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EXTENDED NEO-FUZZY NEURON IN THE TASK OF IMAGES FILTERING

The paper describes a modification of the neo-fuzzy neuron called as «extended neo-fuzzy neuron» (ENFN) that characterized by improved approximating properties. The adaptive learning algorithm for ENFN is proposed, that has both following and smoothing properties and allows to solve problems of prediction, filtering and smoothing of non-stationary disturbed stochastic and chaotic signals. A distinctive feature of ENFN is its implementation computational simplicity compared with artificial neural networks and neuro-fuzzy systems. These properties of the proposed neo-fuzzy neuron make it very effective in suppressing noise in image filtering.

Keywords: color images, disturbance, contours, filtering, neo-fuzzy neuron.

INTRODUCTION

Digital images are often exposed to noise when they are created and transmitted over communication channels. For reasons of noise and distortion can be attributed atmospheric phenomena (for images obtained on TV), originals surface defects (scanning), and low-light during shooting (for digital cameras). The main problem in this case is the need for effective compensation of distortion and noise while preserving image features such as edges, textures, and small details. Existing image smoothing filters, suppressing noise, greatly blur contours and reduce image sharpness.

The aim of this work is to develop an adaptive filter, which can compensate the noise on digital images without significant reducing their quality.

Artificial neural networks (ANN) and fuzzy inference system (FIS) in recent years have proliferated to address a large class of data mining tasks of various natures under a priori and the current uncertainty. Hybrid neuro-fuzzy system (NFS), that have appeared at the junction of the two main areas of computational intelligence [1–4], and absorbed their best features. Thus, the neuro-fuzzy system is capable of learning like ANN and provide linguistic interpretability and «transparency» of the results like FIS. However, NFS's calculation bulkiness and low speed training limit their applicability to image processing problems.

To overcome some of the noted problems, neuro-fuzzy system,called by the authors as «neo-fuzzy neuron (NFN)», was introduced and studied in [5–7]. Fig. 1 shows the architecture of the neo-fuzzy neuron.

Neo-fuzzy neuron is a nonlinear learning system with multiple inputs and one output, that realizes the mapping

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

where x_i – i-th component of the n-dimensional input signals vector, $x = \left(x_1, ..., x_i, ..., x_n\right)^T \in R^n$, $\hat{y}$ – scalar

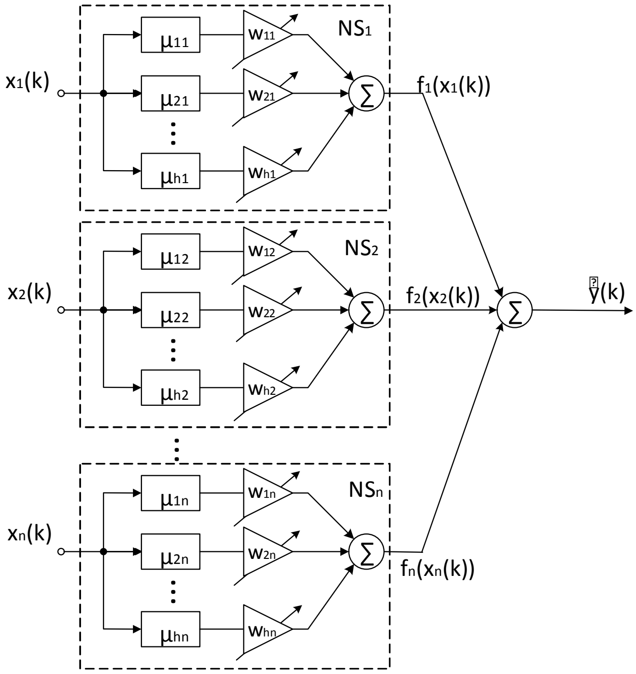

Fig. 1. Neo-fuzzy neuron

NFN's output. Neo-fuzzy neuron structural blocks are nonlinear synapses NS_i, performing a nonlinear transformation of the i-th component x_i in the form

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

where w_{li}– l-th synaptic weight of i-th nonlinear synapse, $l = 1, 2, ..., h$, $i = 1, 2, ..., n$; $\mu_{li}\left(x_i\right)$ – l-th membership function in the i-th nonlinear synapse, producing a fuzzification of crisp component x_i.

Thus, transformation, realized by NFN, can be written as

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

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A fuzzy inference implemented by this same NFN, has the form

IF x_i IS x_{li} THEN THE OUTPUT IS $w_{li}, l = 1, 2, ..., h$,

i.e. actually nonlinear synapse implements zero order Takagi-Sugeno fuzzy inference [8, 9].

