TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.7, July 2014, pp. 5476 ~ 5483
DOI: 10.11591/telkomnika.v12i7.5309

An ICVBPNN Algorithm for Time-varying Channel Tracking and Prediction

Sufang Li, Mingyan Jiang* and Dongfeng Yuan
School of Information Science and Engineering, Shandong University
Jinan, 250100, China
*Corresponding author, e-mail: jiangmingyan@sdu.edu.cn

Abstract

An improved complex-valued back propagation neural network (ICVBPNN) algorithm is proposed in this paper. In allusion to the defect of gradient descent of traditional complex-valued back propagation network (CVBPNN) algorithm, additive momentum has been introduced. It is used for time-varying channel tracking and prediction in wireless communication system and better application results are acquired. Firstly, with the use of the learning ability of the neural network, the tracking training is started based on the obtained channel state information (CSI), thus the nonlinear channel model is constructed. Secondly, the unknown channel state information is predicted using the ICVBPNN trained model. The simulation results demonstrate that the proposed method has less estimated error, and can track the channel more accurately than the traditional CVBPNN and the Kalman Filter algorithm.

Keywords: *ICVBPNN, CSI, channel tracking, channel prediction*

1. Introduction

The complex-valued back propagation neural network (further CVBPNN) is a straight forward generalization of the real-valued BPNN. The algorithm which is used for CVBPNN is complex-valued error back propagation (CVEBP, call CVBP for short) algorithm, which is a new evolutionary algorithm proposed by Nitta & Furuya in 1991. It stems from the real-valued error back propagation algorithm. The CVBP algorithm has been used for communication signal processing and adaptive channel equalization [1], classification of carotid artery Doppler signals [2] and surface classification [3]. CVBPNN is a highly nonlinear dynamical system that exhibits a rich and complex dynamical behavior [4]. They have been proven better than traditional signal processing methods in modeling, predicting nonlinear and chaotic time series and in a wide variety of applications ranging from speech processing and channel equalization [5]. Until now, there are no applications of channel tracking and prediction based on the complex-valued back propagation neural network (CVBPNN), we are interested in looking at the improvement of the traditional CVBPNN algorithm and its application in wireless communication system.

The core of the traditional CVBPNN algorithm is the gradient descent method [6]. Due to the defect of gradient descent such as relatively low convergence speed [7] and being easy to get into the local optima, an improved CVBPNN (ICVBPNN) algorithm is proposed in this paper. In this new scheme additive momentum is produced, which can be in allusion to the defect of gradient descent of the traditional CVBPNN.

In wireless communication system, many techniques require the transmitter to know the exact channel state information (CSI) in order to play their best performance, the beam forming precoding and adaptive modulation and coding for example. In time division multiplexing system, CSI can be acquired by the reciprocity of the uplink/downlink; in the frequency division multiplexing system, the CSI estimated by the receiver is feed backed to the transmitter using the feedback link. However, due to time-varying performance of the wireless channel, there will be the time delay error between the CSI obtained by the receiver and the real CSI in the transmitting time, which will be even more evident in the fast fading channels. To improve the system performance, the compensation for the CSI delay will be performed using the channel prediction techniques. Fading time-varying channel can be described by Sine wave superposition process or autoregressive (AR) process with time-varying parameters, so spectrum estimation plus linear prediction model or subspace algorithm to predict the CSI [8]

Received December 8, 2013; Revised February 13, 2014; Accepted February 25, 2014

such as the channel prediction methods [9, 10] based on the Multiple Signal Classification (MUSIC) [11] and Estimating Signal Parameters via Rotational Invariance Technique (ESPRIT) [12]. Real-valued neural network has been widely used in channel prediction because it has better learning ability, the real channel prediction based on the Rosenblatt's recurrent neural network and the Vappnik's support vector machine (SVM) [13, 14], for example. Complex-valued neural network has complex structure, which has better learning ability, generalization ability [10] and reducing ability [15] and faster convergence speed [16] than the traditional real-valued neural network, thus has some advantages such as less data is needed for the network training, lower computational complexity and so on, which can be used for communication signal processing [17], such as channel equalization [18], channel estimation [19] and channel prediction [20]. Currently, the often used methods for channel tracking and prediction are as follows, Kalman filter [21], particle filter [22] and Least Mean Square (LMS) algorithm [23] and so on. Pilot signals are needed in [21], which will lead to a waste of frequency band resources, and the Kalman filter needs lots of data. Pilot signals are not needed in [22], but larger amount of calculation is caused because random variable iteration is used to complete the unknown distribution. [23] has slower convergence speed, and it is not applicable in fast time varying system.

