I.J. Intelligent Systems and Applications, 2017, 9, 29-36
Published Online September 2017 in MECS (http://www.mecs-press.org/)
DOI: 10.5815/ijisa.2017.09.04

A Multidimensional Extended Neo-Fuzzy Neuron for Facial Expression Recognition

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Received: 27 May 2017; Accepted: 10 July 2017; Published: 08 September 2017

Abstract**—**An article introduces a modified architecture of the neo-fuzzy neuron, also known as a "multidimensional extended neo-fuzzy neuron" (MENFN), for the face recognition problems. This architecture is marked by enhanced approximating capabilities. A characteristic property of the MENFN is also its computational plainness in comparison with neuro-fuzzy systems and neural networks. These qualities of the proposed system make it effectual for solving the image recognition problems. An introduced MENFN's adaptive learning algorithm allows solving classification problems in a real-time fashion.

Index Terms**—**Computational Intelligence, Facial Expression, Image Recognition, Extended Neo-Fuzzy Neuron, Machine Learning, Data Stream.

I. INTRODUCTION

Automatic analysis of signals on a human face is used in different subsystems of vision, including tracking a viewing direction and focus of attention, lip reading, bimodal speech processing, synthesis of visual morphemes, forming teams based on facial expressions. Tracking the viewing direction or focus of attention can be used for releasing a user from using a mouse or a keyboard. To realize a robust speech interface, the speech lip reading opportunity can be very useful. Automatic detection of fatigue, boredom and stress will be valuable in situations where some constant attention is crucial for a person, for example, onboard the aircraft or while driving a truck, a train or a car. In real-world applications, this sort of tasks is usually solved by means of various fuzzy clustering techniques [1-6]. Identification of such facial expressions is based on processing real-time video streams, where the required features are allocated. Thus, recognition of facial expressions may be reduced to clustering multidimensional data in a real-time mode.

A goal of the developed research is to synthesize a clustering architecture, which enables distributing the real-time multivariate data through a set of clusters automatically.

Fuzzy Inference Systems (FISs) and Artificial Neural Networks (ANNs) have dilated into a large class of Data Mining problems of variant nature under conditions of the prior doubt and instant ambiguity. Hybrid neuro-fuzzy systems (HNFS) [7-10] combine learning abilities typical for artificial neural networks as well as both interpretability and results' "clarity" peculiar to fuzzy inference systems. Basic limitations of the hybrid neuro-fuzzy systems are simulation awkwardness and a quite slow training speed.

To overpass some of the outlined above problems, a neuro-fuzzy system also known as a "neo-fuzzy neuron" (NFN) was taken into consideration and explored in [11-13]. Fig.1 gives a demonstration of the neo-fuzzy neuron's organization.

The NFN structure is a non-linear learning mechanism that has control over multiple inputs and an only one output. This framework generally brings into action a presentation

$$\hat{y} = \sum_{i=1}^{n} f_i\left(x_i\right)$$

where x_i is a component i of the $n-$dimensional vector of input signals, $x = \left(x_1, ..., x_i, ..., x_n\right)^T \in R^n$, $\hat{y}$ denotes a scalar output for the NFN. NFN's structural blocks are non-linear synapses NS_i that guarantee a non-linear permutation for the component i of x_i in the type of

$$f_i\left(x_i\right)=\sum_{l=1}^{h} w_{li}\mu_{li}\left(x_i\right)$$

where w_{li} stands for a synaptic weight l of the nonlinear synapse i, $l=1,2,...,h$, $i=1,\ 2,...,n$; $\mu_{li}\left(x_i\right)$ signifies a membership function l in the nonlinear synapse i, which finally yields a fuzzified element x_i. In this way, an NFN-implemented conversion may be marked down in the following manner

