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Evolving spiking wavelet-neuro-fuzzy self-learning system

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ABSTRACT

The paper introduces several modifications to self-learning fuzzy spiking neural network that is used as a base for evolving system design. The adaptive wavelet activation-membership functions are utilized to improve and generalize receptive neuron activation functions and the temporal Hebbian learning algorithm. The proposed evolving spiking wavelet-neuro-fuzzy self-learning system retains native features of spiking neurons and reveals evolving systems' capabilities in detecting overlapping clusters of irregular form.

1. Introduction

Self-learning spiking neural networks have appeared to be a powerful computational intelligence tool for fast and efficient data clustering [1–3]. Moreover, being more realistic models of biological neural systems than artificial neural networks of the previous generations [4,5], spiking neural networks present another step of computational intelligence paradigm evolving toward biologically plausible computing [6]. Hybrid intelligent systems designed on the basis of self-learning spiking neural networks and fuzzy clustering approaches were shown to be successfully applied for data clustering in the presence of overlapping classes [7–9].

Another area where self-learning spiking neural networks and hybrid systems based on them can be successfully used is a hierarchical clustering. Previously, multilayered spiking neural network with feed-forward adjustable lateral connections in the hidden layers was suggested for solving tasks of such kind [1]. While the obtained results of hierarchical clustering produced by the network were sufficiently successful, approach to application of the lateral connections within spiking neurons layers seems to be rather unnatural. Such network requires two learning algorithms, namely, one that adjusts synaptic weights between layers for initial data partitioning and another one that adjusts weights of lateral connections for complex clusters detecting. Apparently, several learning algorithms usage increases learning time. Furthermore, the network layers number is set a priori and does not change through the network functioning. Architecture of multilayered self-learning spiking neural network that uses lateral connections for spikes transmitting only was introduced thereafter [10]. Capability of irregular form clusters detecting was achieved by improving biologically inspired learning algorithm that adjusted solely connections between layers. The network operation was considered from control theory point of view, in terms of Laplace transform. Such approach allowed of network architecture designing on a general technically plausible ground that provided researchers and engineers with a powerful framework for various hardware implementations of intelligent systems based on spiking neural networks.

Though self-learning spiking neural networks can successfully perform various clustering tasks, they, like any technical tool, have certain limitations. The most important one is that some network architecture adjustable parameters lack for rules on their initial setup. The first and foremost issue here is how to determine number of spiking neurons layers when performing hierarchical data clustering. Both multilayered spiking neural networks mentioned above require a priori setup for hidden layers number that is usually hard to do. In this paper an evolutionary approach is proposed to be used for fuzzy spiking neural network architecture setup that allows researcher to tune number of spiking neurons layers during the network learning.

The paper also introduces a generalization of receptive neuron activation function. Originally Gaussian-like functions were

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suggested for receptive neurons [1] but their setup proposed looks rather unnatural because it almost does not consider input data specifics. Later it was shown activation functions of receptive neurons in a pool can be treated as membership functions of a certain linguistic variable, thus allowing researcher to setup receptive neurons according to a priori knowledge of input data structure. Mitaim and Kosko revealed, though, that membership function in some cases may take negative values in order to present non-membership levels [11,12], and Gaussian-likes functions do not meet that requirement. In order to overcome the difficulty, an adaptive wavelet activation-membership function is introduced in this paper as a generalization of receptive neuron activation function.

In summary, a computational intelligence hybrid system [13] driven from the liquid computations paradigm [14] and combining the merits of conventional spiking neural networks, fuzzy clustering, wavelet membership functions, and evolving systems [15,16] is suggested in this paper, such that it builds up its layers in the course of data processing for achieving the required clustering quality in the presence of overlapping irregular form classes.

2. The system's architecture

Evolving spiking wavelet-neuro-fuzzy self-learning system for data clustering has a heterogeneous multilayered feed-forward architecture that includes population coding layer and several layers of spiking neurons. Population coding layer (the first hidden layer) transforms input signals into pulse-position form. Layers of spiking neurons perform hierarchical clustering. The overall architecture of the system is depicted on Fig. 1 and is a modification of architectures introduced in [1,10].

2.1. Population coding layer

Similar to biological neurons, spiking neurons process information presented in pulse-position form [5]. One of the major purposes of population coding layer is to perform transformation of input patterns from pulse-amplitude form to pulse-position one. Another purpose of the layer is to improve cluster separation capability of spiking neurons [1].

Population coding layer consists of pools of receptive neurons. Each dimensional component of input pattern is processed by all receptive neurons of a certain pool.

