RIGA TECHNICAL UNIVERSITY

Information Technology and Management Science

ISSN 2255-9094 (online)
ISSN 2255-9086 (print)
December 2018, vol. 21, pp. 24–28
doi: 10.7250/itms-2018-0003
https://itms-journals.rtu.lv

2D-Neo-Fuzzy Neuron and Its Adaptive Learning

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Abstract – **In the paper, 2D-neo-fuzzy neuron (NFN) is presented. It is a generalization of the traditional NFN for data in matrix form. 2D-NFN is based on the matrix adaptive bilinear model with an additional fuzzification layer. It reduces the number of adjustable synaptic weights in comparison with traditional systems. For its learning, optimized adaptive procedures with filtering and tracking properties are proposed. 2D-NFN can be effectively used for image processing, data reduction, and restoration of non-stationary signals presented as 2D-sequences.**

Keywords – **2D network, data mining, hybrid systems, neo-fuzzy neuron.**

I. Introduction

Artificial neural networks (ANNs) and fuzzy inference systems (FISs) are now widely used for solving a large class of data mining tasks, including such modern directions as data stream mining, dynamic data mining, web mining, text mining etc. At the edge of these two approaches, hybrid systems of computational intelligence (HSCI) have emerged, combining the universal approximation properties of ANNs and their ability to learn, and the possibility of linguistic interpretation of the results provided by FIS. Although HSCI have a number of advantages over ANNs and FISs, their main disadvantage is rather low learning speed provided by gradient algorithms, with the learning rate parameter that is usually chosen from empirical considerations. The use of optimal procedures of the second order (Gaussian-Newtonian optimization methods) is limited by their computational complexity and the "curse of dimensionality", arising with the growth of the input space dimension.

These shortcomings can be avoided using an HSCI, known as neo-fuzzy neuron (NFN) [1]–[4], which is close to the zero-order Takagi–Sugeno–Kang system, but much simpler in computational implementation and allowing one to use high-speed optimization procedures for its training.

The architecture of the conventional NFN with n inputs and one output is shown in Fig. 1.

When a vector signal

$$x(k)=\left(x_1(k),x_2(k),...,x_i(k),...,x_n(k)\right)^{\mathrm{T}}\in R^n$$

is fed to the input of the NFN (here, $k=1,2,...$ is the index of the current discrete time), its components $x_i(k)$ are first fuzzified in the layer of membership functions which contains hn kernel functions μ_{li}, $l=1,2,...,h$; $i=1,2,...,n$. Then the fuzzified values $\mu_{li}(x_i(k))$ are fed into the layer of tunable synaptic weights w_{li} that are adjusted during the process of learning to provide the extremum of the adopted learning criterion.

Thus, the output signal of the NFN at the kth time instant can be written in the form

$$\hat{y}(k)=\sum_{i=1}^{n}f_i\left(x_i(k)\right)=\sum_{i=1}^{n}\sum_{l=1}^{h}w_{li}(k-1)\mu_{li}\left(x_i(k)\right),\qquad(1)$$

where $w_{li}(k-1)$ is the value of the corresponding synaptic weight obtained after previous $(k-1)$ observations.

Since the standard NFN uses triangular membership functions that meet the conditions of a unity partition, only two neighbouring ones are fired at each instant of the current time k at each input. This means that at the same time only $2n$ synaptic weights are tuned. It simplifies and speeds up the learning process.

Further modifications of NFN were aimed at improving its approximating properties. For example, the extended NFN was proposed in [2], and in [5], [6] the same authors proposed the usage of wavelets instead of triangular membership functions, that led to the emergence of a wavelet neuron.

