Al-Khwarizmi Engineering Journal, Vol. 7, No. 2, PP 36 - 46 (2011)

Al-Khwarizmi Engineering!!! Journal

Performance Improvement of Neural Network Based RLS Channel Estimators in MIMO-OFDM Systems

Alaa Abdulameer Hassan
Department of Mechatronics Engineering/ Al-Khawarizmi College of Engineering/ University of Baghdad
E-mail: alaa_ah76@yahoo.com

(Received 14 Febrewary 2011; accepted 12 May 2011)

Abstract

The objective of this study was tointroduce a recursive least squares (RLS) parameter estimatorenhanced by using a neural network (NN) to facilitate the computing of a bit error rate (BER) (error reduction) during channels estimation of a multiple input-multiple output orthogonal frequency division multiplexing (MIMO-OFDM) system over a Rayleigh multipath fading channel.Recursive least square is an efficient approach to neural network training:first, the neural network estimator learns to adapt to the channel variations then it estimates the channel frequency response. Simulation results show that the proposed method has better performance compared to the conventional methods least square (LS) and the original RLS and it is more robust at high speed mobility.

Keywords: *MIMO-OFDM, RLS, NN, BER, SNR, channel, estimation.*

1. Introduction

The multiple-input-multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) technology has been considered as a strong candidate for the next generation wireless communication systems [1]. Using multiple transmit as well as receive antennas, a MIMO-OFDM system gives a high data rate without increasing the total transmission power or bandwidth compared to a single antenna system. Recently, research suggests that the implementation of MIMO-OFDM is more efficient because of the straightforward matrix algebra invoked for processing the MIMO-OFDM signals. It thus seems to be an attractive solution for future broadband wireless systems [2].

The arrangement of multiple antennas at the transition end and reception end results increase in the diversity gain refers the quality of signal and multiplexing gain refers the transmission capacity [3, 4, 5].

Further, the frequency-selective problem that exists in a conventional wireless system can be well solved by the OFDM technique in the MIMO-OFDM system. On the other hand, the performance of MIMO-OFDM systems depends largely upon the availability of the knowledge of the channel. However, MIMO relies upon the knowledge of channelstate information (CSI) at the receiver for data detection and decoding. It has been proved that when the channel is Rayleigh fading and perfectly known to the receiver, the capacity of a MIMO–OFDM system grows linearly with the number of transmit or receive antennas, whichever is less [1, 6]. Therefore, an accurate estimation of the wireless channel is of crucial importance to MIMO–OFDM systems.

Recent works tackled theperformance assessment (both through simulation and measurements) of MIMO-OFDM systems in the presence of practicalimpairments, such as synchronization and channel estimation errors [7].

The major challenge faced in MIMO-OFDM systems is howto obtain the channel state information accurately and promptlyfor coherent detection of information symbols. The channel stateinformation can be obtained through trainingbased, blind and semiblind channel estimation. The blind channel estimation iscarried out by evaluating the statistical information of thechannel and certain properties of the transmitted signals [3].

Blind Channel Estimation has its advantage in that it has nooverhead loss; it is only applicable to slowly time-varyingchannels due to its need for a long data record. In training basedchannel estimation algorithms, training symbols or pilot tonesthat are known *a priori* to the receiver, are multiplexed alongwith the data stream for channel estimation. Semiblindchannel technique is hybrid of blind and training technique,utilizing pilots and other natural constraints to perform channelestimation [3].

The training basedmethods employ known training signals to render accuratechannel estimation. One of the most efficient trainingbasedmethods is the least squares (LS) algorithm. When thefull or partial information of the channel correlation is known, abetter channel estimation performance can be achieved via someminimum mean square error (MMSE) methods[1].

In this work, we propose a channel estimation algorithmfor MIMO-OFDM systems by employing backpropagationmultilayer neural networks to improve the performance ofa standard recursive least squares (RLS) strategy in a Rayleigh fading channel. The RLS approachis an efficient semi-second-order training that leads toa faster convergence compared with the first-order approaches such as backpropagation (BP) algorithms [8]; and is (RLS) widely used for parameter estimation because of its simplicity and fast rates of convergence.

The model used by the standard RLSalgorithm is based on Multi-LayeredPerceptrons (MLP). This type of neural network isknown as a supervised network because it requires adesired output in order to learn model.

The method described in this paper, however, uses a neural network to learn the parameter updating process of a standard RLS algorithm and then to relate the parameters so obtained to the operating conditions. To achieve this, the operating conditions are used as input patterns to a neural network and the neural network is then trained by comparing the parameters obtained from RLS algorithms with those from the neural network. This method combines the advantages of the simplicity and speed of convergence of RLSalgorithms with the ability of neural networks tolearn any complex process to any desired accuracy.

Also, further enhancement of performance can be achieved through maximum diversity Space Time Block Coding (STBC) and Maximum Likelihood (ML) Detection at transmission and reception ends respectively. STBCs have theability to greatly reduce the bit error rate (BER) or increase the data rate, and have gained much attention as they are able to integrate the techniques of spatial diversity and channel coding, and can provide significant capacity gains in MIMO (OFDM/CDMA) systems.