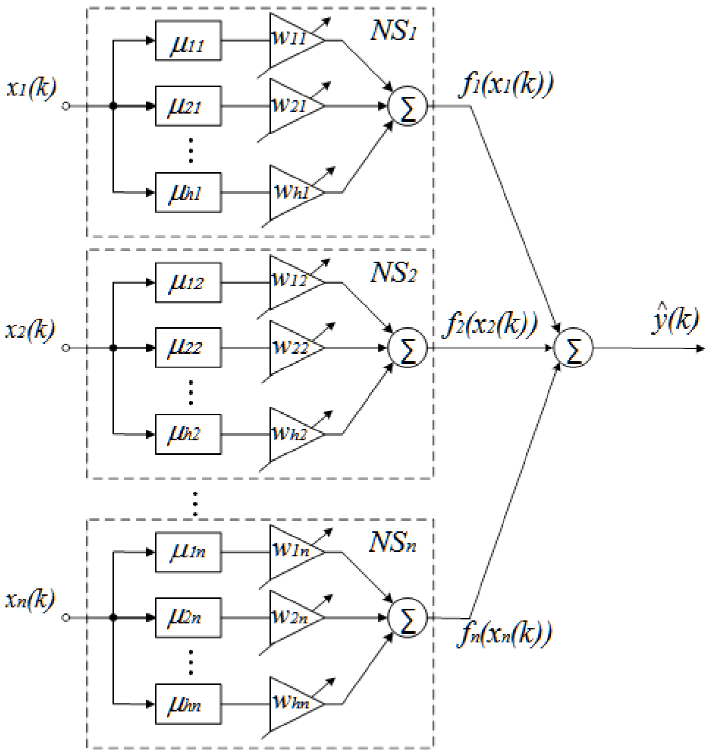

Fig.1. A neo-fuzzy neuron

$$\hat{y}=\sum_{i=1}^{n}\sum_{l=1}^{h} w_{li}\mu_{li}\left(x_i\right).$$

An NFN-realized fuzzy inference is given by

$$IF\ \ x_i\ \ IS\ \ x_{li}\ \ THEN\ \ AN\ OUTPUT\ \ IS\ \ w_{li},\ l=1,2,\ldots h$$

$$\mu_{li}=\begin{cases}\dfrac{x_i-c_{l-1,i}}{c_{l,i}-c_{l-1,i}}, & if\ \ x_i\in\left[c_{l-1,i},c_{l,i}\right],\\ \dfrac{c_{l+1,i}-x_i}{c_{l+1,i}-c_{l,i}}, & if\ \ x_i\in\left[c_{l,i},c_{l+1,i}\right],\\ 0, & otherwise\end{cases}$$

where c_{li} specifies selected (usually distributed uniformly) centroids (at random fashion) of membership functions in the interval [0,1], although in a natural way $0\le x_i\le 1$.

NFN's inventors [11-13] brought into requisition common triangular frameworks as membership functions that meet the requirements of the unity partition.

Certainly, some other functions apart from triangular frameworks may be employed as membership functions, first of all, B-splines [14-18] that proved successfully their effectiveness just being parts of the neo-fuzzy neuron. A generalized view of B-spline-based membership functions of the $q-$ order may be put forward in the shape of

$$\mu_{li}^{B}\left(x_i,q\right)=\begin{cases}\begin{Bmatrix}1, if\ \ x_i\in\left[c_{li},c_{l+1,i}\right]\\ 0,\ otherwise\end{Bmatrix} for\ \ q=1,\\ \dfrac{x_i-c_{li}}{c_{l+q-1,i}-c_{li}}\mu_{li}^{B}\left(x_i,q-1\right)+\\ +\dfrac{c_{l+q,i}-x_i}{c_{l+q-1,i}-c_{l+1,i}}\mu_{l+1,i}^{B}\left(x_i,q-1\right)\\ for\ \ q>1,\ \ l=1,\ 2,\ ...,\ h-q.\end{cases}$$

In case when $q=2$, the conventional triangular constructions are gained. It also bears mentioning that the B-splines may ensure the unity partition by way of

$$\sum_{l=1}^{h}\mu_{li}^{B}\left(x_i,q\right)=1$$

which are non-negative, i.e.

$$\sum_{l=1}^{h} \mu_{li}^{B}\left(x_i, q\right) \geq 0$$

and have a support area

$$\sum_{l=1}^{h} \mu_{li}^{B}\left(x_i, q\right) = 0 \text{ for } x_i \notin \left[c_{li}, c_{l+q,i}\right].$$

Consequently, the input vector signal $x(k) = \left(x_1(k), ..., x_i(k), ..., x_n(k)\right)^T$ (here $k = 1, 2, ...$ marks a current discrete time indicator) being fed to the NFN's input yields a scalar value at its output

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

where $w_{li}(k-1)$ stands for a current value of tuned synaptic weights to have been gained (as a result of learning) by previous $(k-1)$ observations.