Neo-fuzzy neuron authors [5–7] as membership functions were used traditional triangular construction that meet the conditions of unity partition

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

where c_{li} – rather arbitrarily selected (usually uniformly distributed) centers of membership functions on the interval $[0, 1]$, thus, naturally $0 \le x_i \le 1$.

Such choice of the membership functions leads to that i-th component of the input signal activates only the two adjacent functions, thus their sum is equal to unity, i.e.

$$\mu_{li}(x_i) + \mu_{l+1,i}(x_i) = 1$$

and

$$f_i(x_i) = w_{li}\mu_{li}(x_i) + w_{l+1,i}\mu_{l+1,i}(x_i).$$

It is this circumstance allowed to synthesize simple and effective adaptive controllers for nonlinear control objects [10, 11].

Of course, besides triangular as membership functions can be used and other forms and, first of all, the B-splines [12], proved to be effective in the composition of neo-fuzzy neuron [13]. The general form of membership functions based on q-th degree B-spline can be presented in the form:

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

In the case when $q = 2$ we obtain the traditional triangular functions. It should be noted also that the B-splines also provide a single partition in the form of

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

are non-negative, i.e.

$$\mu_{li}^B(x_i, q) \ge 0$$

and have local domain

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

Thus, when applied to NFN's input the vector signal $x(k) = (x_1(k), ..., x_i(k), ..., x_n(k))^T$ ($k = 1, 2, ...$ here – the current discrete time) at its output appears scalar value

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

where $w_{li}(k-1)$ – the current value of the adjusting synaptic weights resulting from learning on previous k–1 observations.

Introducing the $(nh \times 1)$ vector of membership functions $\mu(x(k)) = (\mu_1(x_1(k)), ..., \mu_{h1}(x_1(k)), \quad \mu_1(x_1(k)), ..., \mu_{12}(x_2(k)), ..., \mu_{li}(x_i(k)), ..., \mu_{hn}(x_n(k)))^T$ and the corresponding vector of synaptic weights $w(k-1) = (w_{11}(k-1), ..., w_{h1}(k-1), w_2(k-1), ..., w_{li}(k-1), ..., w_{hn}(k-1))^T$, we can rewrite the transformation (1), implemented by NFN, in a compact form

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

To adjust the neo-fuzzy neuron parameters, the authors used the gradient procedure that minimizes the learning criterion

$$E(k) = \frac{1}{2}(y(k) - \hat{y}(k))^2 = \frac{1}{2}e^2(k) =$$

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

and having the form

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

where $y(k)$ – external training signal, $e(k)$ – learning error, η – learning rate parameter.

To accelerate the NFN learning process in [14] special algorithm was introduced, having both following (for non-stationary signal processing) and filtering (for «noisy» data processing) properties

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

Wherein when $\alpha = 0$, algorithm (3) is identical in structure to the Kaczmarz-Widrow- Hoff one-step learning algorithm [15], and when $\alpha = 1$ – to Goodwin-Ramage-Caines stochastic approximation algorithm [16].

Note also, that the neo-fuzzy neuron synaptic weights learning can be used by many other algorithms for learning and identification, including the traditional method of least squares with all its modifications.

EXTENDED NEO-FUZZY NEURON

As was noted above, the neo-fuzzy neuron is nonlinear synapse NS_i implements zero-order Takagi-Sugeno inference, thus being the Wang-Mendel elementary neuro-fuzzy system [17–19]. It is possible to improve approximating properties of such system using a structural unit, which we called «extended nonlinear synapse» (ENS_i) (see Fig. 2) and synthesized on its basis the «extended neo-fuzzy neuron» (ENFN), containing as elements ENS_i instead of the usual nonlinear synapses NS_i.

By introducing the additional variables

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

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

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

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

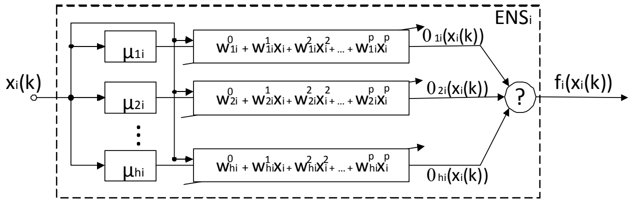

Fig. 2. Extended non-linear synapse

we can write

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

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

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

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

It's easy to see that ENFN contains $(p+1)hn$ adjusting synaptic weights and fuzzy output, implemented by each ENSi, has the form

IF x_i IS x_{li} THEN THE OUTPUT IS

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

i.e. essentially coincides with p-order Takagi-Sugeno inference.

Let's note also that ENFN has a much simpler architecture than the traditional neuro-fuzzy system that simplifies its numerical implementation.