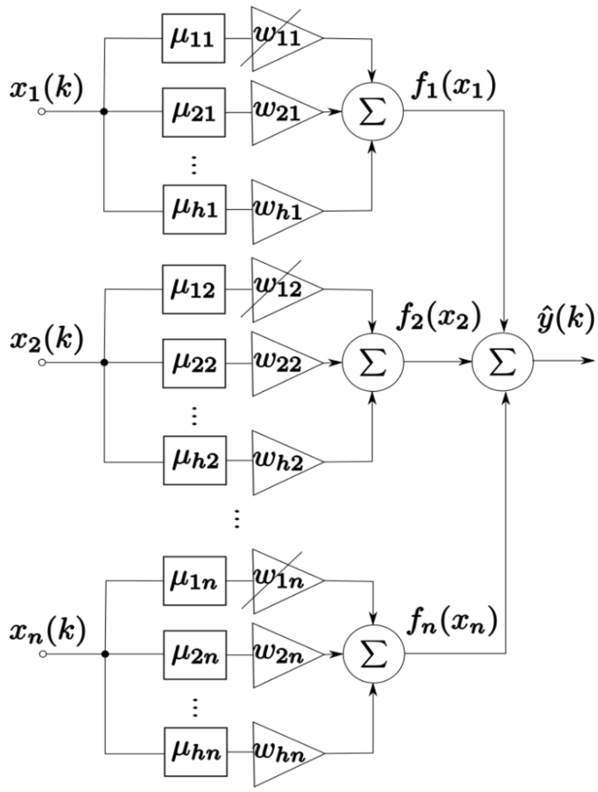

Fig. 1. Neo-fuzzy neuron.

Since NFN is a system with one output, which limits its capabilities, in [7]–[9] a generalized NFN was proposed to the case of multiple outputs, which allowed restoring of nonlinear mappings $R^n \to R^m$.

Further development was evolving NFN [10], [11], where not only synaptic weights were tuned in the training process, but also the number and the form of membership functions. All the described modifications allowed extending the functionality of the original NFN.

Flexible neo-fuzzy neuron, double neo-fuzzy neuron, double wavelet neuron, spline-based neo-fuzzy neuron, neuro-fuzzy unit, optimized learning algorithms and HSCI architectures were proposed in [12]–[32], containing these modifications as nodes to solve problems of identification, approximation, filtration, prediction, signal restoration, adaptive and robust control, classification and image recognition, data reduction and compression, characterised by high speed and quality of the resulting solution.

In [33], examples of solutions based on NFN for industrial tasks are described.

All the above-mentioned modifications of NFN imply that the input signal $x(k)$ is a $(n\times 1)$–vector, which in general is traditional in most data mining tasks. At the same time, there is a fairly wide class of problems related to the processing of fields of observations, first of all images, where the input information enters the processing in the form of matrices

$$x(k)=\{x_{i_1i_2}(k)\}\in R^{n\times m},\ i_1=1,2,...,n;\ i_2=1,2,...,m.$$

In principle, the matrix $x(k)$ can be vectorized to the form of $\vec{x}(k)\in R^{nm}$, but the number of tunable synaptic weights takes on a value of hnm that somehow leads to the appearance of the “curse of dimensionality” effect.

In this connection, it seems expedient to develop a 2D-NFN and an algorithm for its online learning for problems where information for processing comes not in the form of traditional vectors but in the form of $(n\times m)$–matrices.

II. 2D-Neo-Fuzzy Neuron Based on the Adaptive Bilinear Model

Let us introduce a $(hn\times 1)$–vector of membership functions

$$\mu(x(k))=\left(\mu_{11}(x_1(k)),\mu_{21}(x_1(k)),...,\mu_{h1}(x_1(k)),...,\right.$$
$$\left.\mu_{li}(x_i(k)),...,\mu_{hn}(x_n(k))\right)^{\mathrm{T}}$$

and a corresponding vector of adjustable synaptic weights

$$w(k-1)=\left(w_{11}(k-1),w_{21}(k-1),...,w_{li}(k-1),...,w_{hn}(k-1)\right)^{\mathrm{T}}.$$

Now we can rewrite (1) in the form

$$\hat{y}(k)=w^{\mathrm{T}}(k-1)\mu(x(k))$$

that corresponds to the adaptive linear model, which is used in the tasks of control object identification.

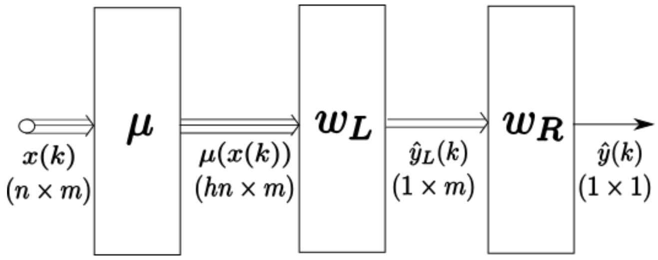

Fig. 2. 2D-neo-fuzzy neuron.

In the case of matrix input signal $x(k)$, similarly an adaptive bilinear model can be introduced [34], [35]

$$\hat{y}(k)=w_L(k-1)x(k)w_R(k-1) \tag{2}$$

where $w_L(k-1)$, $w_R(k-1)$ are $(1\times n)$, $(m\times 1)$–vectors of adjustable synaptic weights that are obtained using previous $(k-1)$ observations.

