OUTLIERS RESISTANT LEARNING ALGORITHM FOR RADIAL-BASIS-FUZZY-WAVELET-NEURAL NETWORK IN STOMACH ACUTE INJURY DIAGNOSIS TASKS

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Abstract: In this paper an outliers resistant learning algorithm for the radial-basis-fuzzy-wavelet-neural network based on R. Welsh criterion is proposed. Suggested learning algorithm under consideration allows the signals processing in presence of significant noise level and outliers. The robust learning algorithm efficiency is investigated and confirmed by the number of experiments including medical applications.

Keywords: computational intelligence, hybrid architecture, wavelet, fuzzy-wavelet neural network, robust learning algorithm, outliers resistant.

ACM Classification Keywords: I.2.6 Learning – Connectionism and neural nets.

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Introduction

Nowadays artificial neural networks (ANN) have gained the significant prevalence for solving the wide class of the information processing problems, uppermost for the identification, emulation, intelligence control, time series forecasting of arbitrary kind under significant noise level, and also the structural and parametric uncertainty.

The multilayer feedforward networks of three-layer perceptron type, where the elementary nodes are so-called P - neurons with monotonic activation functions are the most known and popular. The efficiency of the multilayer networks is explained by their universal approximation properties in combination with relative compact presentation of the simulated nonlinear system. It means, that they can be used successfully in the tasks of the simulation (emulation) non-linear systems, which can be described by the equation

$$y(k) = F(x(k)) + \xi(k), \tag{1}$$

where $y(k)$ is the output system signal in k -th instant of discrete time $k = 0,1,2,\ldots,$ $x(k) \in X$ - $(n \times 1)$ is the vector of input signal, including both exogenous variables and previous values of the output signal, $F(\bullet)$ is the arbitrary function, generally in some unknown form, $\xi(k)$ is the unobserved disturbance with unknown characteristics. Usually it is assumed that function $F(\bullet)$ is defined either on the unit hypercube or on the orthotop

$$x_i(k) \in [x_i^{\min}, x_i^{\max}],\ i = 1,2,\ldots,n,$$

where $x_i^{\min}$, $x_i^{\max}$ are the known low and upper limits of the i -th input influence variation.

The principal disadvantage of the multilayer networks is the low learning rate which is based on backpropagation algorithm which makes their application in the real time tasks impossible.

Alternative to the multilayer ANNs are the radial basis function networks, having one hidden layer consisting of, so-called, R-neurons. These networks learning is realized on the level of the output layer which is usually represented by the adaptive linear associator [1-6]. Unlike P-neurons, R-neurons conventionally have bell-shaped activation function $f_j(x)$, where the argument is a distance (usually in Euclidean metric) between the current value of input signal $x(k)$ and the center c_j of the j -th neuron, i.e.

$$\varphi_j(x(k)) = \varphi_j\left(\sum_{i=1}^{n}(x_i(k)-c_{ji})^2\right) = \varphi_j\left(\left\|x(k)-c_j\right\|^2\right). \quad (2)$$

The principal advantage of RBFN is the high learning rate in the output layer, because the turning parameters are linearly included to the network description. At the same time the problem of R-neurons centers allocation is remaining, and its unsuccessful solving leads to the «curse of dimensionality» problem. Using clustering techniques though allows reducing the size of the network, but excludes the possibility of on-line operation. Here it can be noted, that in [7] the gradient recurrent procedure of the component-wise tuning parameters c_{ji} is described, but it is characterized by the low learning rate.

Along with neural networks for the arbitrary type signals processing, in the last years the wavelet theory is used sufficiently often [8-9], providing the compact local signal presentation both in the frequency and time domains. At the turn of the artificial neural network and wavelets theories the wavelet neural networks [10-15] have evolved their efficiency for the analysis of nonstationary nonlinear signals and processes.

Elementary nodes of the wavelet neural networks are so-called radial wavelons [16], where the activation functions are the even wavelets with argument in form the Euclidian distance between $x(k)$ and wavelet translation vector c_j, where that every component of distance $\left|x_i(k)-c_{ji}\right|$ is weighted by the dilation parameter σ_{ji} such, that

$$\varphi_j(x(k)) = \varphi_j\left(\sum_{i=1}^{n}\left((x_i(k)-c_{ji})/\sigma_{ji}\right)^2\right), \quad (3)$$

where $\varphi_j(\bullet)$ is wavelet activation function. The receptive fields for such wavelons are hyperellipsoids with axes which are collinear to coordinate axes of the space X.