When the ENFN's input is vector signal $x(k)$, at the output scalar value appears

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

whereby this expression differs from (2) only in that it comprises in a $(p+1)$ times more number of tuning parameters than conventional NFN. It is clear that learning parameters ENFN algorithm may be used such as (3), obtaining in this case the form

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

Fig. 3 shows the architecture of an extended neo-fuzzy neuron.

EXPERIMENT

The effectiveness of the proposed architecture has been investigated on a set of test images (Fig. 4).

Images were damaged by different types of noise: the Poisson, Gaussian, impulse, multiplicative. Neo-fuzzy neuron performance for noise compensation was estimated by two objective measures (MSE, PSNR) and subjective visual evaluation. Mean square error MSE is calculated by the formula:

$$MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_{1_{ij}} - I_{2_{ij}}\right)^2}{MN},$$

where $I_{1_{ij}}$, $I_{2_{ij}}$ – the original and filtered images, respectively, $i = 1, 2, ..., M$, $j = 1, 2, ..., N$ – numbers of image pixels, M, N – image sizes.

To calculate the signal/noise ratio PSNR used:

$$PSNR = 10 \cdot \lg\left(\frac{R^2}{MSE}\right),$$

where R is a coefficient depending on the encoding of images (for 8-bit encoding R = 255, for floating-point R = 1). For comparison were also used standard filters – averaging, median, and Wiener filter. Neo-fuzzy neuron learning was carried out in two versions: for pure signal and the Wiener preliminary filtered, that can be used in cases there is no clear signal.

Image quality estimations after filtering are given in Table 1, some examples of images before and after the noise compensation are shown in Fig. 5.

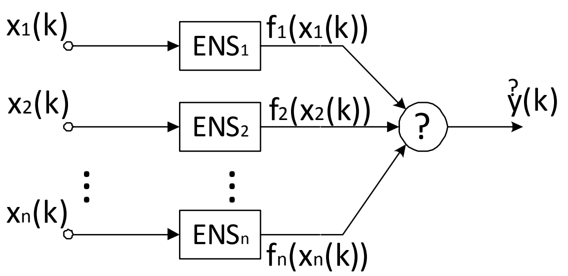

Fig. 3. Extended neo-fuzzy neuron

It is obvious that, although numerical estimates demonstrate higher quality filtering for some standard filters, visual evaluation certainly suggests a high efficiency of the neo-fuzzy neuron. This is appeared in the keeping contours, fine details and textures. If a clean signal for training is available, can use the Wiener filter for learning signal for the neo-fuzzy neuron.

CONCLUSION

The paper proposes an extended architecture of neo-fuzzy neuron, which is a generalization of the standard neo-fuzzy neuron in case of fuzzy inference order above zero. The learning algorithm is introduced having both following and filtering properties. Considered NFN has improved approximating properties, characterized by a high learning rate, has simple numerical implementation.