Bilinear model (2) can be used as the basis for 2D-NFN. The architecture of the 2D-NFN is shown in Fig. 2.

When a matrix signal $x(k)=\{x_{i_1i_2}(k)\}$ is fed to the 2D-NFN input, its components $x_{i_1i_2}(k)$ are first fuzzified in the layer of membership functions with hnm functions $\mu_{li_1i_2}(k)$, $l=1,2,...,h;\ i_1=1,2,...,n;\ i_2=1,2,...,m$ (with h functions per component $x_{i_1i_2}(k)$), resulting in a matrix signal $\mu(x(k))$ of dimension $(hn\times m)$. Then this signal is fed to the layer of left-sided tunable synaptic weights $w_L(k-1)$, presented as a $(1\times hn)$–vector. At the output of this layer a $(1\times m)$–vector appears, that is fed to the layer of right-sided synaptic weights $w_R(k-1)$ in the form of a $(m\times 1)$–vector. As a result, a scalar signal $\hat{y}(k)$ appears at the output of 2D-NFN described by the expression

$$\hat{y}(k)=w_L(k-1)x(k)w_R(k-1).$$

In principle, it would be possible to vectorize the matrix signal $x(k)$ and process it using the conventional NFN. However, in this case the number of adjustable synaptic weights would be determined by the value hnm. 2D-NFN contains only $hn+m$ such weights, which are much smaller, i.e.,

$$hn+m<hnm.$$

III. 2D-Neo-Fuzzy Neuron Learning

Let us introduce three types of errors (one a priori and two a posteriori) that arise in the learning process

$$\begin{cases} e(k)=y(k)-w_L(k-1)\mu(x(k))w_R(k-1)=y(k)-\hat{y}(k),\\ e_L(k)=y(k)-w_L(k)\mu(x(k))w_R(k-1),\\ e_R(k)=y(k)-w_L(k)\mu(x(k))w_R(k) \end{cases}$$

(here $y(k)$ is the external reference signal) and two criteria that characterize its quality:

$$\begin{cases} E_L(k) = \|e(k)\|^2, \\ E_R(k) = \|e_L(k)\|^2. \end{cases} \tag{3}$$

The minimization of the first criterion of (3) by the weight vector w_L using the gradient procedure leads to the algorithm

$$\begin{aligned} w_L(k) &= w_L(k-1) + \eta_L(k)\big(y(k) - w_L(k-1)\times \\ &\times \mu(x(k))w_R(k-1)\big)\big(\mu(x(k))w_L(k-1)\big)^{\mathrm{T}} = \\ &= w_L(k-1) + \eta_L(k)\big(y(k) - w_L(k-1)\times \\ &\times \mu_L(x(k))\big)\mu_L^{\mathrm{T}}(x(k)), \end{aligned} \tag{4}$$

and the second criterion of (3) by w_R –

$$\begin{aligned} w_R(k) &= w_R(k-1) + \eta_R(k)\big(y(k) - w_L(k)\mu(x(k))\times \\ &\times (w_R(k-1))\big)\big(w_L(k)\mu(x(k))\big)^{\mathrm{T}} = w_R(k-1) + \\ &+ \eta_R(k)\big(y(k) - \mu_R(x(k))w_R(k-1)\big)\mu_R^{\mathrm{T}}(x(k)), \end{aligned} \tag{5}$$

where $\eta_L(k)$, $\eta_R(k)$ are learning rate parameters.

The optimization of the learning rates [12]–[14] leads to the learning algorithm of the 2D-NFN in the form

$$\begin{cases} w_L(k) = w_L(k-1) + r_L^{-1}(k)\times \\ \quad\times\big(y(k) - w_L(k-1)\mu_L(x(k))\big)\mu_L^{\mathrm{T}}(x(k)), \\ r_L(k) = \alpha r_L(k-1) + \|\mu_L(x(k))\|^2, \\ w_R(k) = w_R(k-1) + r_R^{-1}(k)\times \\ \quad\times\big(y(k) - \mu_R(x(k))w_R(k-1)\big)\mu_R^{\mathrm{T}}(x(k)), \\ r_R(k) = \alpha r_R(k-1) + \|\mu_R(x(k))\|^2 \end{cases} \tag{6}$$

(here $0 \le \alpha \le 1$ is a smoothing parameter) that have both tracking and filtering properties.