Bringing in the membership functions' $(nh \times 1)$ – vector

$$\mu\left(x(k)\right) = \left(\mu_1\left(x_1(k)\right), ..., \mu_{h1}\left(x_1(k)\right),\right.$$

$$\left.\mu_1\left(x_1(k)\right), ..., \mu_{12}\left(x_2(k)\right), ..., \mu_{li}\left(x_i(k)\right), ..., \mu_{hn}\left(x_n(k)\right)\right)^T$$

and $w(k-1) = \left(w_{11}(k-1), ..., w_{h1}(k-1), w_{21}(k-1), ...,\right.$

$$\left.w_{li}(k-1), ..., w_{hn}(k-1)\right)^T$$

which conforms with the vector of synaptic weights, the conversion (1) carried out by the NFN may be marked down in a slightly different manner

$$\hat{y}(k) = w^T(k-1)\mu\left(x(k)\right). \tag{2}$$

To set the NFN's parameters, its developers put into use the gradient procedure for minimization of a training criterion

$$E(k) = \frac{1}{2}\left(y(k) - \hat{y}(k)\right)^2 = \frac{1}{2}e^2(k) =$$
$$= \frac{1}{2}\left(y(k) - \sum_{i=1}^{n}\sum_{l=1}^{h} w_{li}\mu_{li}\left(x_i(k)\right)\right)^2$$

and has the shape of

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

where $y(k)$ designates an external reference signal, $e(k)$ denotes a learning error, η refers to a parameter of a learning rate.

To speed the NFN's training process up, a special-type algorithm was introduced in [19] having both tracking (for processing non-stationary signals) and filtering (for "noisy" data) properties

$$\begin{cases} w(k) = w(k-1) + r^{-1}(k)e(k)\mu\left(x(k)\right), \\ r(k) = \alpha r(k-1) + \left\|\mu\left(x(k)\right)\right\|^2, 0 \leq \alpha \leq 1. \end{cases} \tag{3}$$

In the circumstances of $\alpha = 0$, the scheme (3) is credible in its organization to the one-step Kaczmarz-Widrow-Hoff learning algorithm [20], and when $\alpha = 1$, it's similar to the method of stochastic approximation by Goodwin-Ramage-Caines [21].

It will be observed that training the NFN's synaptic coefficients (weights) can be utilized by an amount of other methods for identification and learning inclusive of the common least-squares method with its upgrades.

II. An Extended Neo-Fuzzy Neuron

As previously stated, the neo-fuzzy neuron's non-linear synapse NS_i performs the zero-order Takagi-Sugeno inference, which is in fact the elementary Wang-Mendel neuro-fuzzy system [22-24].

It seems certain that approximating inferiorities of this system may be amended by dint of a system node also known as an "extended non-linear synapse" (ENS_i, Fig.2). A framework of an "extended neo-fuzzy neuron" [25-26] (ENFN) is built with reference to the ENS_i elements in exchange for the common NS_i nodes.

By establishing several additional variables

$$y_{li}\left(x_i\right) = \mu_{li}\left(x_i\right)\left(w_{li}^0 + w_{li}^1 x_i^1 + w_{li}^2 x_i^2 + ... + w_{li}^p x_i^p\right),$$

$$f_i\left(x_i\right) = \sum_{l=1}^{h}\mu_{li}\left(x_i\right)\left(w_{li}^0 + w_{li}^1 x_i^1 + w_{li}^2 x_i^2 + ... + w_{li}^p x_i^p\right) =$$
$$= w_{1i}^0\mu_{1i}\left(x_i\right) + w_{1i}^1 x_i^1\mu_{1i}\left(x_i\right) + ... + w_{1i}^2 x_i^2\mu_{1i}\left(x_i\right) + ...$$
$$+ w_{1i}^p x_i^p\mu_{1i}\left(x_i\right) + ... + w_{2i}^0\mu_{2i}\left(x_i\right) + ... +$$
$$+ w_{2i}^p x_i^p\mu_{2i}\left(x_i\right) + ... + w_{hi}^p x_i^p\mu_{hi}\left(x_i\right),$$

$$w_i = \left(w_{1i}^0, w_{1i}^1, ..., w_{1i}^p, w_{2i}^0, ..., w_{2i}^p, ..., w_{hi}^p\right)^T,$$

$$\tilde{\mu}_i(x_i) = \left(\mu_{1i}(x_i), x_1\mu_{1i}(x_i), \ldots, x_i^p \mu_{1i}(x_i), \mu_{2i}(x_i), \ldots, x_i^p \mu_{2i}(x_i), \ldots, x_i^p \mu_{hi}(x_i)\right)^T,$$