The rest of the paper is organized as follows. In the following section the MIMO-OFDM with STBC system model is described. The next sectionpresents a general method to channel estimation worked out on RLS approach and describes the chosen NN architecture and its application on RLS estimation. Then, some simulation results and discussionsare given and finally, the least section concludes the paper.

2. System Description

2.1. MIMO-OFDM System

The configuration of multiple antennas can be divided intothree categories [10]: (1) MISO (multiple input single output): uses more than one antenna at the transmitter and only oneat the receiver; (2) SIMO (single input multiple output):uses one transmitting antenna and more than one receivingantenna; and (3) MIMO: uses more than one antenna at thetransmitter and more than one at the receiver.

By using more than one transmit/receive antenna, multiplechannels are employed between each pair of transmit andreceive antennas. The transmitted signalwill travel through different channels to arrive at thereceiver side. If one of the channels is sufficiently strong,the receiver will be able to recover the transmitted signal.

If different channels are independent, then the probabilityof all channels failing is very small [10].

We consider a MIMO wireless communication systememploying N_t transmit and N_r receive antennas (figure(1)), hence, thecorresponding MIMO wireless communication channel is constitutedby $(N_r \times N_t)$ propagation links. Furthermore, each ofthe corresponding $(N_r \times N_t)$ single-input single-output (SISO) propagation links comprises multiple statistically independentcomponents, termed as paths [3, 11, 12, 13, 14, 15].

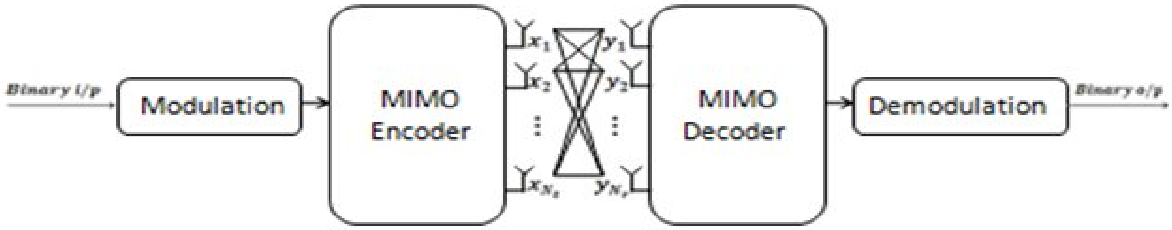

Fig.1. MIMO Architecture.

In this system, first of all the binaryinput data is modulated (the data to be transmitted on each sub-carrier is mapped into one of M-ary PSK or M-ary QAM constellation format, as determined). Then, the modulated data is encoded with a MIMO encoder andtransmitted from $N_t$transmit antennas.

For a Rayleigh fading MIMO system with $N_t$transmit antennas and $N_r$receive antennas, the received signal at the jth receive antenna can be expressed as:

$$= \sum \quad h \quad + \qquad \ldots(1)$$

wherex_i is the symbol transmitted from the ith transmit antenna, $h_{ij}$is the complex channel coefficients from transmit antenna i to receive antenna j and $w_j$is the additive noise which is modeled as Gaussian that is assumed to be independent and identically distributed (i.i.d.) with zero mean and variance $\quad = —$.

The transmitted signals fromall transmit antennas overlap in time, space and frequency so that the received signal is asuperposition of all transmitted signals distorted by the channel noise.

The channel coefficient matrix H with dimensions $(N_r \times N_t)$is denoted as:

$$H = \begin{matrix} h & \cdots & h \\ \vdots & \ddots & \vdots \\ h & \cdots & h \end{matrix} \qquad \ldots(2)$$

as a result, we can write the received signal given in (1) in the matrix form as:

$$Y = HX + W \qquad \ldots(3)$$

where,

$$Y = \vdots \;, X = \vdots \;, \text{and } W = \vdots \qquad \ldots(4)$$

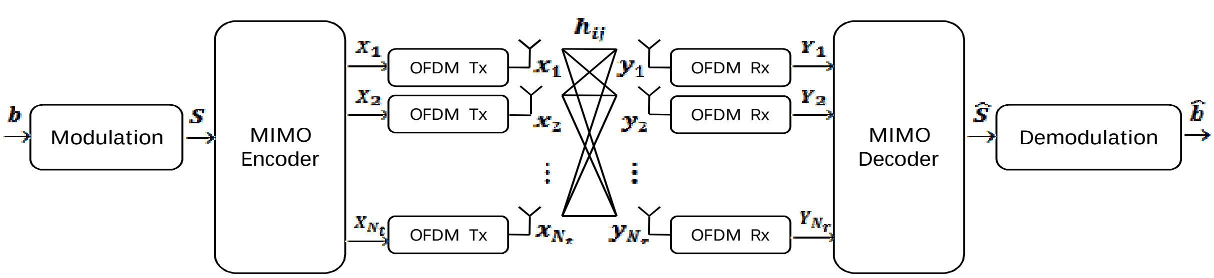

Fig.2. MIMO-OFDM System.