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Fig. 4. Test images

Table 1. Image quality estimation after filtration

	Averaging Filter		Median Filter		Wiener Filter		Neo-Fuzzy Neuron with clear learning signal		Neo-Fuzzy Neuron with Wiener filtered learning signal	
Image «Car»										
Poisson	0,0209	16,8	0,0138	18,6	0,0078	21,1	0,0068	21,7	0,0093	20,3
Gaussian, m=0, σ=0,0005	0,0296	15,3	0,0231	16,4	0,0154	18,1	0,0159	17,9	0,0172	17,6
Gaussian, m=0, σ=0,001	0,0418	13,8	0,0365	14,4	0,0263	15,8	0,0292	15,3	0,0284	15,5
Gaussian, m=0, σ=0,05	0,0423	13,7	0,0366	14,4	0,0265	15,8	0,0370	14,3	0,0290	15,4
Gaussian, m=0, σ=0,01	0,0418	13,8	0,0364	14,4	0,0263	15,8	0,0292	15,3	0,0285	15,5
Gaussian, m=0, σ=0,1	0,1968	7,1	0,2075	6,8	0,1519	8,2	0,2083	6,8	0,1591	7,9
Impulse, σ=0,005	0,0203	16,9	0,0132	18,8	0,052	22,9	0,0154	18,1	0,118	9,3
Impulse, σ=0,01	0,0248	16,1	0,0178	17,5	0,0069	21,6	0,0118	19,3	0,0307	15,1
Multiplicative, σ=0,005	0,0198	17,0	0,0128	18,9	0,0068	21,7	0,0057	22,5	0,0084	20,8
Multiplicative, σ=0,001	0,0168	17,8	0,0094	20,2	0,0042	23,7	0,0021	26,8	0,0085	20,7
Multiplicative, σ=0,01	0,0234	16,3	0,0168	17,7	0,0098	20,1	0,0095	20,2	0,0117	19,3
Multiplicative, σ=0,1	0,0739	11,3	0,0752	11,2	0,0393	14,1	0,0673	11,7	0,0426	13,7
Image «Lena»										
Poisson	0,0126	18,9	0,0093	20,3	0,0065	21,8	0,0070	21,5	0,0083	20,8
Gaussian, m=0, σ=0,0005	0,0366	14,4	0,0336	14,7	0,0260	15,8	0,301	15,2	0,0285	15,4
Gaussian, m=0, σ=0,001	0,0365	14,4	0,0336	14,7	0,0260	15,8	0,0300	15,2	0,0285	15,5
Gaussian, m=0, σ=0,05	0,0366	14,4	0,0333	14,8	0,0256	15,9	0,0373	14,3	0,0289	15,4
Gaussian, m=0, σ=0,01	0,0365	14,4	0,0335	14,8	0,0259	15,9	0,0304	15,2	0,0286	15,4
Gaussian, m=0, σ=0,1	0,0361	14,4	0,0324	14,9	0,0248	16,1	0,0583	12,3	0,0293	15,3
Impulse, σ=0,005	0,0133	18,8	0,0086	20,6	0,0034	24,7	0,0046	23,3	0,0045	23,5
Impulse, σ=0,01	0,0177	17,5	0,0132	18,8	0,0049	23,1	0,0096	20,2	0,0062	22,1
Multiplicative, σ=0,005	0,0136	18,7	0,0091	20,4	0,0060	22,2	0,0059	20,9	0,0081	20,9
Multiplicative, σ=0,001	0,0101	19,9	0,0054	22,7	0,0030	25,2	0,0018	27,4	0,0045	23,5
Multiplicative, σ=0,01	0,0175	17,6	0,0136	18,7	0,0097	20,1	0,0105	19,8	0,0120	19,1
Multiplicative, σ=0,1	0,0782	11,1	0,0812	10,9	0,0540	12,7	0,0788	11,1	0,0582	12,3
Image «Parrot»										
Poisson	0,0109	19,6	0,0083	20,8	0,0044	23,6	0,0031	25,1	0,0049	23,1
Gaussian, m=0, σ=0,0005	0,0318	14,9	0,0308	15,1	0,0222	16,5	0,0244	16,1	0,0224	16,5
Gaussian, m=0, σ=0,001	0,0318	14,9	0,0308	15,1	0,0223	16,5	0,0244	16,1	0,0224	16,5
Gaussian, m=0, σ=0,05	0,0343	14,7	0,0330	14,8	0,0244	16,1	0,0349	14,6	0,0249	16,0
Gaussian, m=0, σ=0,01	0,0325	14,9	0,0314	15,0	0,0228	16,4	0,0255	15,9	0,0230	16,4
Gaussian, m=0, σ=0,1	0,0355	14,5	0,0340	14,7	0,0257	15,9	0,0584	12,3	0,0266	15,7
Impulse, σ=0,005	0,0134	18,7	0,0108	19,7	0,0032	24,9	0,0060	22,2	0,0037	24,3

