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Neo-Fuzzy Encoder and Its Adaptive Learning for Big Data Processing

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Abstract – **In the paper a two-layer encoder is proposed. The nodes of encoder under consideration are neo-fuzzy neurons, which are characterised by high speed of learning process and effective approximation properties. The proposed architecture of neo-fuzzy encoder has a two-layer bottle neck" structure and its learning algorithm is based on error backpropagation. The learning algorithm is characterised by a high rate of convergence because the output signals of encoder's nodes (neo-fuzzy neurons) are linearly dependent on the tuning parameters. The proposed learning algorithm can tune both the synaptic weights and centres of membership functions. Thus, in the paper the hybrid neo-fuzzy system-encoder is proposed that has essential advantages over conventional neurocompressors.**

Keywords – **Artificial neural networks, computational intelligence, data compression, machine learning.**

I. Introduction

A major problem of Data Mining, which is related to high dimensional big data processing [1], [2], is a task of data reduction without significant loss of information that is contained in this data store. For solving such tasks, a lot of approaches are proposed, and, first of all, the principal component analysis, principal manifold analysis, discriminant analysis, specialised neural networks such as Hebb-Sanger neural network, Oja-Karhunen neural network, "bottle neck" and others [3], [4].

The necessary element of deep neural networks [5]–[7], which are intensively developed at the present day, is autoencoder. It solves the problem of data reduction and forms the input layers of neural networks. The autoassociative multilayer perceptron "bottle neck" and restricted Boltzmann machine are most often used as autoencoder. The nodes of such autoencoders are the elementary Rosenblatt perceptrons with the sigmoidal activation functions. These autoencoders provide a high quality of data compression but are characterised by a low speed of their parameter tuning, which is implemented based on multi-epoch learning.

Due to the intensive development of the studies in Data Stream Mining [8], [9], it is important to synthesise the high-speed autoencoders, which allow processing information in online mode, when data is fed to a system sequentially.

II. Architecture of the Neo-Fuzzy Autoencoder

The proposed autoencoder has a two-layer architecture and is autoassociative "bottle neck" modification of the Kolmogorov's neuro-fuzzy network (KNFN), which was proposed and investigated in [10]–[14]. The vector signals $x(k)=(x_1(k),\ldots,x_i(k),\ldots,x_n(k))^{\mathrm{T}}\in R^n$, which have to be compressed, are fed to the receptor layer of the network (here $k = 1, 2,\ldots, N$ is an observation number in a sample (in case of batch mode) or an instant of discrete time (in case of online mode)).

The first hidden network's layer consists of m ($m < n$) tuned nonlinear units. The output of these units is values of compressed signals $y(k)=(y_1(k),\ldots,y_j(k),\ldots,x_m(k))^{\mathrm{T}}\in R^m$ that are fed to nonlinear tuned units of the output layer. At the output of the second layer, the recovered signals $x(k)=(x_1(k),\ldots,x_i(k),\ldots,x_n(k))^{\mathrm{T}}\in R^n$ are defined and the error $e_i(k)=x_i(k)-\hat{x}_i(k)$ is used for the synaptic weight learning of both layers. Therefore, the neo-fuzzy autoencoder implements the nonlinear mapping in the form:

$$\hat{x}_i(k)=(x_1,x_2,\ldots,x_n)=\sum_{j=1}^{n}f_{ij}^{[2]}(y_j)=\sum_{j=1}^{n}f_{ij}^{[2]}\left(\sum_{i=1}^{n}f_{ji}^{[1]}(x_i)\right);$$
$$\forall i=1,2,\ldots,n.$$

where $f_{ji}^{[1]}(\cdot)$ and $f_{ij}^{[2]}(\cdot)$ are nonlinear transforms, which are implemented by units of the first hidden and the second output layers, respectively.

The nonlinear synapses $NS_{ji}^{[1]}$, $NS_{ij}^{[2]}$ and the neo-fuzzy neurons $NFN_j^{[1]}$, $NFN_i^{[2]}$ (that were proposed in [15]–[17]), which have high approximation properties and are used as "building blocks" of the proposed neo-fuzzy autoencoder. The neo-fuzzy neuron is the Wang-Mendel neuro-fuzzy system of zero order.

