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A REVIEW ON CHANNEL ESTIMATION USING BP NEURAL NETWORK FOR OFDM

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ABSTRACT

OFDM systems are limited by multipath fading. Previously channel estimation was carried out by transmitting pilot symbols in OFDM .The techniques used were comb type pilot arrangement and block type arrangement using LSE, MMSE etc. In this paper we are providing review of using neural network (BPN) based approach for estimation and comparing it with both LSE and MMSE. BPN makes use of learning property of neural network and is more efficient because is less complex than pilot based technique. This paper provides survey of available literature of some methodologies employed by different researchers to utilize ANN for channel estimation.

KEYWORDS: Artificial neural network (ANN), Back Propogation Neural Network (BPN), LSE , MMSE , OFDM.

INTRODUCTION

Orthogonal frequency-division multiplexing (OFDM) is high bit rate multicarrier modulation technique used for combating the effect of multipath fading. It is based on concept of frequency division multiplexing .It divides the total signal bandwidth into subcarriers and carriers are orthogonal to each other on which data is being transmitted. OFDM has many advantages such as high spectral efficiency ,low complex receivers ,high data rate transmission, robust to frequency selective fading .To estimate channel parameters there are various techniques such as blind ,semi blind and pilot based channel estimation techniques .In Blind estimation techniques we do not have knowledge of transmitted data and no training sequence is required. Where bandwidth is limited mostly blind estimation technique is used which makes use of underlying mathematical property of sent data. In pilot based estimation wastage of bandwidth is there due to insertion of pilots. Pilots are being sent in each data frame and then estimation of channel parameter is carried out with help of received pilot signals.

Various channel estimation technique for pilot based estimation are Least square error (LSE), Minimum mean square error (MMSE), Least mean square (LMS). LSE estimation is less complex and has better performance but suffers from high Mean square error (MSE) at low signal to noise ratio (SNR).MMSE algorithm has better MSE performance than LSE but at the same time is more complex. Neural network can be also implemented for channel estimation.

Implementation of these algorithms has been done by some researchers. According to work in [1] MLP(Multilayer Perceptron) neural network are trained using channel impulse response obtained by assistance of pilot symbols and are used as channel estimator.MLP estimator have better performance in terms of MSE and BER than LSE and RBF neural network. MMSE algorithm has better performance but this network does not need channel statistics and noise information which is problem in real time transmission. In [2] BPN algorithm is used as channel estimator which has better performance than ideal channel parameters, no channel parameters and Added Pilot Semi-Blind channel estimation (APSB).The comparison have been done in presence of Rayleigh fading and Rician fading channel with different modulation technique such as 4-PSK,8-PSK but has the disadvantage of computational complexity of neural network algorithm and small extra Bandwidth requirement. In [3] it is given that BPN network has better performance than conventional equalizer for channel estimation when their BER and MSE comparison is done. In [4] [5] Levenberg -Marquardt (LM) algorithm was used for channel estimation over Rayleigh fading channel using different modulation schemes .It has better performance than low pass, second order and decision feedback.

In this paper we implemented Back Propagation neural network (BPN) channel estimator as alternative to Comb type pilot arrangement (LSE, MMSE) estimator.BPN makes use of learning property of neural network. We have compared the performance using 16 QAM modulations over Rayleigh fading channel then we found that it has better performance than LSE but not MMSE which has more complex implementation and mathematical calculations

The rest of paper is organized as follows: - In section 2, system description is there which covers OFDM and Channel estimation techniques (LSE, MMSE, and BPN). In section 3 system design is given, section 4 consist of result and discussion, section 5 is conclusion.

SYSTEM DESCRIPTION

A. OFDM

In OFDM at transmitter side initially serial binary data is modulated by using appropriate modulation scheme. Then modulated data is converted from serial to parallel. Pilot symbols are inserted in serial to parallel converted data to get channel impulse response. After pilot symbols are inserted then IFFT of data is taken to transform modulated symbol S (k) into time domain signal s (n) and is given by:

$$s(n) = \mathrm{IFFT}\{S(k)\}, \quad n = 0, 1, 2 \ldots, N-1 \quad (1)$$

$$= \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} S(k) e^{j2\pi kn/N}$$

where N is number of subcarriers, n is sample number. After IFFT is taken then cyclic prefix is inserted which is copy of the end part of that symbol to prevent inter symbol interference. The symbol extended with cyclic prefix is given as:

$$S_t(n) = \begin{cases} s(N+n), & n = -N_c, -N_c+1, \ldots, -1 \quad (2) \\ s(n), & n = 0, 1, \ldots, N-1 \end{cases}$$

where N_c is length of cyclic prefix. The resultant signal is transmitted over channel and noise is added to it which is given by:

$$Y_t(n) = s_t(n) \otimes h(n) + w(n) \quad (3)$$

h(n) is impulse response of channel, w(n) is AWGN.