Figure (2) depicts a high level block diagram of the MIMO-OFDM system. We consider MIMO-OFDM system model with $N_t$transmit antennas and $N_r$receive antennas.At the transmission time n, a binary data block b is modulated and then passed through the serial-to-parallel converter and a complex data matrix S with a length $K \times N$ is obtained, where N is the total number of OFDM symbols and K is the total number of subcarriers [3, 15].Then the complex data is passed through the MIMO encoder to produce $N_t$data streams, $(\;,\;)$ for $i = 1,\ldots,N_t$, for transmission over the multipleantennas. Each of these signals forms an OFDM block.

Basically, the MIMO-OFDM transmitter has $N_t$parallel transmission paths which are very similar to the singleantenna OFDM system, each branch performing pilot insertion, IDWT before the final T_X signals are up-converted to RF andtransmitted. It is worth noting that the channel encoder and thedigital modulation, in some spatial multiplexing systems, canalso be done per branch, where the modulated signals are thenspace-time coded using the Alamouti algorithm beforetransmitting from multiple antennas not necessarilyimplemented jointly over all the $N_t$branches [3].

The DWT used here rather than the FFT since it is capable of reducing the power of intersymbolinterference (ISI) and intercarrier interference (ICI), which are caused by the loss in orthogonality between the carriers as a result of the multipath wireless channel (see [16, 17, 18]). It analyzes the signal at different frequency bands with different resolutions by decomposingthe signal into an approximation containing coarse (the high-scale, low-frequency componentsof the signal) and detailed information (the low-scale, high-frequency components).

DWTemploys two sets of functions, known as scaling and wavelet functions, which are associatedwith low pass and high pass filters. The decomposition of the signal into different frequencybands is simply obtained by successive high pass and low pass filtering of the time domainsignal [17, 18]. The original signal $x_i[n]$ is first passed through a half-band high pass filter anda half-band low pass filter (see figure (3)). A half-band low pass filter removes all frequencies that areabove half of the highest frequency, while a half-band high pass filter removes all frequenciesthat are below half of the highest frequency of the signal. The low pass filtering halves theresolution, but leaves the scale unchanged. The signal is then sub-sampled (down-sampling, achieved by discarding alternate samples) by two since halfof the number of samples is redundant, according to the Nyquist's rule.We produce two sequences called c_A (of low frequency) and c_D (of high frequency).

Decomposition halves the time resolution since only half the number of samples then comes to characterize the entire signal. Conversely it doubles the frequency resolution, since the frequency band of the signal spans only half the previous frequencyband effectively reducing the uncertainty by half. This procedure, which is also known as subband coding, can be repeated for further decomposition (see figure (4)). At every level, the filtering and sub-sampling will result in half the number of samples (and hence half the time resolution) and half the frequency bands being spanned (and hence doubles the frequency resolution).

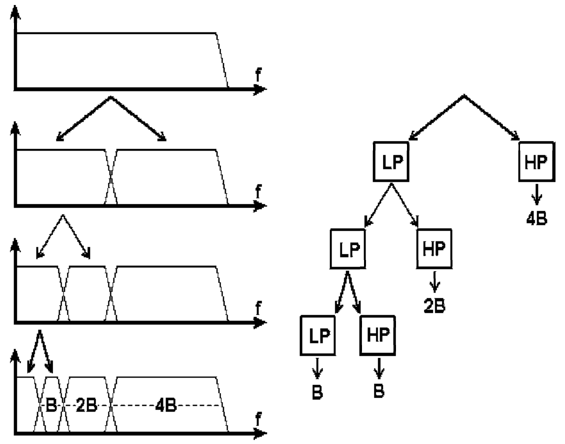

Fig.3. Subband Coding; (Left): Frequency Domain Representation, (Right): Tree-Structure [17].

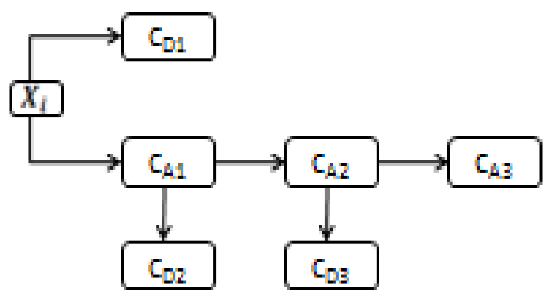

Fig.4. Decomposition of Input Signal.

Assuming the channel impulse response remains constant during the entire OFDM block, the received signal vector that belongs to the jth receive antenna, is simply the linear convolution of transmitted symbols and the channel impulse response vector; each of those $N_r$received signals is a combination of all the $N_t$transmitted signals and the distorting noise.Meanwhile compared to the SISO system, it complicates thesystem design regarding to channelestimation and symboldetection due to the hugely increased number of channelcoefficients.

Subsequently at thereceiver, the DWT is performed perreceiver branch. Next, thetransmitted symbol per T_X antenna iscombined and outputted for the subsequent operations likedigital demodulation and decoding. Finally all the input binarydata are recovered with certain BER.

