2012 International Conference on Conference on Signal Processing Systems (ICSPS 2012)
IPCSIT vol. 58 (2012) © (2012) IACSIT Press, Singapore
DOI: 10.7763/IPCSIT.2012.58.4

Enhanced Channel Estimation Technique for MIMO-OFDM Based Communications Using Neuro Fuzzy Approach

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Abstract. Multiple-input multiple-output (MIMO) system using orthogonal frequency division multiplexing (OFDM) technique has become a promising method for reliable high data-rate wireless transmission system in which the channel is dispersive in both time and frequency domains. Due to multiple co-channel interferences in a MIMO system, the accuracy of channel estimation is a vital factor for proper receiver design in order to realize the full potential performance of the MIMO-OFDM system. In this paper, we investigate an enhanced channel estimation technique for MIMO-OFDM based systems using neuro fuzzy approach. To validate the performance of our proposed method, several simulation results are given and compared with those of other methods. When considering the time-varying velocity of the mobile station communication in the MIMO-OFDM system, the enhanced equalizer based on the Takagi-Sugeno (T-S) fuzzy-based neural network performs better than those based on the conventional channel estimators in terms of symbol error rate.

Keywords: OFDM, multiple-input multiple-output (MIMO), takagi-sugeno (T-S), channel estimation, interference.

1. Introduction

High data-rate and reliable transmissions with bandwidth efficiency are the requirements for future wireless communication systems. Multiple-input multiple-output (MIMO) system in which multiple antennas are used in both transmitter and receiver sides is an emerging scheme that is potentially able to provide high data-rate communications with bandwidth efficiency. Also, orthogonal frequency division multiplexing (OFDM) technique, which uses super symbols with a cyclic prefix inserted between them, overcomes the inter-symbol interference (ISI) phenomenon that is one of main challenging issues in reliable wireless transmissions at high data-rate. Thus, a combination of the MIMO scheme and the OFDM technique termed MIMO-OFDM that exploits space and frequency diversities is a good candidate transmission system for future wireless communications [1]-[4].In MIMO OFDM, the channel parameters between each transmit-receive antenna pair are required for coherent detection, and the received signals are superposition of signals transmitted from different transmit antennas simultaneously, which give rise to challenges of channel estimation [5]. When the channel parameters are varying within an OFDM block, the channel estimation requires intensive computation [6].

The frequency selective fading, is caused by multipath could lead to carriers used, being heavily attenuated due to destructive interference at the receiver. The result of this is the carriers being lost in the noise. To increase performance of OFDM system under frequency selective channels; the channel estimation is required before demodulation of OFDM signals. The channel estimation is a process of characterizing the effect of the transmission medium on the input signal. Channel estimation is a crucial and challenging issue in coherent modulation and its accuracy has a significant impact on the overall performance of

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communication system. The channel estimation in MIMO systems becomes more complicated in comparison with single-input single-output systems due to simultaneous transmission of signals from different antennas that cause co-channel interference. This issue highlights that developing channel estimation algorithm with high accuracy is an essential requirement to achieve the full potential performance of the MIMO-OFDM systems.

In this paper, we propose an artificial neural network (ANN) with fuzzy logic based on channel estimation technique as an alternative to Block type pilot based channel estimation technique for OFDM systems over Rayleigh fading channels. The Simulation results show that neuro fuzzy based on channel estimator gives better results as compared to Block type pilot based channel estimator for OFDM systems over the Rayleigh fading channel.

The organization of this paper is as follows. In section 2, description of OFDM system model is given. ANN with fuzzy based channel estimator is described in section 3. Simulation results are offered in section 4 and finally, section 5 Concludes the paper.

2. System model

The system model is given in Fig.1. A MIMO-OFDM system with Ntx transmit and Nrx receive antennas is assumed. The system has K subcarriers in an OFDM block. The incoming bits are modulated to form Xi[n, k], where i is the indexing for transmit antenna, n is the OFDM symbol number, and k is the subcarrier. For each modulated signal, an Inverse Fast Fourier Transform (IFFT) of size K is performed, and the CP is added to mitigate for the residual ISI due to previous OFDM symbol. After parallel-to-serial (P/S) conversion, signal is transmitted from the corresponding antenna.

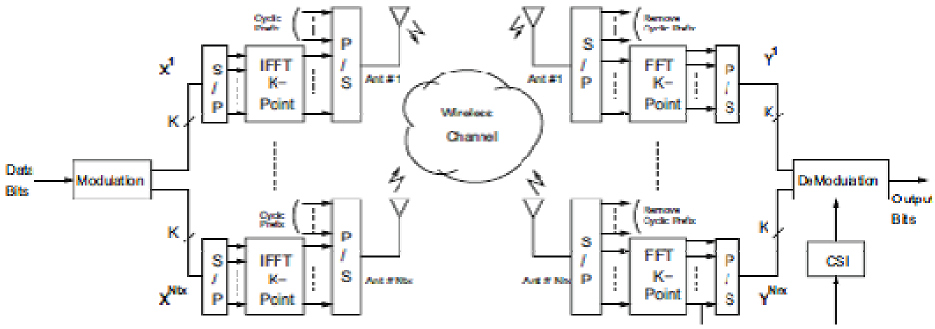

Fig. 1: MIMO-OFDM transceiver model.