In order to demonstrate the better performance of ICVBPNN, channel tracking and prediction based on it is introduced in this paper. The method can avoid the tracking and prediction of the real channel and imaginary channel respectively. The proposed method consists of two processes. Firstly, with the use of the learning ability of the neural network, the tracking training is begun based on the obtained channel state information (CSI), constructing the nonlinear channel model. Secondly, the forward prediction to the future values of the model is continued with the use of parameters obtained by network training and the known channel parameters. Comparing with traditional CVBPNN and the Kalman filter, ICVBPNN algorithm has a better prediction and tracking performance for the time-varying channel.

2. ICVBPNN Algorithm

For the ICVBPNN algorithm, we have to define the error function firstly [24]. Because there are no "greater/less" relations in the complex-valued case, the output of the error function must be a real-valued number in order to make it possible to evaluate the training result and to guide it into the direction of an error reduction. To begin with, let's consider the equations for information processing in the three-layer network. It has in general N external inputs and L fully interconnected hidden units and M external outputs. $\mathbf{W}^H = [w_{ji}]_{L\times N}$ is the complex weight vector on hidden layer, $\mathbf{W}^O = [w_{kj}]_{M\times L}$ is the complex weight vector on the output layer. The input vector $\mathbf{X}_p = (x_{p1}, x_{p1}, \cdots x_{pN})$ and the output vector $Y_p = (y_{p1}, y_{p1}, \cdots y_{pM})$ are all complex values. The activation of any (or all) of the units in the network can be considered as the output of the network and all the units can be trained to produce desired outputs. ICVBPNN training algorithm can be described as follows:

Step 1: Initialization;

Step 2: Present the input values $\mathbf{X}_p$, and the desired output values $\mathbf{Y}_p$;

Step 3: Calculate the net-input values to the hidden layer units net_{pj}^h, and the outputs from the hidden layer i_{pj};

$$\begin{aligned} net_{pj}^h &= net_{pj,R}^h + j net_{pj,I}^h = \sum_{i=1}^{N} w_{ji}^h x_{pi} + \theta_j^h = \sum_{i=1}^{N} (w_{ji,R}^h x_{pi,R} - w_{ji,I}^h x_{pi,I}) + \theta_{j,R}^h \\ &= j\left[\sum_{i=1}^{N} (w_{ji,R}^h x_{pi,I} + w_{ji,I}^h x_{pi,R}) + \theta_{j,I}^h\right] \end{aligned} \tag{1}$$

Where w_{ji} is the complex weight on the connection from the i^{th} input unit, and θ_j^h is the bias term. The "*h*" superscript refers to quantities on the hidden layer. The output of this hidden node is:

$$i_{pj} = i_{pj,R} + ji_{pj,I} = F_j^h(net_{pj}^h) = f_j^h(net_{pj,R}^h) + jf_j^h(net_{pj,I}^h) \tag{2}$$

Where the subscripts "*R*" and the "*I*" refer to quantities on the real part and the imaginary part of the values these subscripts are written, respectively.

Step 4: Calculate the net-input values, net_{pk}^o, to each output layer unit and the outputs, O_{pk}.

$$O_{pk} = O_{pk,R} + jO_{pk,I} = F_k^o(net_{pk}^o) = f_k^o(net_{pk,R}^o) + jf_k^o(net_{pk,I}^o) \tag{3}$$

Where,

$$\begin{aligned} net_{pk}^o &= net_{pk,R}^o + jnet_{pk,I}^o = \sum_{j=1}^{L} w_{kj}^o i_{pj} + q_k^o = \sum_{j=1}^{L}(w_{kj,R}^o i_{pi,R} - w_{kj,I}^o i_{kj,I}) + q_{k,R}^o \\ &= j\left[\sum_{j=1}^{L}(w_{kj,R}^o i_{pi,I} + w_{kj,I}^o i_{kj,R}) + q_{k,I}^o\right] \end{aligned} \tag{4}$$

Where '*o*' superscript refers to quantities on the output layer.