Now at receiver side, firstly the cyclic prefix is removed. Then the signal y(n) without cyclic prefix is applied to FFT to get frequency domain signal Y(k) given by:

$$Y(k) = \mathrm{FFT}\{y(n)\} \quad k = 0, 1, 2, \ldots, N-1 \quad (4)$$

$$= \frac{1}{N} \sum_{n=0}^{N-1} y(n) e^{-j2\pi kn/N}$$

After FFT block demodulated signal is given by

$$Y(k)=S(k)\,H(k) + W(k) \quad (5)$$

H(k) is channel impulse response in frequency domain and is estimated by channel estimation. This is the reason why channel estimation is necessary.

B. Channel Estimation

Channel estimation is a method to inverse the channel effect or for characterizing the effect of transmission media on data sent. Basically in pilot based estimation pilot symbols are inserted and measured at receiver.

In this paper we used LSE, MMSE and BPN algorithm for estimation which are described below:

B1. Least Square Algorithm

Least square algorithm is approach to approximate solution of equations sets in which number of equations are more than unknowns and minimizes the sum of squares of error for each equation. Its implementation is easy but has poor performance. The LS channel estimate[7-8] for each subcarrier can be written as:

$$H_{LS}(k) = \frac{Y(K)}{S(K)}, \quad k=0,1,\ldots\ldots,N-1 \quad (6)$$

B2. *Minimum Mean Square Algorithm*

It minimizes the mean square error (MSE) [9-12] and is obtained by:

$$H_{MMSE} = F\,R_{hY}\,R^{-1}_{YY}\,Y \quad (7)$$

$$Y=SFh + W = SH + W \quad (8)$$

where ,

$$S=\mathrm{diag}\,\{S(0),S(1),\ldots\ldots S(N-1)\}$$

$$Y= [Y(0),Y(1),\ldots\ldots\ldots\ldots Y(N-1)]^T$$

$$W= [W(0),W(1),\ldots\ldots\ldots\ldots W(N-1)]^T$$

$$H= [H(0),H(1),\ldots\ldots\ldots\ldots H(N-1)]^T$$

$$R_{hY}= E\{hY\} = R_{hh}\,F^H\,S^H \quad (9)$$

$$R_{YY}= E\{YY\} = SFR_{hh}\,F^H\,S^H + \sigma^2\, I_N \quad (10)$$

design respectively the covariance matrix between h & Y and auto-covariance matrix of Y. R_{YY} is auto-covariance matrix of h & σ^2 is noise variance of $E\{|w(k)|^2\}$.

B3. *BPN Algorithm*

BPN is based on[6] [13] Gradient descent method and is one of the most popular learning algorithm in neural network. It is in real domain and minimizes the sum of squared error between actual and desired value. It is a multilayer feed forward network consisting of one input layer, number of hidden layer and one output layer. Neurons present in output and hidden layer also have biases and weights. Training of BPN is done in three phases

(i) Feed forward of input training pattern

(ii) Calculation and back propagation of error
(iii) Updation of weights

Even if the training is very slow, the output can be produced very rapidly once network is trained.Each output unit receives target pattern corresponding to input training pattern and computes error correction term

$\S_k = (t_k - y_k)\, f'(yin_k)$, k= 1,2……m (11)

where y_{in} is net input for each output unit y_k ,t is target, f is activation function which can be bipolar/binary sigmoid and m is output neuron units.
Weight and bias update is given by:

$$w_{jk}(new)= w_{jk}(old) + \Delta w_{jk} \quad (12)$$
$$\Delta w_{jk} = \alpha \S_k\, z_j, \; j= 1,2,\ldots\ldots..p \quad (13)$$
$$w_{ok}(new)= w_{ok}(old) + \Delta w_{ok} \quad (14)$$
$$\Delta w_{ok} = \alpha \S_k \quad (15)$$

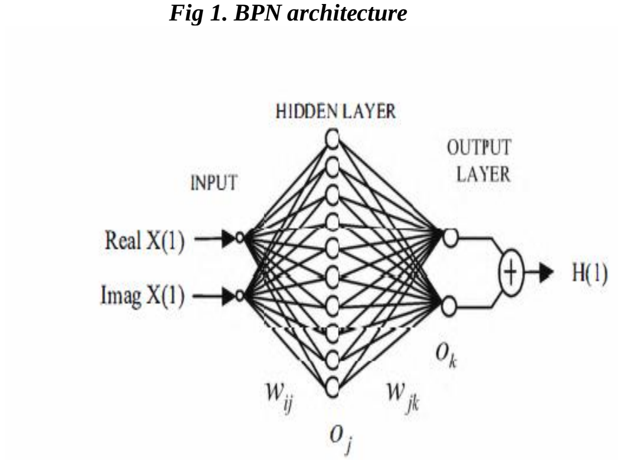
α is learning rate, p is hidden neuron units , w_{jk} and w_{ok} are updated weights and biases, Δw_{jk} and Δw_{ok} are weight and bias updation term.
Now in hidden layer the weights and biases are also updated in same way. Error correction term which is propagated to hidden layer and output layer is given by:

$$\S_j = \S_{inj}\, f'(zin_j) \quad (15)$$
$$\S_{inj} = \sum_{k=1}^{m} \S k\, wjk \quad (16)$$