Taking into consideration the equivalence of radial basis ANN and fuzzy inference systems [17, 18], and also possibility of using even wavelet as a membership function [19, 20], within the bounds of the unification paradigm [16] we can talk about such hybrid system as Radial-Basis-Function-Wavelet-Neuro-Fuzzy Network (RBFWNFN) having the radial-basis function network fast learning ability, fuzzy inferences systems interpretability and wavelet's local properties.

It can be noted, that mostly tuning algorithms based on traditional squared learning criteria in the case of the processing data being contaminated by outliers with unknown distribution law, have shown themselves very sensitive to anomalous outliers. Thus the actual task is a synthesis of the robust learning algorithms, that allow signal processing in presence of anomalous outliers.

This paper is devoted to synthesis of robust learning algorithm for RBFWNN, which has adjustable level of insensitivity to the different kind of outliers, rough errors, non-Gaussian disturbances, has high convergence rate and provides the advanced approximation properties in comparison with conventional computational intelligence systems.

1. Radial-basis-fuzzy-wavelet-neural-network architecture

Let us consider the two-layers architecture shown on fig. 1 that coincides with the traditional radial-basis neural network. The input layer of the architecture is the receptor and in current time instant k the input signal in vector form $x(k) = (x_1(k), x_2(k), \ldots, x_n(k))^T$ is fed on it. Unlike radial basis function network the hidden layer consists of not by R-neurons, but by wavelons with wavelet activation function in the form

$$\varphi_j(x(k)) = \varphi_j\left((x(k)-c_j)^T Q_j^{-1}(x(k)-c_j)\right), \; j = 1, 2, \ldots, h, \quad (4)$$

in which instead of translation parameters σ_{ji} in (1) the positive-definite dilation matrix Q_j is used, i.e. it is not Euclidian distance, but Itakura-Saito metric [21].

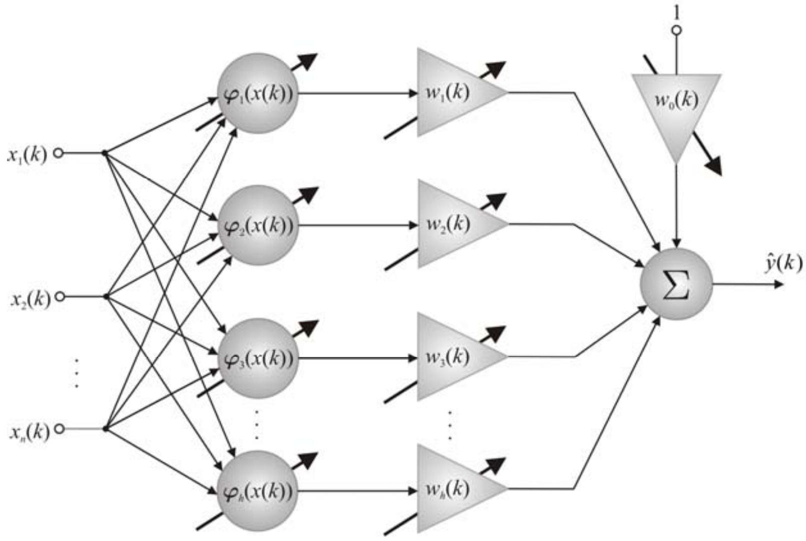
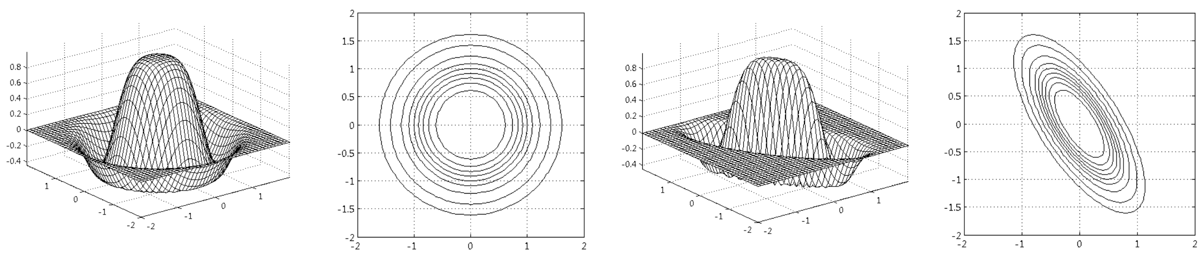