Step 5: Calculate the error terms for the output units.

$$\delta_{pk}^o = f_k^{'o}(net_{pk,R}^o)\,\mathrm{Re}(D_{pk} - O_{pk}) + jf_k^{'o}(net_{pk,I}^o)\,\mathrm{Im}(D_{pk} - O_{pk}) \tag{5}$$

And the error terms for the hidden units.

$$\delta_{pj}^h = f_j^{'h}(net_{pj,R}^h)\,\mathrm{Re}(D_{pj} - O_{pj}) + jf_j^{'h}(net_{pj,I}^h)\,\mathrm{Im}(D_{pj} - O_{pj}) \tag{6}$$

Step 6: Update weights on the output layer according to:

$$w_{kj}^o(t+1) = w_{kj}^o(t) + \eta\delta_{pk}^o i_{pj}^* + m_c w_{kj}^o(t-1) \tag{7}$$

And update weights on the hidden layer according to:

$$w_{ji}^h(t+1) = w_{ji}^h(t) + \eta\delta_{pj}^h x_{pi}^* + m_c w_{ji}^h(t-1) \tag{8}$$

Where the last item on the right hand side is the momentum term, m_c is the momentum factor which is a value between 0 and 1. The momentum term can raise the standard back propagation algorithm speed by introducing the stability in the weight update.

Next, the ICVBPNN algorithm is used for channel tracking and prediction. For the ICVBPNN algorithm, the activation function (AF) must be used in its complex version. The complexactivation function F for the network in this paper is:

$$F(x) = f(x_R) + jf(x_I)\,. \tag{9}$$

The linear function is taken as output layer AF, and the first-order derivative of it is a scalar. The hidden layer AF is the sigmoid function.

$$f^h(x) = \frac{2}{1+e^{-\mathrm{A}x}} - 1\,. \tag{10}$$

The first-order derivative of the above formula is:

$$f^{'h}(x) = \frac{\mathrm{A}e^{-\mathrm{A}x}}{(1+e^{-\mathrm{A}x})^2} - 1\,. \tag{11}$$

3. The Adaptive Channel Model

For a narrowband fading channel, the sampled received signal $r(k)$ is given by:

$$r(k) = c(k)b(k) + n(k) \tag{12}$$

Where $c(k)$ is obtained by sampling the complex-valued fading channel $c(t)$ at the time instant of $t - k\mathrm{T}b$ and $\mathrm{T}b$ is the data symbolduration, $b(k)$ is the k^{th} transmitted symbol value, while $n(k)$ is acomplex-valued discrete AWGN process having a variance of $N_0/2$ per dimension. The channel parameter estimation $\hat{c}(k)$ is obtained from the channel estimator. In order to have a good analysis, we assume the channel estimation is accurate, namely, $\hat{c}(k) = c(k)$. The problem to be resolved is to produce the D-step forward channel prediction values with the use of the current channel parameters and the observed values.

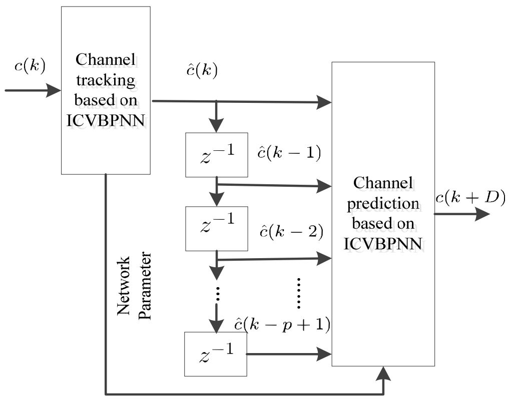


Figure 1. System Block Diagram

The channel prediction is divided into two steps, which is shown in Figure 1. Firstly, the current channel CSI $c(k)$ is estimated using the ICVBPNN, namely, the channel network model is trained and the nonlinear channel tracking model is constructed; secondly, the D-step forward prediction begins making use of the parameters obtained by ICVBPNN training and the known channel parameters $\{c(k), c(k-1), \cdots c(k-P+1)\}$.