The output of DWT at the jth receive antenna can be expressed as;

$$(\ , \ ) = \quad (\ , \ ) \quad (\ , \ ) + \quad (\ , \ )$$

…(5)

where $(\ , \ )$ represents the AWGN with zero mean and $= —$ variance. $(\ , \ )$ denotes the channel frequency response at time for the kth subcarrier between the ith transmit and jth receive antennas. The channel coefficients in frequency domain are obtained as linear combinations of the dispersive channel taps:

$$(\ , \ ) = \sum \quad , (\ ) \quad / \qquad \text{…(6)}$$

and the impulse response of the Rayleigh fading channel can be expressed as

$$h \ (\ , \ ) = \sum \quad , (\ ) \quad (\ - \ ) \qquad \text{…(7)}$$

where Lt denotes the number of non-zero taps, $,$ is the correspondingcomplex amplitude of the lth non-zero tap, T_{OFDM} is the OFDM symbol duration and is the delay associated to the lth tap. This delay and variance are assumed to be the same for each transmit-receive channel link. The power of the lth paths are normalized, such that $\sum \quad = 1$; [6, 10, 15, 19].

2.2. Space-Time Block Coded (STBC) OFDM

STBC introduces redundancy in space, through the addition of multiple antennas, and redundancy in time, through channel coding. Its main feature is to provide diversity gain, with very low decoding complexity. In this method (using two transmit antennas), the input data stream is first mapped into symbols using a constellation mapper, and the symbol stream is then divided into two substreams. The symbols and are transmitted from the first and second antenna respectively at time t and the symbols $- \ ^*$ and * are transmitted fromthe first and second antenna respectively at time $+$ (the transmit sequences from the two transmit antennas are orthogonal). In this case the code matrix can be given as [3, 11, 13, 15]:

$$X = \_ \quad * \quad * \qquad \text{…(8)}$$

The block diagram of the Alamouti scheme is shown in figure (5) with one receiver antenna is used at the receiver. The fading channel coefficients from the first and the second transmit antennas to the receive antenna at time t are denoted by $h_1(t)$ and $h_2(t)$, respectively. By assuming that the channel coefficients do not change in the interval from time t to $+$, they can be expressed as follows:

$$h \ (\ ) = |h \ |$$

$$h \ (\ + \ ) = |h \ | \qquad \text{…(9)}$$

where h and , $(i = 1,2)$ are the amplitude gain and phase shift for the path from antenna i to the receive antenna and Ts is the symbol duration.

The received signals at the receiver antenna over two consecutive symbol periods for time t and $+$ can be expressed as:

$$(\ ) = \quad h \ + \quad h \ +$$

$$(\ + \ ) = - \ ^*h \ + \ ^*h \ + \qquad \text{…(10)}$$

So that,

$$= \_ \ * \quad * \quad \begin{matrix} h \\ h \end{matrix} \quad + \qquad \text{…(11)}$$

Or rewrite (11) as in (3) where the channel matrix is give as:

$$H = \begin{matrix} h & h \\ h^* & -h^* \end{matrix} \qquad \text{…(12)}$$

Now, as in figure (5), and at time n, a data block $(\ , \ )$, k = 0, 1, …, K-1 where K is the number of subcarriers, is coded into two different symbol blocks, $(\ , \ )$ {the DWT of }, i = 1,2. Then the received signal is the superposition of the transmitted signals and can be expressed as:

$$(\ , \ ) = \quad (\ , \ ) \quad (\ , \ ) + \quad (\ , \ ) \quad (\ , \ )$$

$$+ \quad (\ , \ ) \qquad \text{…(13)}$$

Again, $(\ , \ )$ denotes the channel frequency response of the multipath channel and the $k$thsubchannel between the ith transmit and receive antennas.

And previously, we assumed that the channel coefficients do not change in the interval from time to time $+ 1$(the channel gains between two adjacent subchannels are approximately equal); then $(\ , \ ) = (\ + 1, \ ) = (\ )$, and the demodulated signal $(\ , \ )$ is then decoded by the linear maximum-likelihood (ML) space-time decoder [3, 11, 13, 15]:

$$(\ , \quad) = {}^*(\ ) \ (\ , \ ) + \quad (\ ) \ {}^*(\quad + 1, \ )$$

$$(\quad + 1, \ ) = \ {}^*(\ ) \ (\ , \ )$$

$$- \quad (\ ) \ {}^*(\quad + 1, \ ) \qquad \text{…(14)}$$

Finally the estimated symbolsare obtained (see also[6, 20])so that to minimize the Euclidean distance to the received signal.

$$\hat{S}\ (\ ,\ ) = \quad |\ (\ ,\ ) - \ {}^{*}(\ )\ (\ ,\ )|$$
$$\hat{S}\ (\ +1,\ ) = \quad |\ (\ +1,\ ) - (\ )\ {}^{*}(\ +1,\ )| \qquad \ldots(15)$$