Weight and bias update at hidden layer are given by:

$$V_{ij}(new) = V_{ij}(old) + \Delta V_{ij} \quad (17)$$
$$V_{oj}(new) = V_{oj}(old) + \Delta V_{oj} \quad (18)$$

Fig 1. BPN architecture



SYSTEM DESIGN

In our model we basically transmit OFDM symbols frame by frame through Rayleigh fading channel .On receiver side channel estimation is carried out initially by LSE and MMSE algorithm. After using pilot based estimation we use BPN neural network as a channel estimator. For that we use symbols at transmitter as target data and symbols at receiver after FFT as training data. The data we are using for training and target both are complex in nature so we separate real and imaginary part. We designed BPN architecture having three layers i.e. input layer, hidden layer and output layer. In input layer only data is transmitted forward and acts as interface.
The input layer has two input one for real part of signal and other for imaginary part of signal same as output layer .The separated signals are given as input to network and network is trained as we have explained above. For this separated signal we calculate output which is the impulse response of channel. The activation function we are using is sigmoid function. The weights are initialized with pseudorandom value and learning rate is chosen between 0 & 1.We take learning rate 0.05 value for training of network. The training is finished if error between actual output and original training sequence is less than the predetermined value or maximum numbers of epochs are reached.

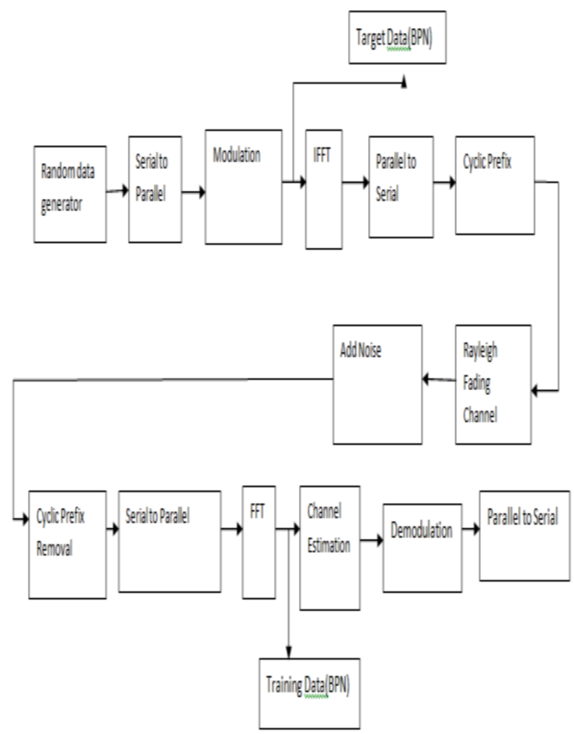


Fig 2. System model for simulation

In working phase the received data signal is taken as input to network and the output we get is equalized data signal.

RESULT AND DISCUSSION

In this paper simulation are carried to compare the performance of LSE, MMSE and BPN algorithm. The criteria for comparing the performance are BER versus SNR graph and MSE verses SNR graph

.Parameters for simulation are given in Table 1 below.

Table 1

SNO	Parameters	Value
1	***Number of Subcarriers***	***256***
2	***FFT and IFFT size***	***256***
3	***Guard Length***	***16***
4	***Modulation Technique***	***16 QAM***
5	***Noise Model***	***AWGN***
6	***Channel Type***	***Rayleigh fading***
7	***Epochs***	***500***
8	***Learning Rate***	***0.05***
9	***Average SNR***	***0:40***

The channel used is 6-tap Rayleigh fading channel. Fig 3. shows that estimation based on BPN has better performance than LSE and somewhat near to MMSE which is same as implemented by researchers given in review above.

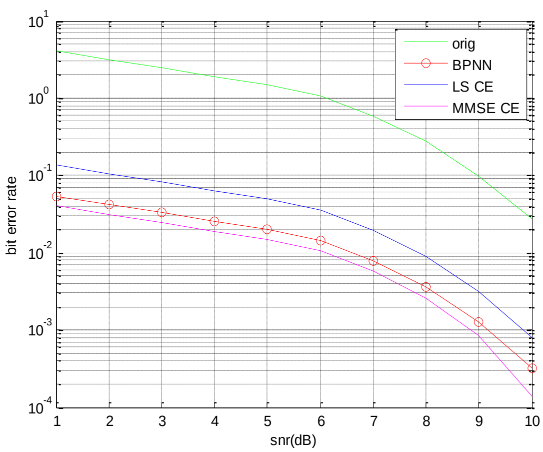


Fig 3. BER comparision of BPN with LS and MMSE

Fig 4. shows the MSE graph which shows that BPN and MMSE has lower mean square error than LSE.