It is obvious that with $\alpha = 0$ it is the Kaczmarz-Widrow-Hoff algorithm that is optimal by speed in the class of gradient procedures. In this case it takes the form

$$\begin{cases} w_L(k) = w_L(k-1) + \dfrac{y(k) - w_L(k-1)\mu_L(x(k))}{\|\mu_L(x(k))\|^2}\mu_L^{\mathrm{T}}(x(k)) = \\ \quad = w_L(k-1) + \big(y(k) - w_L(k-1)\mu_L(x(k))\big)\mu_L^{+}(x(k)), \\ w_R(k) = w_R(k-1) + \dfrac{y(k) - \mu_R(x(k)w_R(k-1))}{\|\mu_R(x(k))\|^2}\mu_R^{\mathrm{T}}(x(k)) = \\ \quad = w_R(k-1) + \big(y(k) - \mu_R(x(k))w_R(k-1)\big)\mu_R^{+}(x(k)). \end{cases} \tag{7}$$

It is possible to increase the speed of the learning process and improve its smoothing properties by moving from one-step learning criteria (3) to their multi-step variants and using the exponentially weighted recurrent least squares method (EWRLSM), which, however, can be numerically unstable at high dimensions of input signals and small values of the smoothing parameter α.

In this situation, it is advisable to use the optimal gradient recurrent exponentially weighted algorithm (OGREWA) [36], which is a gradient modification of EWRLSM.

For the problem under consideration, taking into account relations (5) and (6), the OGREWA can be written as follows:

$$\begin{cases} w_L(k) = w_L(k-1) + \dfrac{\bar{e}^2(k)\big(p_L(k) - w_L(k-1)P_L(k)\big)}{\|p_L(k) - w_L(k-1)P_L(k)\|^2}, \\ \bar{e}^2(k) = \alpha\bar{e}^2(k-1) + e^2(k), \\ p_L(k) = \alpha p_L(k-1) + y(k)\mu_L^{\mathrm{T}}(x(k)), \\ P_L(k) = \alpha P_L(k-1) + \mu_L(x(k))\mu_L^{\mathrm{T}}(x(k)) \end{cases} \tag{8}$$

and

$$\begin{cases} w_R(k) = w_R(k-1) + \dfrac{\bar{e}_L^2(k)\big(p_R(k) - P_R(k)w_R(k-1)\big)}{\|p_R(k) - P_R(k)w_R(k-1)\|^2}, \\ \bar{e}_L^2(k) = \alpha\bar{e}_L^2(k-1) + \bar{e}_L^2(k), \\ p_R(k) = \alpha p_R(k-1) + y(k)\mu_R^{\mathrm{T}}(x(k)), \\ P_R(k) = \alpha P_R(k-1) + \mu_R^{\mathrm{T}}(x(k))\mu_R(x(k)). \end{cases} \tag{9}$$

Algorithms (8), (9) combine the high speed of convergence, tracking and filtering properties, and are stable (unlike EWRLSM) for any value of the smoothing parameter α.

IV. Results of Simulation

The efficiency of the proposed 2D-neo-fuzzy system was demonstrated on the binary classification task. The experiment was carried out on the hand-written digit dataset from the UCI repository [37]. Two classes (digits 0 and 1) were used from this dataset. Some examples of the images from this dataset are presented in Fig. 3.

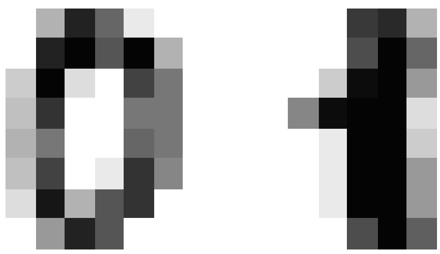

Fig. 3. Examples from the digit dataset.

Each observation from this dataset is presented as an 8x8 matrix of digits that represents pixel values. These values were preprocessed before training using normalization.

The results of the experiment and system parameters are presented in Table I.

TABLE I

RESULTS OF THE EXPERIMENT

Number of membership functions	5
Number of adjusted parameters	48
Accuracy on training set, %	97.91
Accuracy on test set, %	97.22

V. CONCLUSION

The article proposes a 2D (matrix)-neo-fuzzy neuron, designed to solve a wide range of data stream mining tasks. The 2D-NFN, being a hybrid system of computational intelligence, is intended for processing signals in the matrix form, for example, images. It is characterized by good approximating properties, high speed of learning processes; it possesses both tracking and filtering properties. 2D-NFN is simple in the computational implementation and allows processing information coming into it in online mode.

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