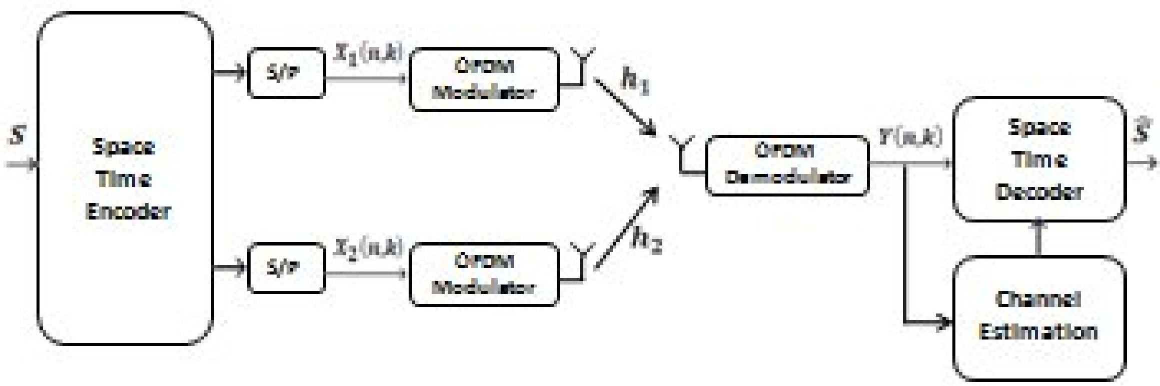

Fig.5. STBC-OFDM System Model.

3. Proposed Channel Estimation Method

3.1. MLP Predictor

The most common neural network model is the feed-forward Multi-Layered Perceptrons (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. These networks are widely used for their capability in minimizing cost functions.And among other advantages, they can be entirely made ofsimple electronic devices, such as capacitors, resistors, and operational amplifiers, also suitable for the implementation in very large scale integration(VLSI) technology. This implementation can keep the complexity of the receiver low [21], because it is not directly related to the number of additions and multiplications needed for the problem resolution.
Thus, to minimize error functions, these networks are trained, here, with the use of the RLS algorithm.

Our networkuses two hidden layers where each element *i j* of a weight ($_{ij}$) matrix represents the connection weight connecting neuron *i* of the downstream layer (i/p, hidden and o/p layers) to neuron *j* of the upstream layer.
Now,

$$\hat{S}\ (\ ,\ ) = \quad (\ )|\ (\ ,\ )| + \ (\ ) \qquad \ldots(16)$$

where $(.)$ is a sigmoid function of each neuron, expressed as, $(\ ) = \frac{}{}$, and $(\ )$ is a bias vector.

The required goal, is the learning of associations equations (15) & (16): the network must restore the desired output in (15) close to the actual one in (16). Therefore an error signal will present, $(\ )$. If an error has occurred, then only the weights on the connections from units that sent a non-zero signal to the output unit will be adjusted; i.e.

$$(\ ) = (\ ) + |\ (\ ,\ )| \qquad \ldots(17)$$

where is the target value (=1) and is the learning rate $(0 < \ < 1)$ [22].

The same thing is for $\hat{S}\ (\ +1,\ )$.

3.2. RLS Learning Algorithm

From the viewpoint of adaptive filtering theory, it is well known that the recursive least squares (RLS) algorithm is typically an order of magnitude faster than the LMS algorithm [23]. Thus, to speed up the convergence of MLP algorithm, the weightsin each layer can be adjusted using the RLS algorithm.

The RLS attempts to minimize the cost function created from the exponentially weighted and windowed sum of the squared error.
The channel estimate of $(\ )$ in (15) will be derived and updated as follows.

$$(\ ,\ ) = \sum \quad |\ (\ ,\ )| \qquad \ldots(18)$$

where the error signal (,) may be expressed as:

(,) = (,) − *( ) (,) …(19)

while denotes the forgetting factor (0 < < 1) that enables the receiver to track the change in a nonstationary environment by forgetting past observed data.

The channel estimate ( ) is the one that minimizes (,).Solving $\frac{(,)}{( )}$= 0 gives [14, 24]:

( ) = ( ) ( ) …(20)

where ( ) is an autocorrelation function which may be calculated recursively as follows:

( ) = ∑ | (,)|

= ( ) + | (,)| …(21)

while ( ) is a crosscorrelation matrix and may be expressed as:

( ) = ∑ | (,)|| (,)|

= ( ) + | (,)|| (,)|

…(22)

The same procedure is applied for (+ 1,)and (+ 1,).

4. Results and Discussion

The performance limit of MIMO-OFDM system for different antenna configuration is quantified through BER which is particularly anattractive measurement for wireless communications. A system equipped with two transmit antennas and arbitrary number of receive antennas is considered for this purpose. In the simulation scenarios the QPSK modulation is used and Rayleigh fading radio channel is assumed.

In the first simulation, the STBC is applied for two transmit antennas and different number of receive antennas to demonstrate the performance of the considered system atperfect channelknowledge.

Figure (6) shows the BER performance comparison between 2×2, 2×4 and 2×6 STBC systems. As can be observed from the figure, the 2×6 system performs better than others. For example, the BER of $8*10^{-5}$ is achieved at SNR = 2 dB for 2×6 system, whereas the same BER is achieved at SNR = 5dB for 2×4 and at SNR = 7 dB for 2×2 system. It rejects that the BER performance increases as the number of receive antennas increases for the same number of transmit antennas (see [11] to compare these results).