Fig. 1 – Radial-basis fuzzy wavelet neural network

This results to the fact that receptive fields – wavelons hyperellipsoids (2) can have the arbitrary orientation relatively to the coordinate axes of space X , what extends the functional properties of RBFWNN.

Fig. 2 shows the wavelons activation function (2) with arbitrary matrices Q_j .



a) $Q_1 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$ b) $Q_3 = \begin{pmatrix} 4 & 3 \\ 1 & 2 \end{pmatrix}$

Fig. 2 – Wavelons activation function with arbitrary matrices Q_j

And at last, the output layer is the common adaptive linear associator with tuning synaptic weights w_j

$$\hat{y}(k) = w_0 + \sum_{j=1}^{h} w_j \varphi\left((x(k) - c_j)^T Q_j^{-1} (x(k) - c_j) \right) = w^T \varphi(x(k)), \qquad (5)$$

where $\varphi_0(x(k)) \equiv 1$, $w = (w_0, w_1, w_2, \ldots, w_h)^T$, $\varphi(x(k)) = (1, \varphi_1(x(k)), \varphi_2(x(k)), \ldots, \varphi_h(x(k)))^T$.

Thus the tuning parameters of architecture to be determined in the learning process form the set of the $h+1$ synaptic weights w_j , h $(n \times 1)$ -vectors c_j and h $(n \times n)$ -matrices Q_j^{-1}. In total such network includes h $(1 + n + n^2) + 1$ adjustable parameters.

2. The robust learning algorithm for radial-basis-fuzzy-wavelet neural network

The experience shows that the identification methods based on the least square criterion are extremely sensitive to the deviation of real data distribution law from Gaussian distribution. In presence of various type outliers, an outrage errors, and non-Gaussian disturbances with "heavy tails" the methods based on the least squares criterion loose their efficiency.

In this case the methods of robust estimation and identification [22] which have obtained the wide spread for the learning of the artificial neural networks [23-25] appear on the first role.

Let's introduce into the consideration the learning error

$$e(k) = y(k) - \hat{y}(k) = y(k) - w^T(k)\varphi(k) \tag{6}$$

and robust identification criterion by R. Welsh [26, 27]

$$E(k) = f(k) = \beta^2 \ln\left(\cosh\left(e(k)/\beta\right)\right), \tag{7}$$

where β is a positive parameter, that is chosen from empirical reasons and defining the size of zone of tolerance to outliers. It is necessary to note, that robust criterion (7) satisfies to all metric space axioms.

Further we shall consider synthesis of the learning algorithms. For the synaptic weights and the waveleon parameters (vectors c_j and matrices Q_j^{-1}) tuning we use gradient minimization of criterion (7), thus unlike the component-wise learning considered in [7], we make some corrections in the vector-matrix form, that, firstly is easier from computing point of view, and secondly it allows to optimize learning process on the operation rate.

In general case the learning algorithm can be written in form

$$\begin{cases} w(k+1) = w(k) - \eta_w \nabla_w E(k), \\ c_j(k+1) = c_j(k) - \eta_{c_j} \nabla_{c_j} E(k), \;\; j = 1,2,\ldots,h, \\ Q_j^{-1}(k+1) = Q_j^{-1}(k) - \eta_{Q_j^{-1}} \left\{\partial E(k) \big/ \partial Q_j^{-1}\right\}, \;\; j = 1,2,\ldots,h, \end{cases} \tag{8}$$

where $\nabla_w E$ is vector-gradient of the criterion (7) on w, $\nabla_{c_j} E$ is $(n\times 1)$-vector-gradient criterion (7) on c_j; $\left\{\partial E(k) \big/ \partial Q_j^{-1}\right\}$ is $(n\times n)$-matrix, formed by partial derivatives E on components Q_j^{-1}; η_w, η_{c_j}, $\eta_{Q_j^{-1}}$ are the learning rates.

