs, which already require a high computational time because of the use of multiple synapses for each connection between a presynaptic and a postsynaptic neuron.

The shortcomings with the gradient descent-based and evolutionary approaches give rise to the development of sliding mode control (SMC) theory-based algorithms for the parameter adaptation of the neuro-fuzzy systems [26–33], by means of which robust system response in handling the uncertainties and imprecision and faster convergence than the traditional learning techniques in online tuning can be achieved. In this study, a sliding mode theory-based supervised training algorithm that implements fuzzy reasoning on a spiking neural network is developed and tested for the trajectory control problem of a robotic manipulator. Stable online tuning of the parameters and a fast learning speed are the prominent characteristics of the proposed algorithm. The Lyapunov stability method has been adopted in the derivations of the conditions to enforce the learning error toward zero in a stable manner.

The paper is organized as follows: Section 2 describes the basic concepts and functioning of an SNN. In Section 3, a brief introduction to SMC is presented and in the subsequent section the parameter update rules based on the SMC are derived for a fuzzy spiking neural network (FSNN) structure. The description and the mathematical model of the two-degrees-of-freedom (2-dof) direct drive SCARA robot as well as the obtained results from real-time experiments are given in Section 5. Section 6 is devoted to the concluding remarks.

2. Spiking neural networks

Although the biological neurons may differ in their size and shape from each other, all of them consist of four distinct parts called dendrite, soma, axon and synapse (see Fig. 1). The dendrites of a postsynaptic neuron collect electrical signals coming from the neighboring presynaptic neurons and transmit these signals to the soma of the postsynaptic neuron. If the weighted sum of the incoming signals is above a certain threshold value, then a spike is generated and propagated along the axon and its branches to other neurons. When this spike arrives at a synapse, which refers to the connection between the axon branch of a presynaptic neuron and the dendrite of a postsynaptic neuron, it triggers a complex chain of biochemical reactions. These biochemical processes give rise to a change in the postsynaptic membrane potential. This process is relatively slow and it is associated with a certain delay specific to that synapse.

Studies on the biological neurons [34,35] show that the spikes of a neuron have similar shapes and the information is encoded in the number and precise timing of the spikes rather than in their form. Neural networks consisting of spiking neurons take a further step in terms of biological similarity to their biological counterparts by using the timing of the spikes as the means of communication and neural computation instead of utilizing their magnitudes; i.e. the inputs and the outputs of an SNN are the temporal information of the spikes, whose magnitude information is omitted.

A number of neuron models have been proposed throughout the literature to formulate the information transmission between spiking neurons. These models differ from each other with regard to their degree of biological accuracy and computational efficiency. In this paper, the Spike Response Model (SRM) [36], which is extensively used in many research works owing to its mathematical simplicity, has been utilized to describe the generation of the new spike train from incoming spikes.

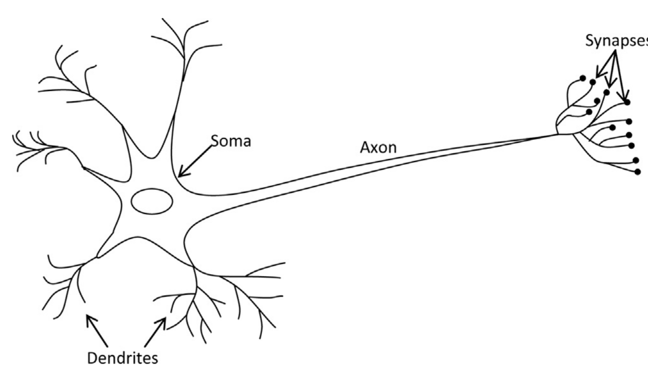

Fig. 1. A simplified neuron diagram.

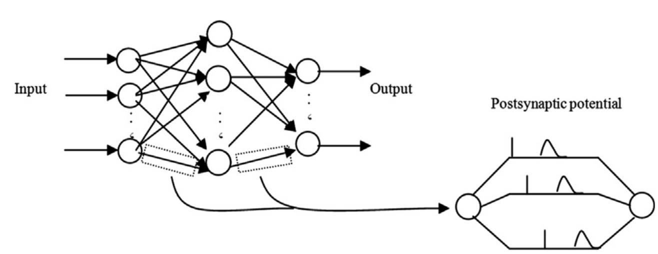

Fig. 2. The structure of an SNN.