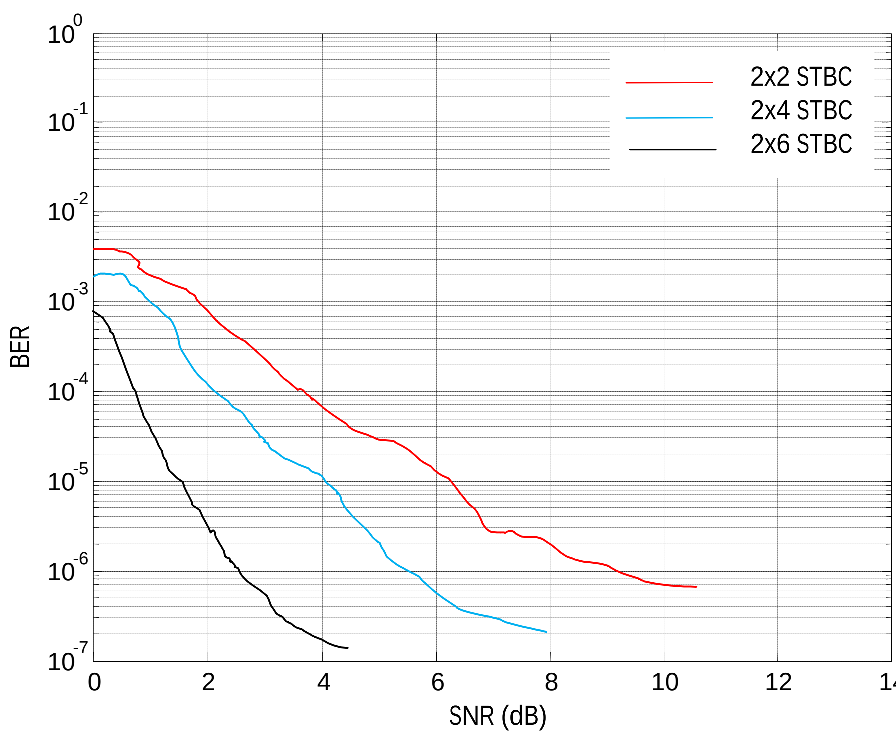

Fig.6. BER Performance Comparison between 2×2, 2×4 and 2×6 STBC Systems.

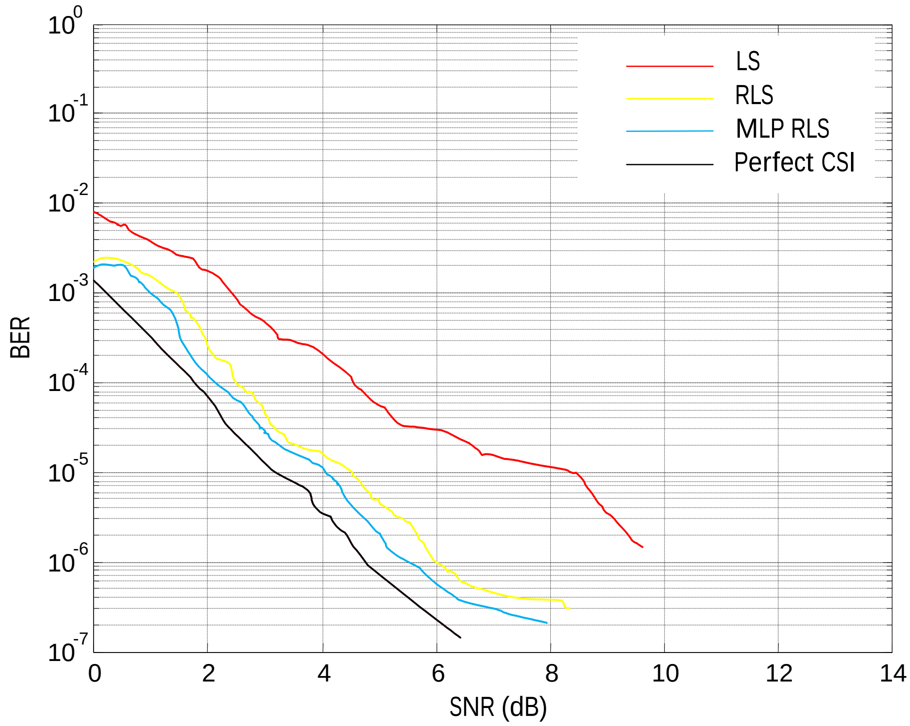

Fig.7. Performance Comparison between Different Channel Estimations.