Figure 1 shows the architecture of the neo-fuzzy autoencoder, while Fig. 2 demonstrates the structure of the neo-fuzzy neuron $NFN_j^{[1]}$ in the hidden layer of autoencoder. Such a neo-fuzzy neuron consists of n nonlinear synapses $NS_{ji}^{[1]}$, where each of them contains h membership functions $\mu_{jil}^{[1]}$ and h tuning synaptic weights $w_{jil}^{[1]}$. The first hidden layer contains mnh membership functions and the same number of synaptic weights.

The output layer contains n neo-fuzzy neurons $NFN_i^{[2]}$, where each of them consists of m nonlinear synapses $NS_{ij}^{[2]}$, at that, each of these synapses has also h membership functions $\mu_{ijl}^{[2]}$ and h synaptic weights $w_{ijl}^{[2]}$.

Thus, autoencoder contains $2mnh$ tuning parameters. Finally, the transformations, which are implemented by an autoassociative neo-fuzzy network, can be written in the form:

$$NS_{ji}^{[1]}:\ f_{ji}^{[1]}(x_i)=\sum_{l=1}^{h} w_{jil}^{[1]}\mu_{jil}^{[1]}(x_i), \qquad (1) \qquad NFN_j^{[1]}:\ y_j=\sum_{i=1}^{n} f_{ji}^{[1]}(x_i)=\sum_{i=1}^{n}\sum_{l=1}^{h} w_{jil}^{[1]}\mu_{jil}^{[1]}(x_i),$$

$$NS_{ij}^{[2]}:\ f_{ij}^{[2]}(y_j)=\sum_{l=1}^{h} w_{ijl}^{[2]}\mu_{ijl}^{[2]}(y_j), \qquad (2) \qquad NFN_i^{[2]}:\hat{x}_i=\sum_{j=1}^{m} f_{ij}^{[2]}(y_j)=\sum_{j=1}^{m}\sum_{l=1}^{h} w_{ijl}^{[2]}\mu_{ijl}^{[2]}(y_j),$$

$$\hat{x}_i(x_1,\ldots,x_i,\ldots,x_n)=\sum_{j=1}^{m}\sum_{l=1}^{h} w_{ijl}^{[2]}\mu_{ijl}^{[2]}\left(\sum_{i=1}^{n}\sum_{l=1}^{h} w_{jil}^{[1]}\mu_{jil}^{[1]}(x_i)\right). \qquad (3)$$