For arbitrary wavelet $\varphi((x(k)-c_j)^T Q_j^{-1}(x(k)-c_j))$ we can write

$$\begin{cases} \nabla_w E(k) = -\beta \tanh\left(e(k)/\beta\right)\varphi_j((x(k)-c_j(k))^T Q_j^{-1}(k)(x(k)-c_j(k))) = -\tanh\left(e(k)/\beta\right) J_w(k), \\ \nabla_{c_j} E(k) = \beta \tanh\left(e(k)/\beta\right) w_j(k)\varphi_j'((x(k)-c_j(k))^T Q_j^{-1}(k)(x(k)-c_j(k)))\cdot \\ \qquad \cdot Q_j^{-1}(k)(x(k)-c_j(k)) = \tanh\left(e(k)/\beta\right) J_{c_j}(k), \\ \left\{\partial E(k) \big/ \partial Q_j^{-1}\right\} = -\beta \tanh\left(e(k)/\beta\right) w_j(k)\varphi_j'((x(k)-c_j(k))^T Q_j^{-1}(k)(x(k)-c_j(k)))\cdot \\ \qquad \cdot (x(k)-c_j(k))(x(k)-c_j(k))^T = -\tanh\left(e(k)/\beta\right) J_{Q_j^{-1}}(k), \end{cases} \tag{9}$$

where $\varphi_j'(\bullet)$ is the derivative j-th wavelet on the argument $(x(k)-c_j(k))^T Q_j^{-1}(k)(x(k)-c_j(k))$.

Then the wavelons learning algorithm of the hidden layer subject to (9) is taking the form

$$\begin{cases} w(k+1) = w(k) + \eta_w \beta \tanh\left(e(k)/\beta\right) \varphi_j((x(k)-c_j(k))^T Q_j^{-1}(k)(x(k)-c_j(k))) = \\ \qquad = w(k) + \eta_w \tanh\left(e(k)/\beta\right) J_w(k), \\ c_j(k+1) = c_j(k) - \eta_{c_j} \beta \tanh\left(e(k)/\beta\right) w_j(k) \varphi_j'((x(k)-c_j(k))^T Q_j^{-1}(k)(x(k)-c_j(k))) \cdot \\ \qquad \cdot Q_j^{-1}(k)(x(k)-c_j(k)) = c_j(k) - \eta_{c_j} \tanh\left(e(k)/\beta\right) J_{c_j}(k), \\ Q_j^{-1}(k+1) = Q_j^{-1}(k) + \eta_{Q_j^{-1}} \beta \tanh\left(e(k)/\beta\right) w_j(k) \varphi_j'((x(k)-c_j(k))^T Q_j^{-1}(k)(x(k)-c_j(k))) \cdot \\ \qquad \cdot (x(k)-c_j(k))(x(k)-c_j(k))^T = Q_j^{-1}(k) + \eta_{Q_j^{-1}} \tanh\left(e(k)/\beta\right) J_{Q_j^{-1}}(k), \end{cases} \tag{10}$$

at that convergence rate to the optimal value w, c_j and Q_j^{-1} is completely defined by learning rate parameters η_w, η_{c_j} and $\eta_{Q_j^{-1}}$.

The learning rate increasing can be achieved by using procedures more complex than gradient ones, such as Hartley or Marquardt procedures, that for the first relation (10) can be written in general form [28]

$$w(k+1) = w(k) - \lambda_w (J_w(k) J_w^T(k) + \eta_w I)^{-1} J_w(k) \tanh\left(e(k)/\beta\right), \tag{11}$$

where I is the $(n \times n)$-identity matrix, λ_w is a positive dampening parameter, η_w is a momentum term parameter.