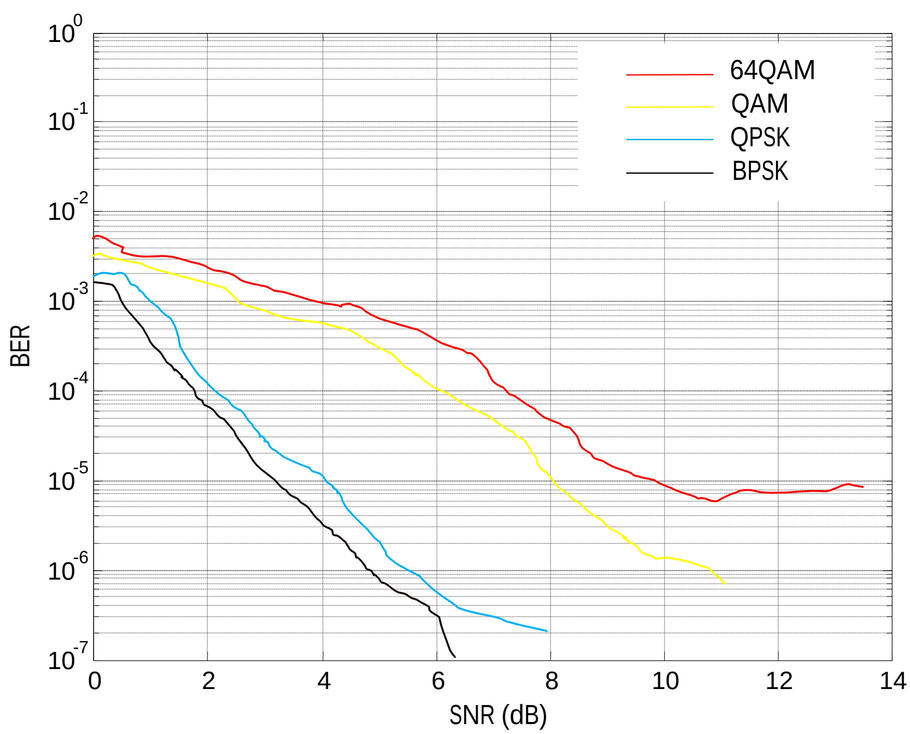

Fig.8. Performance of the Proposed Method in Different Modulation Types.

Figure (7) illustrates a performance comparison between differenttraining based channel estimations for 2×4 MIMO system. Anideal channel estimation is also calculated for comparison.From the figure,it can be observed that the BER performance of RLS estimation (with/without intelligent algorithm) isslightly worse than perfect CSI, but much better than LS estimation.

Figure (8) demonstrates the performance of the proposed channelestimation method for different modulation techniques (also under 2×4STBC system). As seen in this figure for a certain level of BER (say $1*10^{-4}$), different values obtained of SNR against the corresponding modulation type; 1.78 dB (BPSK), 2.31 dB (QPSK), 5.95 dB (QAM) and 7.16 dB (64QAM).

5. Conclusion

The results of our study can be summarized briefly as follows:

1. An RLSbased MLP algorithm for complex valued neuralnetwork is fully derived.
2. The derived algorithm has been tested over multipath communication channels and implemented using a DWT. The need to this transform is to mitigate theserious interferences, ISI and ICI appeared while usingthe FFT; also there is no need to insert a cyclic prefix between OFDM symbols and then this will eliminate the bandwidth.

   Moreover, the proposed model performance isalso found to be consistent under different signal constellations, and compared with the conventional LS algorithm as described in figures (7&8).
3. The use of the RLSbased MLP for complex valued neuralnetwork has resulted in substantial improvements in termof BER.It is proved that this rate is reduced in all cases as explained previously in the comments on figures (6&7).

6. References

[1] Feng Wan et al, A Semiblind Channel Estimation Approach for MIMO-OFDM Systems, IEEE Transactions on Signal Processing, Vol. 56, No. 7, July 2008.

[2] M. Mitra, Investigating the Impact of Spectrum Efficient of OFDM-MIMO and MC-CDMA-MIMO Communication System for ITS, Journal of Theoretical and Applied Information Technology (JATIT), 2010.

[3] Kala Praveen Bagadi, MIMO-OFDM Channel Estimation Using Pilot Carries, International Journal of Computer Applications (0975 – 8887), VOL. 2, No.3, May 2010.

[4] Eth Zurich, MIMO-OFDM Wireless Systems: Basics, Perspectives, and Challenges, IEEE Wireless Communications, August 2006.

[5] Jari Ylioina, Iterative Detection, Decoding, and Channel Estimation in MIMO-OFDM, Academic dissertation to be presented with the assent of the Faculty of Technology of the University of Oulu for public defense in Auditorium IT116, Linnanmaa, on 10 June 2010.

[6] V. Le Nir et al, Combination of Space-Time Block Coding with MC-CDMA Technique for MIMO systems with two, three and four transmit antennas, European Union IST research project MATRICE (Multicarrier CDMA Transmission Techniques for Integrated Broadband Cellular Systems), 2002.

[7] Marcello Cicerone, Channel Estimation for MIMO-OFDM Systems by Modal Analysis/Filtering, IEEE Transactions on Communication, Vol. 54, No. 11, November 2006.

[8] Yong Xu et al, Generalized RLS Approach to the Training of Neural Networks, IEEE Transactions on Neural Networks, Vol. 17, No. 1, January 2006.