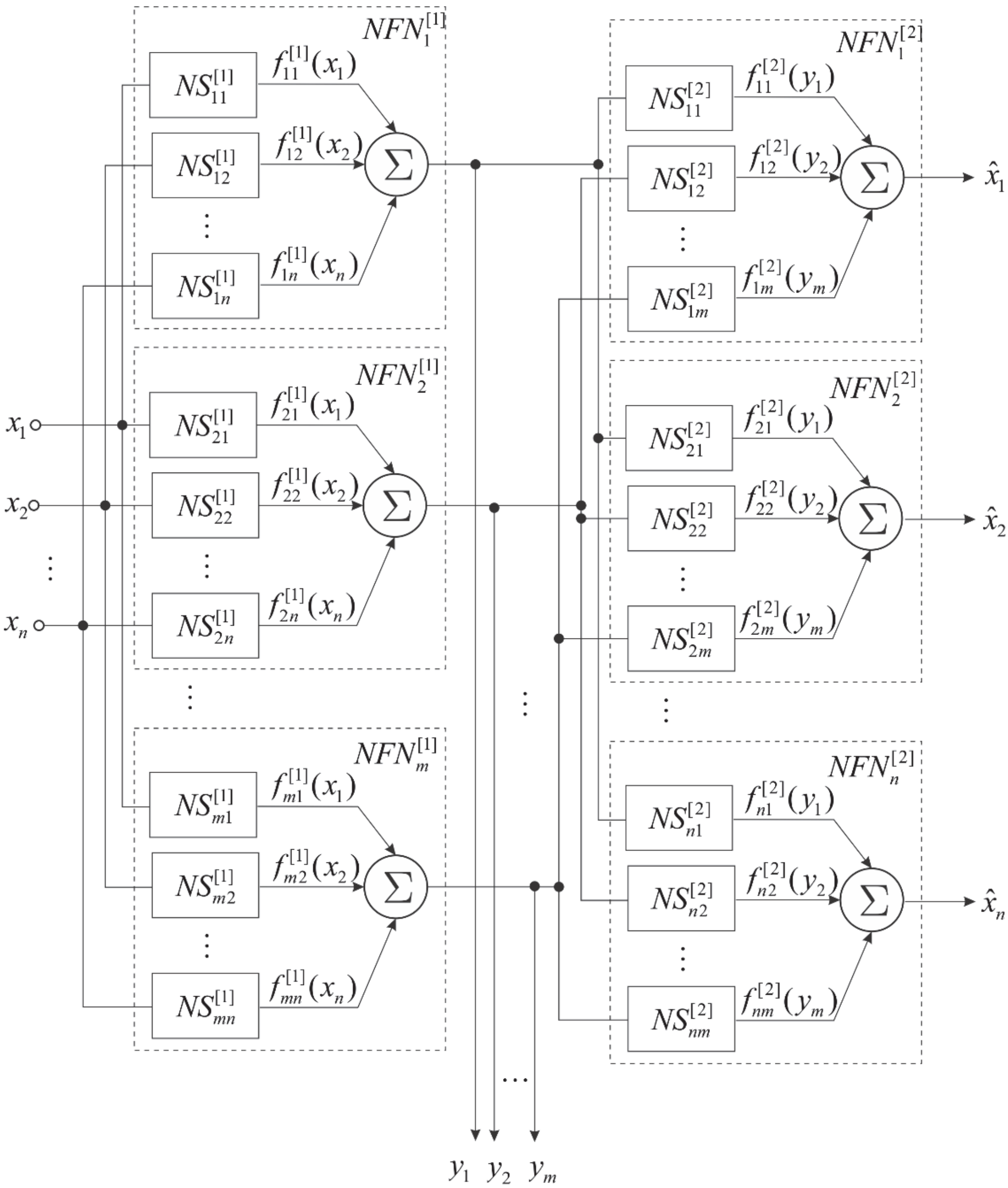


Fig. 1. Neo-fuzzy autoencoder.

The nonlinear synapses (1), (2) are like the Takagi-Sugeno fuzzy inference systems of zero-order [18] and are also universal approximators, i.e., they can approximate any one-variable restricted function with required accuracy in condition that the synaptic weights are correctly tuned and a number of membership functions are correctly selected.

Equation (3) describes the two-layer neuro-fuzzy system with two-level fuzzy rule system, which implements the multiscale approach, i.e., according to the theorem of Yam-Nguyen-Kreinovich [19] this system allows achieving a required accuracy of approximation for any constrained multivariate function.

As membership functions of nonlinear synapses $NS^{[1]}_{ji}$, $NS^{[2]}_{ij}$ the authors of neo-fuzzy neuron [15]–[17] used the conventional triangular functions, which satisfy to unity partitioning in the form:

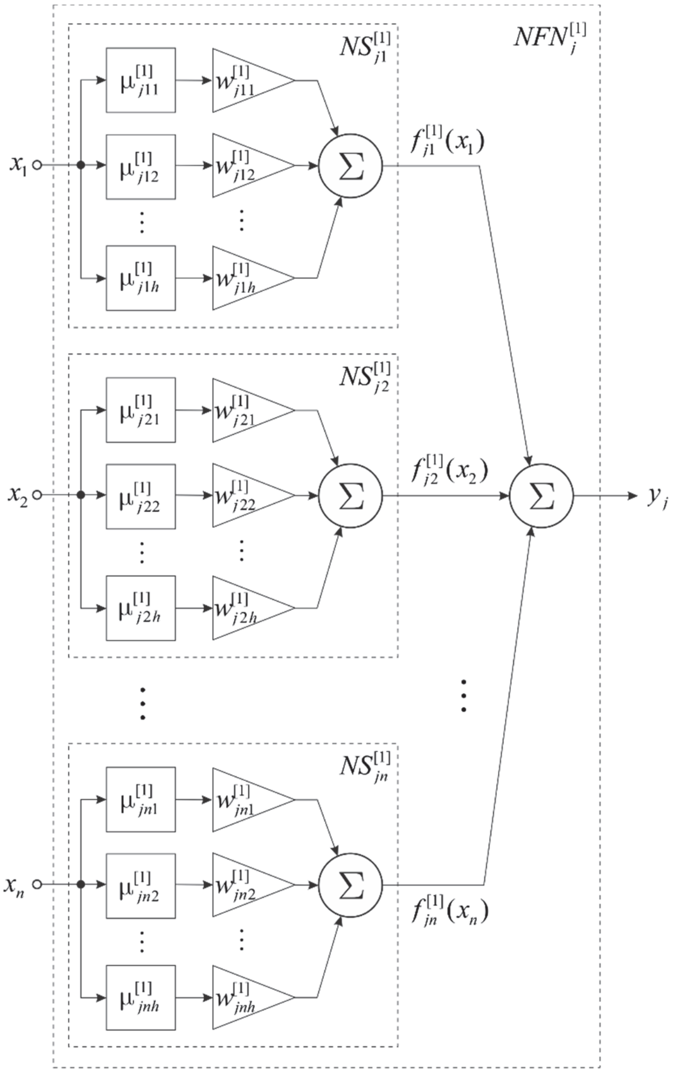


Fig. 2. Neo-fuzzy neuron of the first hidden layer.

$$\mu^{[1]}_{j,i,l}(x_i)=\begin{cases}\dfrac{x_i-c^{[1]}_{j,i,l-1}}{c^{[1]}_{j,i,l}-c^{[1]}_{j,i,l-1}}, & \text{if } x_i\in[c^{[1]}_{j,i,l-1},c^{[1]}_{j,i,l}];\\[2ex] \dfrac{c^{[1]}_{j,i,l-1}-x_i}{c^{[1]}_{j,i,l+1}-c^{[1]}_{j,i,l}}, & \text{if } x_i\in[c^{[1]}_{j,i,l-1},c^{[1]}_{j,i,l}];\\[2ex] 0 & \text{otherwise,}\end{cases} \tag{4}$$

$$\mu^{[1]}_{j,i,l}(x_i)+\mu^{[1]}_{j,i,l+1}(x_i)=1, \tag{5}$$

$$\mu^{[2]}_{i,j,l}(y_j)=\begin{cases}\dfrac{y_j-c^{[2]}_{i,j,l-1}}{c^{[2]}_{i,j,l}-c^{[2]}_{i,j,l-1}}, & \text{if } x_i\in[c^{[2]}_{i,j,l-1},c^{[2]}_{i,j,l}];\\[2ex] \dfrac{c^{[2]}_{i,j,l+1}-y_j}{c^{[2]}_{i,j,l+1}-c^{[2]}_{i,j,l}}, & \text{if } y_j\in[c^{[2]}_{i,j,l},c^{[2]}_{i,j,l+1}];\\[2ex] 0 & \text{otherwise,}\end{cases} \tag{6}$$

$$\mu^{[2]}_{i,j,l}(y_j)+\mu^{[2]}_{i,j,l+1}(y_j)=1, \tag{7}$$

where $c^{[1]}_{j,i,l}$, $c^{[2]}_{i,j,l}$, l = 1, 2,…, h are the centres of the membership functions, in the simplest case these functions are uniformly distributed along the axes x_i and y_j.