Generally speaking, population coding layer acts as follows. It takes $(n \times 1)$ -dimensional input patterns $x(k)$ (here n is the dimensionality of input space, $k = \overline{1, N}$ is a pattern number, N is number of patterns in incoming set) and produces $(hn \times 1)$-dimensional vector of incoming spikes $t^{[0]}(x(k))$ (h is the number of receptive neurons in a pool). In general case firing time of each spike emitted by a receptive neuron lies in a certain interval $[0, t_{\max}^{[0]}]$ referred to as coding interval and is described by the following expression:

$$t_{li}^{[0]}(x(k)) = \left\lfloor t_{\max}^{[0]}(1 - \psi(|x_i(k) - c_{li}^{[0]}|, \sigma_i))\right\rfloor \tag{1}$$

where $\lfloor \bullet \rfloor$ is the floor function, $\psi(\bullet, \bullet)$ is an activation function of receptive neuron, $c_{li}^{[0]}$ is the center of the lth receptive neuron in the pool of the ith input, σ_i is the width of receptive neuron activation function in the pool of the ith input.‘

In this paper, the adaptive wavelet activation-membership functions [17,18] are used for receptive neuron activation functions:

$$\psi(|x_i(k) - c_{li}^{[0]}|, \sigma_i) = (1 - \alpha_{li}\tau_{li}^2)e^{(-\tau_{li}^2/2)} \tag{2}$$

where $\tau_{li}^2 = (x_i(k) - c_{li}^{[0]})^2 \sigma_i^{-2}, \alpha_{li}$ is a tuning parameter $(0 \le \alpha_{li} \le 1)$.

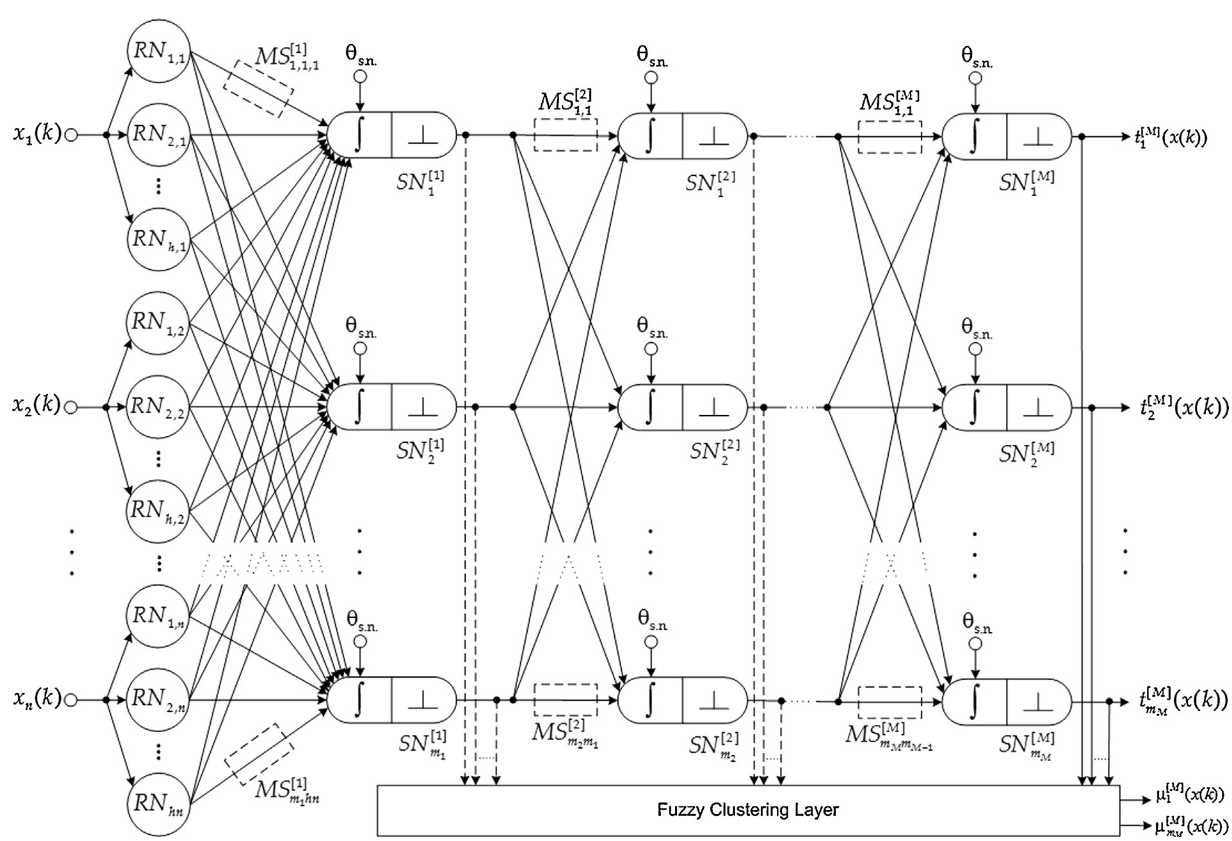

Fig. 1. Architecture of evolving spiking wavelet-neuro-fuzzy self-learning system.