4. ICVBPNN Tracking and Prediction Model

4.1. ICVBPNN Tracking Model

The tracker is essentially atype ofone-step predictor which has doctor training. The unknown signal $c(k)$ is looked as the desired signal, the input signals $[c(k-1), c(k-2), \cdots, c(k-P)]^T$ denotes the complex-valued input vector of at the time index*k*. The architecture of the ICVBPNN tracking model is shown in Figure 2. The basic idea is that weight values are updated based on the error back propagation to the hidden layer until the weight values unchanged, then the optimal parameters is obtained. The back propagation error is:

$$e(k) = c(k) - \hat{c}(k)\,. \tag{13}$$

Then the cost function of:

$$E(k) = \frac{1}{2}|e(k)|^2 \tag{14}$$

Is invoked by a training algorithm to generate the updated ICVBPNN weights until a satisfactorily low mean square error (MSE) is obtained.

The prediction process model belongs to a feed forward tracking structure, that is to say,

$$\hat{c}(k) = \mathrm{g}\left(c(k-1), c(k-2)\cdots, c(k-P)\right) \tag{15}$$

Where g refers to ICVBPNN algorithm.

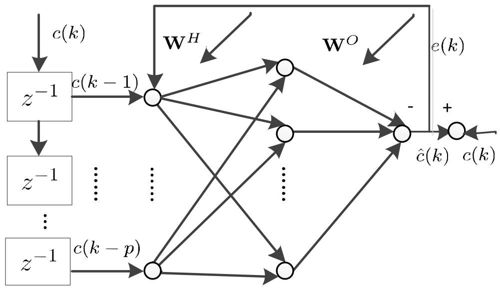


Figure 2. Channel Tracking Model

4.2. ICVBPNN Prediction Model

Synchronize the training network parameters of the tracking process $\mathbf{W}^H$, $\mathbf{W}^O$ to the backward prediction neural network model, and then the prediction process is operated. The prediction process model belongs to a recursivelyforward prediction structure which can be seen in Figure 1, that is to say,

$$\hat{c}(k+i) = \mathrm{g}\left(\hat{c}(k+i-1), \hat{c}(k+i-2)\cdots, \hat{c}(k)\right), \ \forall 1 \le i \le D \tag{16}$$

Where g refers to ICVBPNN algorithm. The back propagation error is:

$$e(k) = c(k) - \hat{c}(k+i), \ \forall 1 \le i \le D\ . \tag{17}$$

Then the cost function is:

$$E(k) = \frac{1}{2}\left|e(k)\right|^2 . \tag{18}$$

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [2, 5]. The discussion can be made in several sub-chapters.

5. Simulation Results

Jakes channel model [25] is used to verify the channel tracking and prediction algorithm based on the proposed ICVBPNN algorithm. Assume that the maximum Doppler frequency shift $f_d = 6.4Hz$, carrier frequency is 2.3GHz; the Doppler normalization coefficient is 0.320. The architecture of the ICVBPNN in this paper is 2-80-1, which means there are 2 nodes in the input layer, 80 nodes in the hidden layer, 1 node in the output layer. Since the hidden layer has the function of storing the predicted information, the number of which cannot be much little, in this paper it is 80. It cannot be too large or too small; otherwise the algorithm will be diverged. The Figure 3 denotes the convergence curves for different hidden layer nodes. The activating factor of the hidden layer activation function is 2 and the linear slope factor of the output layer is 3. For different number of the delayed steps, the tracking error is different, which is shown in Figure 4. The greater the delayed step, the bigger the prediction error.