Conditions (5), (7) denote that the signals $x_i(k)$, $y_j(k)$ are fed to the inputs of $NS^{[1]}_{ji}$, $NS^{[2]}_{ij}$, the outputs of which are defined in the form:

$$\begin{cases} f^{[1]}_{ji}(x_i(k))=w^{[1]}_{j,i,l}\,\mu^{[1]}_{j,i,l}(x_i(k))+w^{[1]}_{j,i,l+1}\mu^{[1]}_{j,i,l+1}(x_i(k));\\ f^{[2]}_{ij}(y_j(k))=w^{[2]}_{i,j,l}\,\mu^{[2]}_{i,j,l}(y_j(k))+w^{[2]}_{i,j,l+1}\mu^{[2]}_{i,j,l+1}(y_j(k)),\end{cases}$$

i.e., in each current instant of time k in each nonlinear synapse, only two neighbouring membership functions can be fired. Finally, not 2*mnh* synaptic weights, but only 4*mn* ones are tuned at each time step that allows accelerating the learning process of the system as a whole.

III. The Learning of Neo-Fuzzy Autoencoder

The learning process of the neo-fuzzy autoencoder is related to defining the synaptic weights of both layers based on minimisation of goal function, which can be written for i-th system's output (i = 1, 2,…, n) in the form:

$$\begin{aligned} E_i(k) &= \sum_{k=1}^{N} e_j^2(k) = \\ &= \sum_{k=1}^{N}\left[x_i(k)-\hat{x}_i(x_1(k),x_2(k),\ldots,x_n(k))\right]^2 = \\ &= \sum_{k=1}^{N}\left[x_i(k)-\sum_{j=1}^{m}\sum_{l=1}^{h} w^{[2]}_{ijl}\mu^{[2]}_{ijl}(y_j(k))\right]^2 = \\ &= \sum_{k=1}^{N}\left[x_i(k)-w_i^{[2]\mathrm{T}}\mu_i^{[2]}(y(k))\right]^2 \end{aligned} \tag{8}$$

where $\boldsymbol{w}_i^{[2]} = (w_{i11}^{[2]}, w_{i12}^{[2]}, \ldots, w_{i1h}^{[2]}, w_{i21}^{[2]}, \ldots, w_{ijl}^{[2]}, \ldots, w_{imh}^{[2]})^{\mathrm{T}}$, $\mu_i^{[2]}(y(k)) = (\mu_{i11}^{[2]}(y_1(k)), \mu_{i12}^{[2]}(y_1(k)), \ldots, \mu_{i1h}^{[2]}(y_1(k)), \mu_{i21}^{[2]}(y_2(k)), \ldots, \mu_{ijl}^{[2]}(y_j(k)), \ldots, \mu_{imh}^{[2]}(y_m(k)))^{\mathrm{T}}$ are the $(mh \times 1)$ – vectors of synaptic weights and membership functions.

In the simplest case, the standard least square method can be used for tuning vectors $\boldsymbol{w}_i^{[2]}$ in the form:

$$\boldsymbol{w}_i^{[2]}(N) = \left(\sum_{k=1}^{N} \mu_i^{[2]}(y(k))\mu_i^{[2]\mathrm{T}}(y(k))\right)^{+} \sum_{k=1}^{N} \mu_i^{[2]}(y(k))x(k).$$

In the case when data are fed to processing in online mode, the learning process is simplified to gradient minimisation of criterion (8) in the form [17]:

$$\begin{aligned} w_{ijl}^{[2]}(k) &= w_{ijl}^{[2]}(k-1) - \eta(k)\frac{\partial e_i^2(k)}{\partial w_{ijl}^{[2]}} = \\ &= w_{ijl}^{[2]}(k-1) + \eta(k)e_i(k)\mu_{ijl}^{[2]}(y_j(k)), \end{aligned} \tag{9}$$

where $\eta(k)$ is a learning rate parameter.