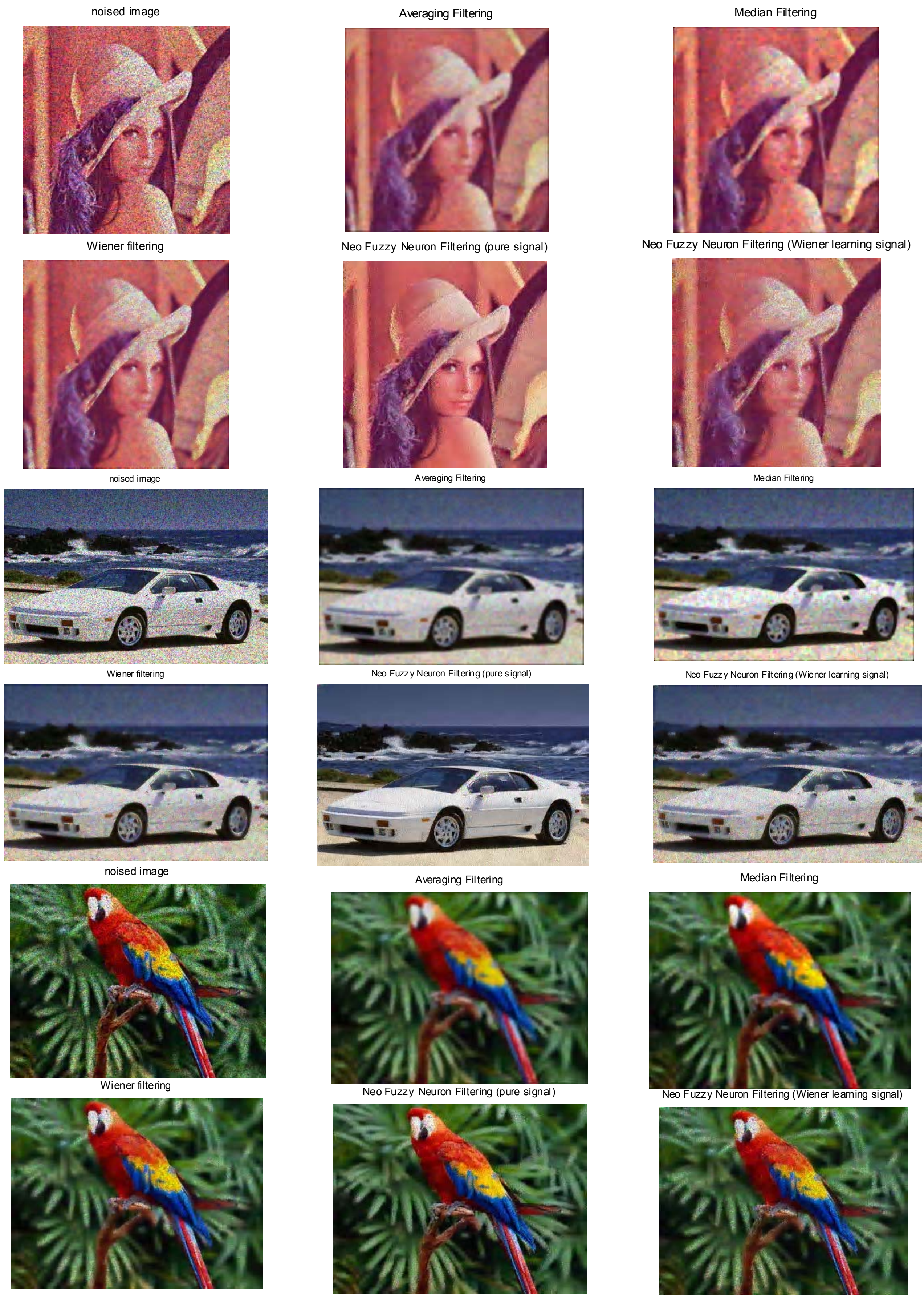

Fig. 5. Images after filtering (multiplicative noise, σ=0,1)

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РАСШИРЕННЫЙ НЕО-ФАЗЗИ НЕЙРОН В ЗАДАЧАХ ФИЛЬТРАЦИИ ИЗОБРАЖЕНИЙ

В статье предлагается модификация нео-фаззи нейрона, названная нами «расширенный нео-фаззи нейрон» (ENFN) и характеризующаяся улучшенными аппроксимирующими свойствами. Введен адаптивный алгоритм обучения ENFN, обладающий следящими и сглаживающими свойствами и позволяющий решать задачи прогнозирования, фильтрации и сглаживания нестационарных «зашумленных» стохастических и хаотических сигналов. Отличительной особенностью ENFN является вычислительная простота его реализации по сравнению с искусственными нейронными сетями и нейро-фаззи системами. Эти свойства предложенного нео-фаззи нейрона делают его очень эффективным при подавлении шумов на изображениях в ходе фильтрации.

Ключевые слова: цветные изображения, помеха, контуры, фильтрация, нео-фаззи нейрон.

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РОЗШИРЕНИЙ НЕО-ФАЗЗІ НЕЙРОН В ЗАДАЧАХ ФІЛЬТРАЦІЇ ЗОБРАЖЕНЬ

У статті пропонується модифікація нео-фаззі нейрона, що названа нами «розширений нео-фаззі нейрон» (ENFN) і характеризується поліпшеними апроксимуючими властивостями. Введено адаптивний алгоритм навчання ENFN, що має слідкуючі і згладжувальні властивості і дозволяє вирішувати завдання прогнозування, фільтрації і згладжування нестаціонарних «зашумлених» стохастичних і хаотичних сигналів. Відмінною особливістю ENFN є обчислювальна простота його реалізації в порівнянні з штучними нейронними мережами і нейро-фаззі системами. Ці властивості запропонованого нео-фаззі нейрона роблять його ефективним для пригнічення шумів на зображеннях в ході фільтрації.

Ключові слова: кольорові зображення, завада, контури, фільтрація, нео-фаззі нейрон.

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