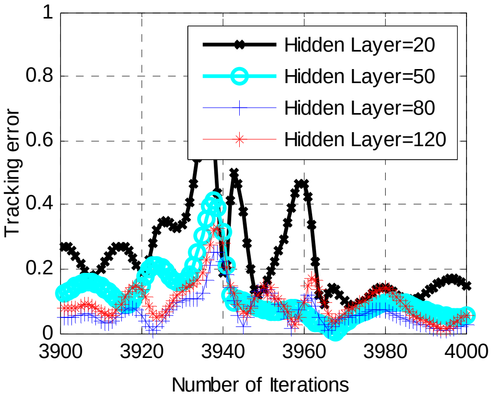


Figure 3. The Tracking Error caused by Different Number of Hidden Nodes

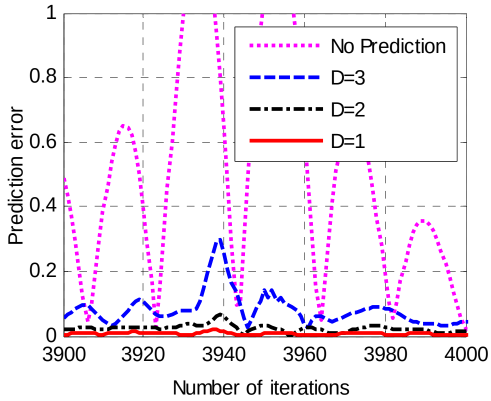
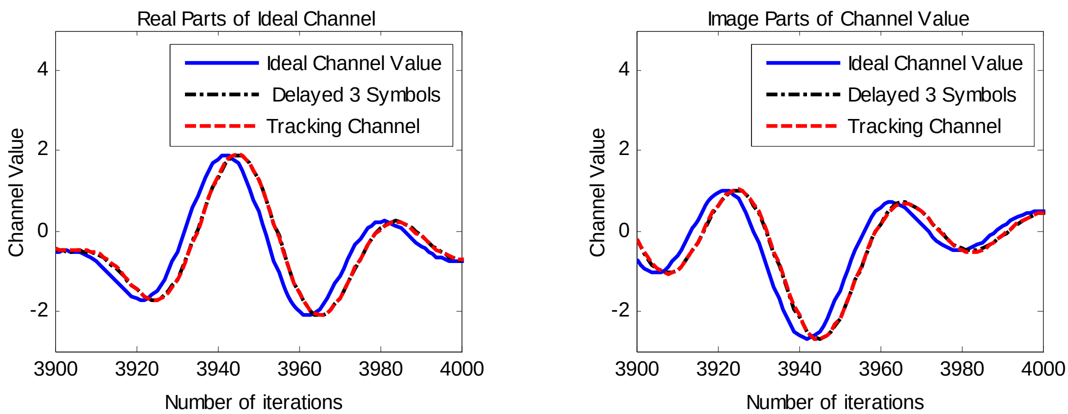


Figure 4. The Tracking Error caused by Different Number of Delayed Step

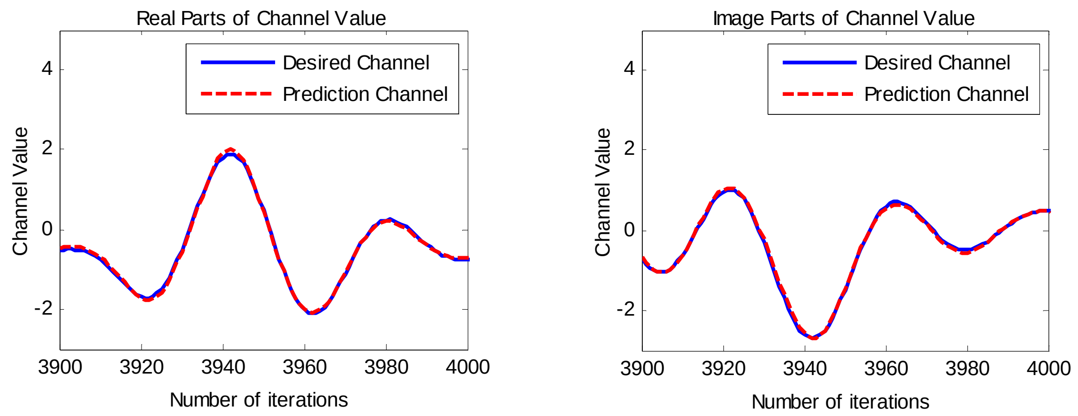
For $D=3$ which means the delayed step is 3, the observed signal that is the delayed CSI is the dotted line as shown in Figure 5. Firstly, the observed signal is trained by the ICVBPNN to construct the nonlinear channel tracking network model. Figure 5 shows the training results. Obviously the estimation error between the training results and the observed signals is less than that between the training results and the ideal CSI. Thus the D-step prediction must be processed using the optimal parameters obtained by the network training and the known channel parameters. The prediction result of the complex channel is shown in the Figure 6. The algorithm for channel prediction is compared with traditional CVBPNN and Kalman Filter [21] in Figure 7. The Kalman Filter uses the AR channel model and the order is 8, 12 respectively.The higher the order the smaller the prediction error. But with the increased number of the order, the amount of the data required is relatively increased. The prediction error of the ICVBPNN is less than Kalman Filter when the order the channel model is equal or less than 12.