[9] F. Sarabchi, and M. E. Kalantari, Space Time Processing with Adaptive STBC-OFDM Systems, World Academy of Science, Engineering and Technology 2009.

[10] Yuri Labrador et al, OFDM MIMO Space Diversity in Terrestrial Channels, IJCSNS International Journal of Computer Science and Network Security, Vol.9, No.10, October 2009.

[11] M. T. Islam et al, Performance and Complexity Improvement of Training Based Channel Estimation in MIMO Systems, Progress In Electromagnetics Research C, Vol. 10, 1-13, 2009.

[12] Ye (Geoffrey) Li et al, MIMO-OFDM for Wireless Communications: Signal Detection with Enhanced Channel Estimation, IEEE Transactions on Communication, Vol. 50, No. 9, September 2002.

[13] Yonghong Zeng et al, Semiblind Channel Estimation and Equalization for MIMO Space-Time Coded OFDM, IEEE Transactions on Circuits and Systems-I: Regular Papers, Vol. 53, No. 2, February 2006.

[14] Jos Akhtman and LajosHanzo, Advanced Channel Estimation for MIMO-OFDM in Realistic Channel Conditions, IEEE Transactions on Communication,1-4244-0353 7/07/$25 ©IEEE 2007.

[15] İlhan BAŞTÜRK, Iterative Channel Estimation Techniques for Multiple Input Multiple Output Orthogonal Frequency Division Multiplexing Systems, Thesis (Master of Science), Graduate School of Engineering and Sciences of İzmir Institute of Technology, July 2007.

[16] B.G. Negash and H.Nikookar, Wavelet Based OFDM for Wireless Channels, International Research Center for Telecommunications-Transmission and Radar Faculty of Information Technology and Systems, Delft University of Technology, 0-780~-6728-6/010.000/2001 IEEE.

[17] M. K. Lakshmananand H. Nikookar, A Review of Wavelets for Digital Wireless Communication, Wireless Personal Communications (2006) 37: 387–420, DOI: 10.1007/s11277-006-9077-y, Springer 2006.

[18] Khaizuran Abdullah and Zahir M. Hussain, Studies on DWT-OFDM and FFT-OFDM Systems, International Conference on Communication, Computer and Power (ICCCP), Muscat, February 15-18, 2009.

[19] HelkaMäättänen, MIMO-OFDM, S-72.333 Postgraduate Course in Radio Communications.

[20] Somkiat Lerkvaranyu and Yoshikazu Miyanaga, ML Detection with Symbol Estimation for Nonlinear Distortion of OFDM Signal, World Academy of Science, Engineering and Technology 2, 2005.

[21] Romano Fantacci et al, A Neural Network Approach to MMSE Receivers in a DS-CDMA Multipath Fading Environment, IEEE Transactions on Communications, Vol. 54, No. 5, May 2006.

[22] S. N. Sivanandam and M. Paulraj, Introduction to Artificial Neural Networks, Book, Vikas Publishing Hous PVT LTD, 2004.

[23] Azzedine Zerguine et al, Recursive Least-Squares Backpropagation Algorithm for Stop-and-Go Decision-Directed Blind Equalization, IEEE Transactions on Neural Networks, Vol. 13, No. 6, November, 2002.

[24] Yohei Kojima et al, RLS Channel Estimation with Adaptive Forgetting Factor for DS-CDMA Frequency-Domain Equalization, IEICE Transactions on Communications, Vol. E92-B, No. 5, May 2009.

تحسين أداء تقديرات القناة باستعمال الشبكة العصبية لتدريب خوارزمية تكرار أقل الأجزاء لتقدير العنصر في أنظمة مزج تقسيمات التردد المتعامد المتعدد الادخالات المتعدد الاخراجات

علاء عبدالأمير حسن
قسم هندسة الميكاترونكس/ كية الهندسة الخوارزمي/ جامعة بغداد
البريد الالكتروني: alaa_ah76@yahoo.com

الخلاصة

أن موضوع هذه الدراسة كان لتقديم خوارزمية تكرار أقل الأجزاء لتقدير العنصر المعتمدة بأستخدام الشبكات العصبية كطريقة لتسهيل أداء وأحتساب معدل الخطأ (أقل أقصاء التطبيق لخوارزمية التقدير لقنوات نظام مزج تقسيمات التردد المتعامدة المتعدد الأدخالات المتعدد الأخراجات عبر قناة البهت متعدد المسار (رايلييف). أن خوارزمية تكرار أقل الأجزاء يمكن أعتبارها فعالة جداً لتدريب الشبكة العصبية : أولاً من حيث تدريب الشبكة العصبية لتقدير تغييرات القناة بأستمرار، ثم تقدير أستجابة القناة للتأخير. أظهرت نتائج التمثيل للطريقة المعتمدة أداءاً "جيداً" إذا ما قورنت الطريقة بغيرها من الطرق الأخرى كخوارزمية أقل الأجزاء (تكرار أقل الأجزاء التقليدية وغير الذكية). أظهر الطريقة المعتمدة كذلك كفاءة في فعاليات النظام السريعة.