we can note down

$$f_i(x_i) = w_i^T \tilde{\mu}_i(x_i), \tag{4}$$

$$\hat{y} = \sum_{i=1}^{n} f_i(x_i) = \sum_{i=1}^{n} w_i^T \tilde{\mu}(x_i) = \tilde{w}^T \tilde{\mu}(x) \tag{5}$$

where $\tilde{w}^T = \left(w_1^T, \ldots, w_i^T, \ldots, w_n^T\right)^T$, and

$$\tilde{\mu}(x) = \left(\tilde{\mu}_1^T(x_1), \ldots, \tilde{\mu}_i^T(x_i), \ldots, \tilde{\mu}_n^T(x_n)\right)^T.$$

As one can notice, the ENFN embodies $(p+1)hn$ synaptic weights to be tweaked, and a fuzzy output performed by every ENS_i takes on a form

$$IF\ x_i\ IS\ x_{li}\ THEN\ AN\ OUTPUT\ IS$$

$$w_{1i}^0 + w_{1i}^1 x_i + \ldots + w_{li}^p x_i^p,\ l = 1, 2, \ldots, h \tag{6}$$

which is essentially in agreement with the *p*-order Takagi-Sugeno inference.

It should be also marked that ENFN stands seized of a simpler architecture as opposed to the common neuro-fuzzy system that leads to its simplified numerical realization.

When the ENFN's input is given as a vector signal $x(k)$ in the system, there appears an output scalar value

$$\hat{y}(k) = \tilde{w}^T(k-1)\tilde{\mu}(x(k)) \tag{7}$$

whereby the listed above expression stands out from the formula (2) only by the fact that it embraces $(p+1)$ times more parameters to be set as contrasted with the conventional NFN. It stands to reason that ENFN settings may be trained with the algotirhm (3) that acquires in this case a shape of

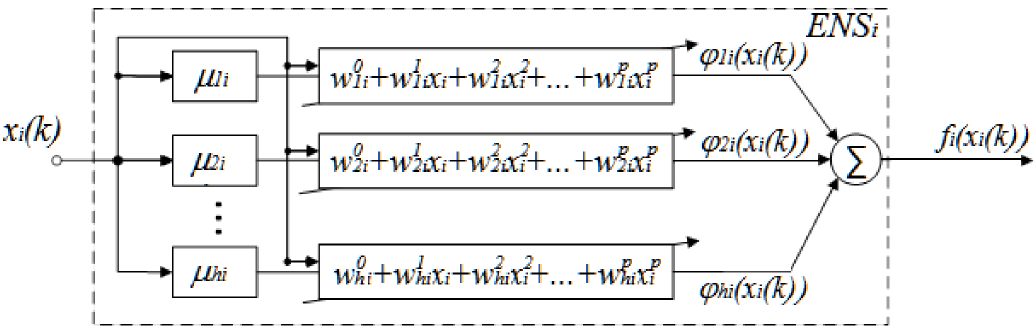

Fig.2. An extended non-linear fuzzy synapse

$$\begin{cases} \tilde{w}(k) = \tilde{w}(k-1) + \left(1/\tilde{r}(k)\right)e(k)\tilde{\mu}(x(k)), \\ \tilde{r}(k) = \alpha\tilde{r}(k-1) + \left\|\tilde{\mu}(x(k))\right\|^2, 0 \le \alpha \le 1. \end{cases} \tag{8}$$

Fig.3 displays a scheme of an extended neo-fuzzy neuron.

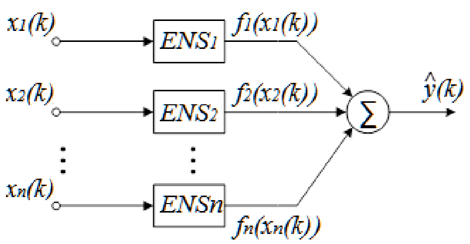

Fig.3. An extended neo-fuzzy neuron

The extended neo-fuzzy neuron is a building block for the multidimensional neo-fuzzy neuron (MENFN). Its architecture is depicted in Fig. 4.

That looks on reasonable grounds to put in several layers in the MENFN for solving the pattern recognition task. The first layer encapsulates the extended neo-fuzzy neurons, and their quantity brings into accordance with the output vector's $\tilde{y}_m(k)$ dimensionality.