(a) Real part tracking (b) Image part tracking

Figure 5. Tracking Performance of the Complex Channel

The running time of the ICVBPNN and CVBPNN is 6.140s, 6.105s. As for the Kalman Filter, when the channel order is 8 and 12 the running time is 35.8120s and 40.4915s respectively. Obviously, ICVBPNN needs less data and running time than the Kalman Filter. Figure 7 also shows that the ICVBPNN has better stability and less tracking error than the traditional CVBPNN. BER analysis for BPSK modulation with 2×2 MIMO channel is shown in Figure 8, from which we can see the BER is improved after prediction.



(a) Real part prediction (b) Image part prediction

Figure 6. Prediction Performance of the Complex Channel

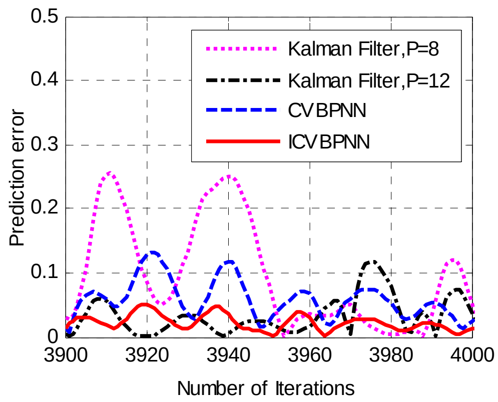


Figure 7. Comparison of the Tracking Error between Kalman Filter, CVBPNN and ICVBPNN

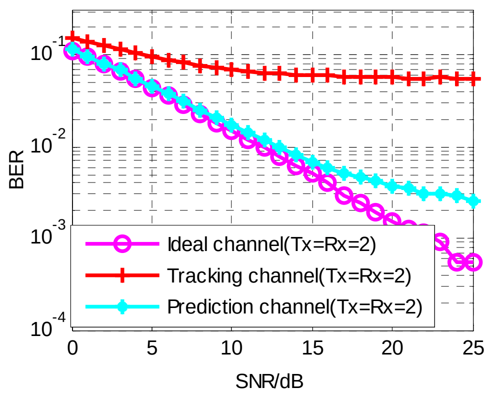


Figure 8. BER Plot for 2×2 MIMO Channel with ICVBPNN Tracking and Prediction

6. Conclusion

In this paper, a narrowband fading channel tracking and prediction algorithm based on ICVBPNN is proposed. Bit error rate analysis for BPSK modulation in Gaussian white noise Jakes channel verifies the correctness of the proposed algorithm. The simulation results demonstrate that the ICVBPNN has better stability than traditional CVBPNN. The ICVBPNN training scheme converges faster than traditional CVBPNN and Kalman Filter and needs less running time. For the high-speed parallel performance of the ICVBPNN, the running speed increases and real-time processing of time-varying channel is achieved.