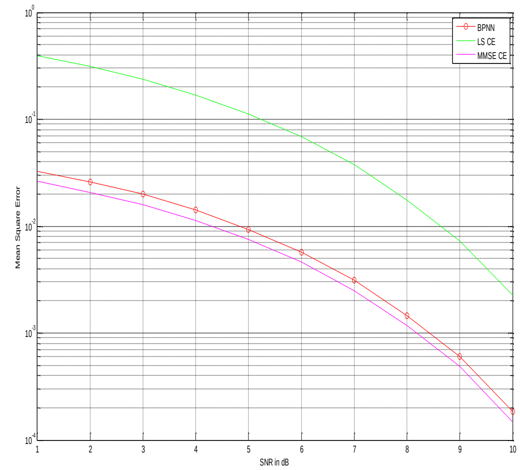


Fig 4. Comparision of MSE performances

CONCLUSION

This paper presents survey that using ANN for channel estimation provides better results when compared to other channel estimation techniques. When we implemented BPN as channel estimator for comparison with pilot based estimation techniques it yield the same result as we have researched. So it could be inferred that using BPN as channel estimator provides better performance than LSE .Also transmission of pilot symbols ,noise information and channel statistics are not needed which are necessary for a MMSE algorithm.

REFERENCES

[1] Necmi Taspmar, and M. Nuri Seyman, "Back Propagation Neural Network Approach for Channel Estimation in OFDM System, " Wireless Communications, Networking and Information Security (WCNIS), 2010 IEEE International *Conference* on, pp. 265-268, June 2010

[2] Mohamed M. A. Moustafa, Salwa H. A. El-Ramly, "Channel Estimation and Equalization Using Backpropagation Neural Networks in OFDM Systems", 978-1-4244-3474-9/09/2009 IEEE.

[3] E. Chen , R. Tao and X. Zhao "Channel equalization for OFDM system based on the BP neural network", *Proc. Int. Conf. Signal Process.*, vol. 3, 2006

[4] Chia-Hsin Cheng, Yung-Pei Cheng, Yao-Hung Huang,Wen-Ching Li, "Using Back Propagation Neural Network for Channel Estimation and Compensation in OFDM Systems", International

Conference on Complex, Intelligent, and Software Intensive Systems, IEEE2013

[5] Cebrail Cifliki,A. Tuncay Ozsahin,A.Cagri Yapici, “Artificial Neural Network Channel Estimation Based on Levenberg Marquardt for OFDM Systems”,Wireless Pers Commun(2009) 51:221-229 DOI 10.1007/S 11277-008-9639-2

[6] de Villiers, J.; Barnard, E., "Backpropagation Neural nets with One and Two Hidden Layers". IEEE Transactions on Neural Networks IEEE Trans. Neural Networks (USA), vol.4, (no.1), Jan

[7] S. Y. Park, Y. G. Kim, C. G. Kang, and D. E. Kang, "Iterative receiver with joint detection and channel estimation for OFDM system with multiple receiver antennas in mobile radio channels," Proc. IEEE GLOBECOM, 2001, pp. 3085 - 3089, November 2001.

[8] C. Li and S. Roy, "Subspace based blind channel estimation for OFDM by exploiting virtual carrier," Proc. IEEE GLOBECOM, 2001, pp. 295 - 299, November 2001.

[9] Y. Xie and C. N. Georghiades, "An EM-based channel estimation algorithm for OFDM with transmitter diversity," Proc. IEEE GLOBECOM, 2001, pp. 871 - 875, November 2001.

[10] C. K. Ho, B. Farhang-Boroujeny, and F. Chin, "Added pilot semiblindchannel estimation scheme for OFDM in fading channels," Proc. IEEE GLOBECOM, 2001, pp. 3075 - 3079, November 2001.

[11] Y. Li, "Simplified channel estimation for OFDM systems with multiple transmit antennas," IEEE Trans. Wireless Communications, vol. 1, pp. 67 - 75, January 2002.

[12] K. I. Ahmed, C. Tepedelenlioglu, and A. Spanias, "On the performance of optimal training-based OFDM with channel estimation error," Proc. IEEE GLOBECOM, 2004, December.

[13] J. H. Manton, "Optimal training sequences and pilot tones for OFDM systems," IEEE Communications Letters, vol. 5, pp. 151 - 153, April 2001

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