A quantity of non-linear synapses that configures each neo-fuzzy neuron complies with dimensionality of the input feature vector $x_n(k)$. The succeeding layer represents an activation function

$$v_j(k) = \psi\left(\hat{y}_j(k)\right) \tag{9}$$

where

$$\psi\left(\hat{y}_j(k)\right) = \begin{cases} \hat{y}_j(k), & \text{if } \hat{y}_j(k) > 0 \\ 0, & \text{otherwise} \end{cases}.$$

An output layer of the MENFN computes values $v_j(k)$ in response to the positive rationing

$$\xi_j(k) = \frac{v_j(k)}{\sum_{j=1}^{m} v_j(k)}, \quad (10)$$

which is necessary if a learning vector is set in the range [0,1].

If a learning vector utilizes the numerical coding of an output signal, the MENFN performs a fuzzy conjunction of elements in the output vector $\xi_j(k)$

$$u(k) = \sup_{j=1}^{m} \{v_j(k)\}. \quad (11)$$

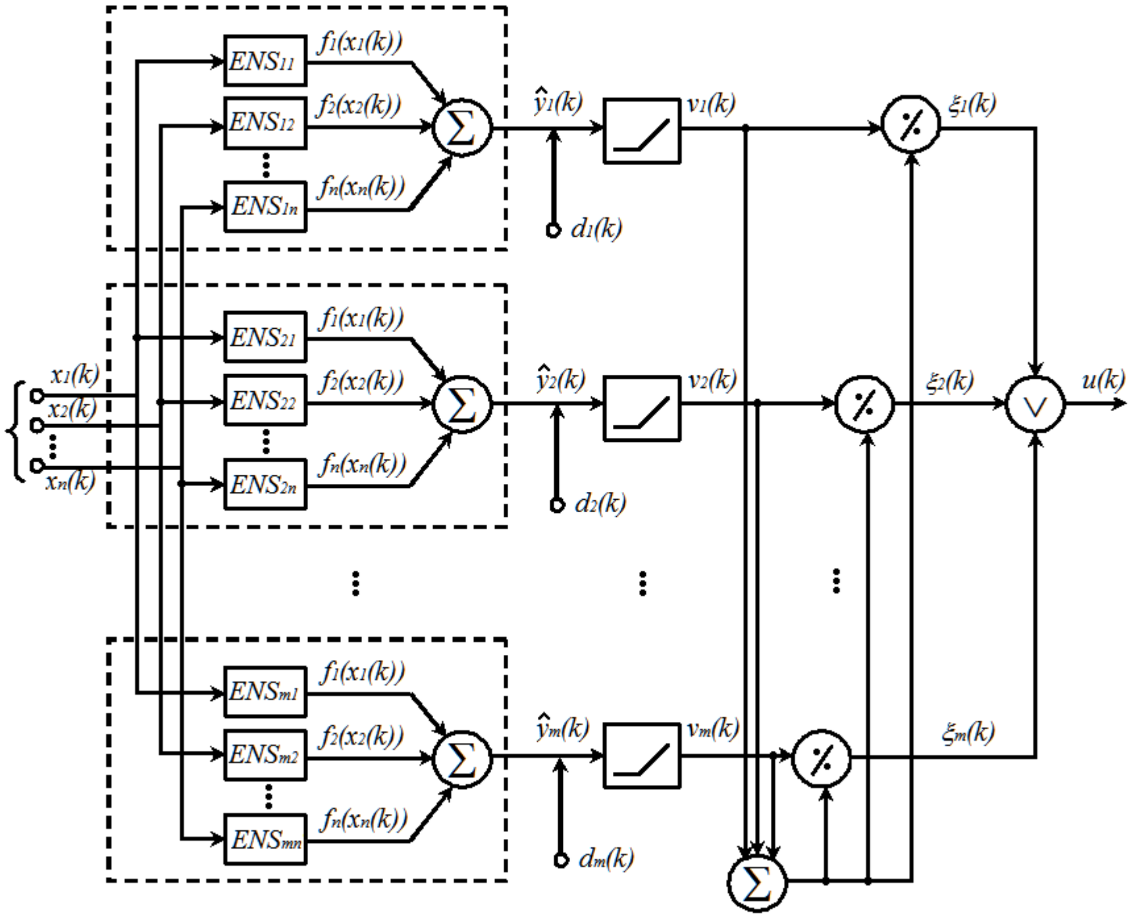

Fig.4. A multidimensional extended neo-fuzzy neuron

III. Experiments

To bear out superiority of the architecture under consideration, several experiments were carried out for the task of basic emotions' recognition. Several depictions from the open-source database Psychological Image Collection at Stirling (PICS) [27], as well as some illustrations partly from the Cohn-Kanade (Extended, CK+) database [28] and some other images taken from public access were mainly used as objects for recognition.