Using the inverse matrices lemma and after applying simple transformations we obtain the effective parameters learning algorithm in the form

$$\begin{cases} w(k+1) = w(k) - \lambda_w \left(\tanh\left(e(k)/\beta\right) J_w(k)\right) \Big/ \left(\eta_w + \|J_w(k)\|^2\right), \\ c_j(k+1) = c_j(k) - \lambda_c \left(\tanh\left(e(k)/\beta\right) J_{c_j}(k)\right) \Big/ \left(\eta_c + \left\|J_{c_j}(k)\right\|^2\right), \\ Q_j^{-1}(k+1) = Q_j^{-1}(k) + \lambda_{Q_j^{-1}} \left(\tanh\left(e(k)/\beta\right) J_{Q_j^{-1}}(k)\right) \Big/ \left(\eta_{Q_j^{-1}} + Tr(J_{Q_j^{-1}}^T(k) J_{Q_j^{-1}}(k))\right). \end{cases} \tag{12}$$

In order to add more smoothing properties, using approach proposed in [29], we can introduce the modified learning procedure:

$$\begin{cases} w(k+1) = w(k) + \lambda_w \dfrac{\tanh\left(e(k)/\beta\right) J_w(k)}{\eta_w(k)}, & \eta_w(k+1) = \alpha_w \eta_w(k) + \|J_w(k+1)\|^2, \\ c_j(k+1) = c_j(k) - \lambda_{c_j} \dfrac{\tanh\left(e(k)/\beta\right) J_{c_j}(k)}{\eta_{c_j}(k)}, & \eta_{c_j}(k+1) = \alpha_c \eta_{c_j}(k) + \left\|J_{c_j}(k+1)\right\|^2, \\ Q_j^{-1}(k+1) = Q_j^{-1}(k) + \lambda_{Q_j^{-1}} \dfrac{\tanh\left(e(k)/\beta\right) J_{Q_j^{-1}}(k)}{\eta_{Q_j^{-1}}(k)}, & \eta_{Q_j^{-1}}(k+1) = \alpha_{Q_j^{-1}} \eta_{Q_j^{-1}}(k) + Tr\left(J_{Q_j^{-1}}^T(k+1) J_{Q_j^{-1}}(k+1)\right) \end{cases} \tag{13}$$

(here $0 \le \alpha_w \le 1, 0 \le \alpha_{c_j} \le 1, 0 \le \alpha_{Q_j^{-1}} \le 1$ are the parameters of weighting out-dated information), being nonlinear hybrid of the Kaczmarz-Widrow-Hoff and Goodwin-Ramadge-Caines algorithms and including both following and filtering properties.

3. Results of the experimental research

In the first experiment the developed robust learning algorithm was tested out on the basis of a signal with intensive outliers. The signal had been obtained using Narendra's nonlinear dynamical system (it is a standard benchmark, widely used to evaluate and compare the performance of neural and neuro-fuzzy systems for nonlinear system modeling and time series forecasting) whose output signal is artificially contaminated by random noise generated according to the Cauchy distribution with the inverse transform method described by equation in form

$$F_X^{-1}(x) = x_0 + \gamma tg\left[\pi\left(x - 0.5\right)\right], \tag{14}$$

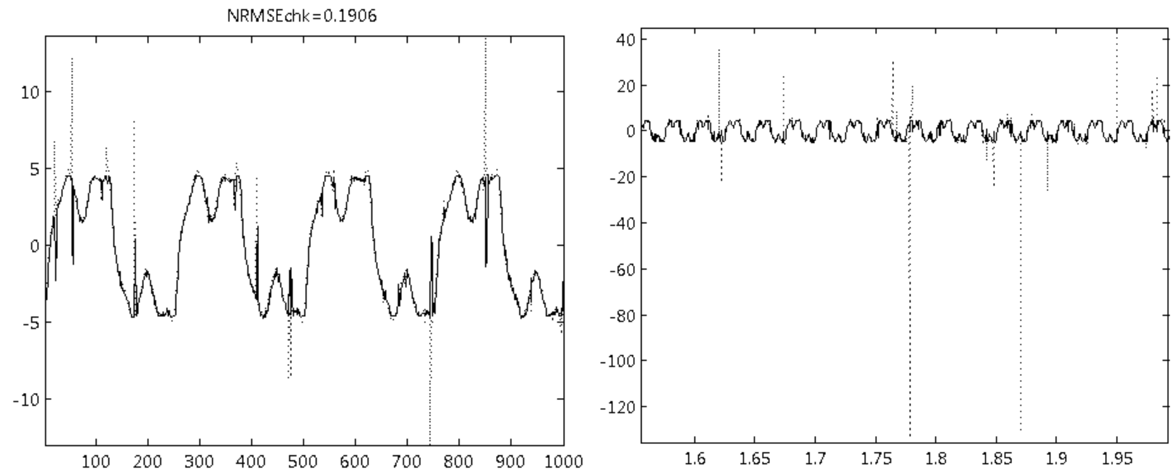
where x_0 is the location parameter, γ is the scale parameter $(\gamma > 0)$, x is the support area ($x \in (-\infty, +\infty)$).