To accelerate the learning process, we can introduce the optimised adaptive algorithm based on the procedure (9) in the form:

$$\begin{cases} \boldsymbol{w}_i^{[2]}(k) = w_i^{[2]}(k-1) + \\ \quad + \dfrac{x_i(k) - w_i^{[2]\mathrm{T}}(k-1)\mu_i^{[2]}(y(k))}{r_i^{[2]}(k)}\mu_i^{[2]}(y(k)); \\ r_i^{[2]}(k) = \alpha r_i^{[2]}(k-1) + \left\|\mu_i^{[2]}(y(k))\right\|^2, \ 0 \le \alpha \le 1, \end{cases}$$

where α is a smoothing parameter, which defines the learning rate parameter:

$$\eta(k) = \left(r_i^{[2]}(k)\right)^{-1}.$$

Tuning the synaptic weights of a hidden layer is performed using a backpropagation algorithm; thus, we can use the procedure (9), which can be rewritten in the form:

$$\begin{aligned} w_{jil}^{[1]}(k) &= w_{jil}^{[1]}(k-1) - \eta(k)\frac{\partial e_i^2(k)}{\partial w_{jil}^{[1]}} = \\ &= w_{jil}^{[1]}(k-1) - \eta(k)\frac{\partial e_i^2(k)}{\partial \hat{x}_i(k)} \cdot \frac{\partial \hat{x}_i(k)}{\partial y_j(k)} \cdot \frac{\partial y_j(k)}{\partial w_{jil}^{[1]}} = \\ &= w_{ijl}^{[1]}(k-1) + \eta(k)e_i(k)\mu_{jil}^{[2]}(x_i(k))\sum_{l=1}^{h} w_{ijl}^{[2]}(k)\frac{\partial \mu_{ijl}^{[2]}(y_j(k))}{\partial y_j}. \end{aligned} \tag{10}$$

It follows from (6) that

$$\frac{\partial \mu_{ijl}^{[2]}(y_j(k))}{\partial y_j} = \begin{cases} \left(c_{i,j,l}^{[2]} - c_{i,j,l-1}^{[2]}\right)^{-1}, \text{ if } y_j \in [c_{i,j,l-1}^{[2]}, c_{i,j,l}^{[2]}]; \\ \left(c_{i,j,l}^{[2]} - c_{i,j,l+1}^{[2]}\right)^{-1}, \text{ if } y_j \in [c_{i,j,l}^{[2]}, c_{i,j,l+1}^{[2]}]; \\ 0 \quad \text{otherwise,} \end{cases} \tag{11}$$

for uniformly distributed centres using the notations in the form:

$$\left(c_{i,j,l}^{[2]} - c_{i,j,l-1}^{[2]}\right)^{-1} = \Delta c,$$
$$\left(c_{i,j,l}^{[2]} - c_{i,j,l+1}^{[2]}\right)^{-1} = -\Delta c,$$

we can rewrite (11) in a more compact form:

$$\frac{\partial \mu_{ijl}^{[2]}(y_j(k))}{\partial y_j} = \begin{cases} \Delta c, \text{ if } y_j \in [c_{i,j,l-1}^{[2]}, c_{i,j,l}^{[2]}]; \\ -\Delta c, \text{ if } y_j \in [c_{i,j,l}^{[2]}, c_{i,j,l+1}^{[2]}]; \\ 0 \text{ otherwise.} \end{cases} \tag{12}$$

Further introducing the notation in the form

$$\sum_{l=1}^{h} w_{ijl}^{[2]}(k) \cdot \begin{pmatrix} \Delta c, \text{ if } y_j \in [c_{i,j,l-1}^{[2]}, c_{i,j,l}^{[2]}] \\ -\Delta c, \text{ if } y_j \in [c_{i,j,l}^{[2]}, c_{i,j,l+1}^{[2]}] \\ 0 \text{ otherwise} \end{pmatrix} = \tilde{w}_{ij}^{[2]}(k), \tag{13}$$

the expression (10) can be rewritten in the compact form:

$$w_{jil}^{[1]}(k) = w_{jil}^{[1]}(k-1) + \eta(k)e_i(k)\mu_{jil}^{[1]}(x_i(k))\tilde{w}_{ij}^{[2]}(k).$$

This procedure is different from an output layer learning algorithm (9) only by multiplayer (13).