The learning dataset contains 344 depictions; learning was repeated during 30, 50, and 80 epochs as the case may be. For the algorithm (8), a learning rate $1/\tilde{r} = \eta$ was taken equal 0.75. A capacity of membership functions for every ENS equals 9; the fuzzy inference represented by the ENS_i can be put down like

$$IF\ x_i\ IS\ x_{li}\ THEN\ AN\ OUTPUT\ IS$$

$$w_{1i}^0 + w_{1i}^1 x_i + \ldots + w_{li}^p x_i^p, l = 1, 2, \ldots, h$$

and agrees with the Takagi-Sugeno inference of the second order.

As noted above, a quantity of neo-fuzzy neurons *m* measures up dimensionality of the output vector. Seven basic emotions are selected for recognition: anger, disgust, fear, surprise, happiness, sadness, and neutral expression. Therefore, *m* = 7. The character features' vector contains the two-dimensional coordinates of 35 feature points position (Fig.5) [29].

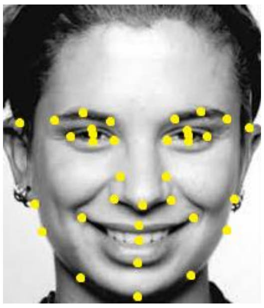

Fig.5. Arrangement of control points

So, dimensionality of the input vector $x_n(k)$ equals 70.

The MENFN's framework confirms a sufficiently higher learning rate as opposed to a scheme described in [30]. A plot for errors' change by epochs is shown in Fig.6; results of learning are demonstrated in Table 1. The algorithm was tested on a sample of 78 images.

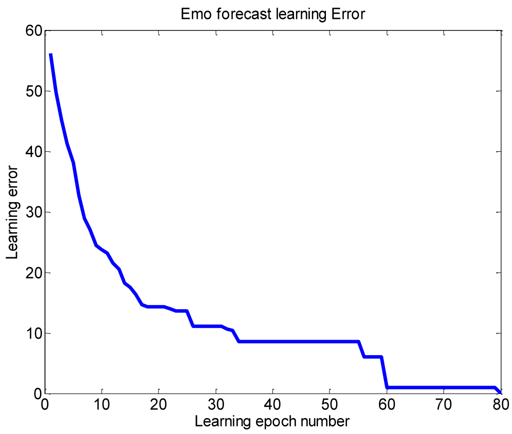

Fig.6. Dependency of a learning error on a number of learning epochs

The developed framework of multidimensional extended neo-fuzzy neuron definitely provides both a high learning rate and the high recognition accuracy for multidimensional data. These inferiorities are particularly useful for detecting facial expressions in a real-time mode.

Table 1. Training MENFN for recognition of 7 emotions. Results

Basic emotions	A number of images in the training set	Percentage of unrecognized images, %		
		30 epochs	50 epochs	80 epochs
Anger	49	2	0	0
Disgust	66	0	0	0
Fear	35	0	0	0
Happiness	45	2	0	0
Sorrow	19	5	0	0
Surprise	50	0	0	0
Neutral	80	4	3	0

IV. Conclusion

The paper proposes a structure of the multidimensional extended neo-fuzzy neuron which is an extension of the conventional neo-fuzzy neuron for a case of the fuzzy inference procedure when its order is higher than a zero order and which possesses both a multidimensional data input and an output. The proposed learning algorithm allows distributing effectively the aggregate data into an amount of previously known clusters. The considered MENFN enhances clustering qualities, incorporates both a high training speed and its quite simple numerical feasibility.

Acknowledgment

This article gets sponsored by RAMECS and CCNU16A02015.

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How to cite this paper: Zhengbing Hu, Yevgeniy V. Bodyanskiy, Nonna Ye. Kulishova, Oleksii K. Tyshchenko, "A Multidimensional Extended Neo-Fuzzy Neuron for Facial Expression Recognition", International Journal of Intelligent Systems and Applications(IJISA), Vol.9, No.9, pp.29-36, 2017. DOI: 10.5815/ijisa.2017.09.04