The nonlinear dynamical system is generated by equation in form [30]

$$y(k+1) = 0.3y(k) + 0.6y(k-1) + f(u(k)), \tag{15}$$

where $f(u(k)) = 0.6\sin(u(k)) + 0.3\sin(3u(k)) + 0.1\sin(5u(k))$ and $u(k) = \sin(2k/250)$, k is discrete time. The values $x(t-4), x(t-3), x(t-2), x(t-1)$ were used to emulate $x(t+1)$. In the on-line mode of learning, RBFWNN was trained with procedure (13) for 20000 iterations. The parameters of the learning algorithm were $\beta_w = 1, \beta_c = 0.5,\ \beta_Q = 0.5,\ \alpha_w = \alpha_c = \alpha_Q = 0.99,$ $\lambda_w = \lambda_{c_j} = \lambda_{Q_j^{-1}} = 0.99$. Initial values were $\eta_w(0) = \eta_{c_j}(0) = \eta_{Q_j^{-1}}(0) = 10000$. After 20000 iterations the training was stopped, and the next 1000 points were used as the testing data set. Initial values of synaptic weights were generated in a random way from -0.1 to $+0.1$.

Fig. 3 a shows the results of the noised signal emulation (real values (dashed line) and emulated values (solid line)). Fig. 3 b shows segment of the learning process; as it can be seen the number of outliers with large amplitude, present in the beginning of the sample, didn't have a significant influence on the learning algorithm.



a) b)

Fig. 3 – Results of noised signal processing based on robust learning algorithm

The comparison of emulation results based on robust learning algorithm with results of emulation based on gradient algorithm and the algorithm based on recurrent least squares method where the structure network and the number of tuning parameters were identical was carried out.

Under RBFWNN learning using the gradient algorithm the first outlier in the beginning of the sample, had a noticeable influence on the learning algorithm. Under RBFWNN learning using the recurrent least-squares method the first occurred outlier leads to the covariance matrix so-called "parameters blow-up" what results in inability to emulate signals noised by anomalous outliers. Thus it is obvious that the proposed robust learning algorithm allows signal processing under high level outliers noise conditions.

In Table 1 the comparison results are shown.

Table 1: The results of noisy signal emulation

Neural Network / Learning algorithm	NRMSE
RBFWNN / Proposed robust learning algorithm (13)	0.1906
RBFWNN / The gradient learning algorithm	1.1242
RBFWNN / RLSM	∞

The second experiment has been made on the data set, presented by Government Institution "Institute of General and Urgent Surgery (Academy of Medical Sciences of Ukraine)". It has been carried out studying of the homeostasis indexes dynamic of the patient with the stomach acute injury [31, 32] based on outliers resistant radial-basis-fuzzy-wavelet-neural network. The indexes of oxygen cascade, system hemodynamics, daily pH-measurement, and hypoxia marker and endotoxemia were analyzed. Result of processing studied clinico-laboratory data set was the degree defining of enteral deficiency, that it has allowed to lead the adequate stomach-protect diagnosis and therapy.

Conclusion

In the paper computationally simple and effective all RBFWNN parameters robust learning algorithm is proposed. The robust learning algorithm has following and smoothing properties and allows on-line processing of non-linear signals under a number of outliers and “heavy tails” disturbances. Addition of wavelons receptor fields, including their transformations (dilation, translation, rotation) allows to improve the network approximation properties, that is confirmed by the experiments research results.

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