Therefore, the backpropagation procedure in a multilayer system, which is based on the neo-fuzzy neurons, is simpler in a computational sense than learning of multilayer perceptron [3], [4].

IV. Results of Simulation

For effectiveness verification of the proposed neo-fuzzy autoencoder, the data sets were taken from UCI Repository [20]: Iris, Wine, Hayes-roth. Data set “Iris” contains 150 observations (Number of Attributes: 4) of 3 classes, Data set “Wine” contains 178 observations (Number of Attributes: 13) of 3 classes, data set “Hayes-roth” contains 160 observations (Number of Attributes: 5) of 3 classes.

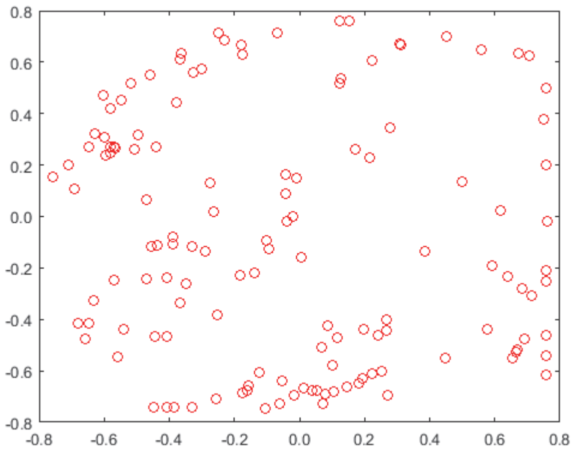
The results, which were obtained using the proposed neo-fuzzy autoencoder, were compared with the results of autoassociative multilayer neural network “Bottle Neck”. The dimension of compression data was 2 components. The simulation was performed 20 times with different initial condition and the results were averaged.

TABLE I

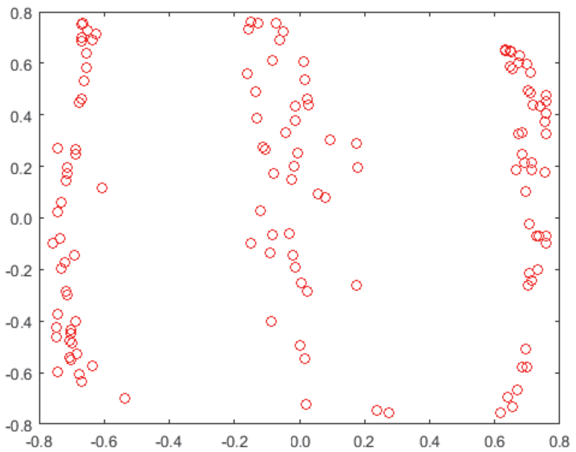
RESULTS OF SIMULATION

Autoencoders	Data Sets	Error	Learning time, sec		
			Min	Avg	Max
Neo-fuzzy autoencoder	Iris	0.238	3.51	4.16	4.82
	Wine	0.521	3.99	4.52	5.06
	Hayes-roth	0.323	2.45	3.13	3.73
Autoassociative three-layer neural network “Bottle Neck”	Iris	0.486	4.04	5.43	6.82
	Wine	0.903	6.54	6.80	7.06
	Hayes-roth	0.593	3.21	3.59	3.98

As it is seen from Fig. 3, data that are compressed using a neo-fuzzy autoencoder are more compact clusters than data that are compressed based on the autoassociative multilayer neural network “Bottle Neck”.



a)



b)

Fig. 3. Data set Hayes-roth after compression based on the autoassociative multilayer neural network “Bottle Neck” (a) and the neo-fuzzy autoencoder (b).

V. CONCLUSION

In the paper, the neo-fuzzy autoencoder has been proposed. This autoencoder has a two-layer architecture with the neo-fuzzy neurons as the units. The simple learning algorithm based on a backpropagation algorithm, which allows information processing in online mode, has also been proposed in the paper. The autoencoder is characterised by the computational simplicity and high learning speed of its parameters.

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