References

[1] Y Cheolwoo, H Daesik. Nonlinear blind equalization schemes using complex-valued multilayer feedforward neural networks. *IEEE Transactions on Neural Networks*. 1998; 9: 1442-1455.
[2] M Ceylan, R Ceylan, F Dirgenali, S Kara, Y Ozbay. Classification of carotid artery Doppler signals in the early phase of atherosclerosis using complex-valued artificial neural network. *Computers in Biology and Medicine*. 2007; 37; 28-36.
[3] A Prashanth, PK Kalra, NS Vyas. *Surface classification using ANN and complex-valued neural network.* Proceedings of the 9th International Conference on Neural Information Processing. 2002; 3: 1094-1098.
[4] H Jin, W Jun. Global Stability of Complex-Valued Recurrent Neural Networks with Time-Delays. *IEEE Transactions on Neural Networks and Learning Systems*. 2012; 23; 853-865.
[5] A Hirose, S Yoshida. Generalization Characteristics of Complex-Valued Feedforward Neural Networks in Relation to Signal Coherence. *IEEE Transactions on Neural Networks and Learning Systems*. 2012; 23; 541-551.
[6] T Nitta. An Extension of the Back-Propagation Algorithm to Complex Numbers. Neural Networks. 1997; 10: 1391-1415.
[7] K Burse, A Pandey, A Somkuwar. *Convergence Analysis of Complex Valued Multiplicative Neural Network for Various Activation Functions.* International Conference on Computational Intelligence and Communication Networks (CICN). 2011: 279-282.
[8] A Duel-Hallen, H Hallen, Y Tung-Sheng. Long range prediction and reduced feedback for mobile radio adaptive OFDM systems. *IEEE Transactions on Wireless Communications*. 2006; 5; 2723-2733.
[9] HA a JP Delmas. MUSIC-Like Estimation of Direction of Arrival. IEEE Transactions On Signal Processing. 2006; 54: 2678-2690.
[10] A Hirose. Nature of complex number and complex-valued neural networks. *Frontiers of Electrical and Electronic Engineering in China*. 2011; 6: 171-180.
[11] CR Berger, Z Shengli, JC Preisig, P Willett. Sparse Channel Estimation for Multicarrier Underwater Acoustic Communication: From Subspace Methods to Compressed Sensing. *IEEE Transactions on Signal Processing*. 2010; 58: 1708-1721.
[12] NY a B Friedlander. Asymptopicperformance analysis of ESPRIT, Higher Order ESPRIT, and Virtual ESPRIT Algorithm. *IEEE Transaction on Signal Pricession*. 1996; 44: 2537-2550.
[13] B Visweswaran, T Kiran. *Channel prediction based power control in W-CDMA systems*. First International Conference on (Conf. Publ. No. 471 3G Mobile Communication Technologies). 2000: 41-45.
[14] NI Sapankevych, R Sankar. Time Series Prediction Using Support Vector Machines: A Survey. *IEEE Computational Intelligence Magazine*. 2009; 4: 24-38.
[15] M Kobayashi. Exceptional Reducibility of Complex-Valued Neural Networks. *IEEE Transactions on Neural Networks*. 2010; 21: 1060-1072.
[16] H Zhang, D Xu, Z Wang, Convergence of an Online Split-Complex Gradient Algorithm for Complex-Valued Neural Networks. *Discrete Dynamics in Nature and Society.* 2010; 1-27.
[17] A Hirose, S Yoshida. Generalization Characteristics of Complex-Valued Feedforward Neural Networks in Relation to Signal Coherence. *IEEE Transactions on Neural Networks and Learning Systems*. 2012; 23: 541-551.
[18] HQ Zhao, XP Zeng, ZY He, WD Jin, TR Li. Complex-valued pipelined decision feedback recurrent neural network for non-linear channel equalization. *IET Communications*. 2012; 6: 1082-1096.
[19] Z Xiaobo, W Xiaodong. Channel estimation for OFDM systems using adaptive radial basis function networks. *IEEE Transactions on Vehicular Technology*. 2003; 52: 48-59.
[20] G Su Lee, DP Mandic. Nonlinear adaptive prediction of complex-valued signals by complex-valued PRNN. *IEEE Transactions on Signal Processing*. 2005; 53: 1827-1836.
[21] Y Zheng. A novel channel estimation and tracking method for wireless OFDM systems based on pilots and Kalman filtering. *IEEE Transactions on Consumer Electronics.* 2003; 49: 275-283.
[22] JIANG MY, YUAN DF. Blind tracking based on Monte Carlo algorithm over MIMO fast time-varying channels. *Journal on Communications*. 2007; 28: 40-44.
[23] JF Galdino, EL Pinto, MS de Alencar. Analytical performance of the LMS algorithm on the estimation of wide sense stationary channels. *IEEE Transactions on Communications.* 2004; 52: 982-991.
[24] A Minin. Complex Valued Recurrent Neural Network: From Architecture to Training. *Journal of Signal and Information Processing*. 2012; 03: 192-197.
[25] YR Zheng, X Chengshan. Simulation models with correct statistical properties for Rayleigh fading channels. *IEEE Transactions on Communications*. 2003; 51; 920-928.