The lth subcarrier received vector at time k is given by

$$y^{(l)}(k) = H^{(l)} s^{(l)}(k) + n^{(l)}(k) \qquad l = 1, 2, \ldots, L \tag{1}$$

where, $y^{(l)}(k) = \left[y_1^{(l)}(k), y_2^{(l)}(k), \ldots\ldots, y_M^{(l)}(k)\right]^T$ is a $M \times 1$ vector, $(\cdot)^T$ stands for transposed operation, $H^{(l)}$ is the $M \times N$ lth sub-channel matrix whose ijth element is $H_{ij}^{(l)}$, $s^{(l)}(k) = \left[s_1^{(l)}(k), s_2^{(l)}(k), \ldots\ldots, s_N^{(l)}(k)\right]^T$ is the N x 1transmitted signal vector from lth sub-channel $n^{(l)}(k) = \left[n_1^{(l)}(k), n_2^{(l)}(k), \ldots\ldots, n_M^{(l)}(k)\right]^T$ is the $M \times 1$ vector of the complex additive white Gaussian noise (AWGN) with zero – mean and autocorrelation matrix $R_{n1} = N_0 I_M$ for $l=1,2,\ldots,L$ while I_M is the $M \times M$ identity matrix. $y_i^{(l)}(k)$, each element of $y^{(l)}(k)$, can be given as

$$y_i^{(l)}(k) = H_i^{(l)} s^{(l)}(k) + n_i^{(l)}(k) \qquad i = 1, 2, \ldots, M, \quad l = 1, 2, \ldots, L \tag{2}$$

where $H_i^l = \left[H_{i1}^{(l)}, H_{i2}^{(l)}, \dots\dots, H_{iN}^{(l)}\right]^T$ is the ith row of $H^{(l)}$ matrix. To expand thr Eq (2) for l=1,2,…….L, we define $y_i(k) = \left[y_i^{(1)}(k), y_i^{(2)}(k), \dots\dots, y_i^{(L)}(k)\right]^T$ that can be given as

$$y_i(k) = \begin{bmatrix} H_i^{(1)} & 0_{1\times N} & 0_{1\times N} & 0_{1\times N} \\ 0_{1*N} & H_i^{(2)} & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ 0_{1*N} & 0_{1*N} & 0_{1*N} & H_i^{(L)} \end{bmatrix} \begin{bmatrix} s^{(1)}(k) \\ s^{(2)}(k) \\ \vdots \\ s^{(L)}(k) \end{bmatrix} + n_i(k) \qquad i = 1, 2, \dots, M \tag{3}$$

Where $n_i(k) = \left[n_i^{(1)}(k), n_i^{(2)}(k), \dots\dots, n_i^{(L)}(k)\right]^T$ and $0_{i\times j}$ is the $i \times j$ zero matrix. By defining $S_j(k) = \text{diag}\left(s_j^{(1)}(k), s_j^{(2)}(k), \dots\dots, s_j^{(L)}(k)\right)$ and $H_{ij} = \left[H_{ij}^{(1)}, H_{ij}^{(2)}, \dots\dots, H_{ij}^{(L)}\right]^T$ for i= 1,2,…….,M and j = 1, 2, . . .,N , Eq.(3) can be written in the following form where $X(k) = [S_1(k), S_2(k), \dots\dots S_N(k)]$ is a L ×LN matrix and $H_i = \left[H_{i1}^T, H_{i2}^T, \dots\dots, H_{iN}^T\right]^T$ is a LN ×1 column vector

$$y_i(k) = X(k)H_i + n_i(k) \qquad i = 1, 2, \dots, M \tag{4}$$

To estimate the H_i vector uniquely, receiving a vector with N successive $y_i(k)$ single is needed. Defining $Y_i(k) = [y_i(k)^T,\ y_i(k-1)^T, \dots\dots y_i(k-N+1)^T]^T$ we have

$$Y_i(k) = X(k)H_i + z_i(k) \qquad i = 1, 2, \dots, M \tag{5}$$

Where

$$X(k) = [X(k)^T, X(k-1)^T, \dots\dots . X(k-N+1)^T]^T$$

$$z_i(k) = [n_i(k)^T, n_i(k-1)^T, \dots\dots\dots . n_i(k-N+1)^T]^T$$

3. Adaptive Neuro – Fuzzy Inference System (ANFIS)

ANFIS is functionally equivalent to a fuzzy inference system. Jang first proposed the ANFIS based on the Sugeno fuzzy model. The network structure of ANFIS is shown in Fig. 2. ANFIS consists of five layers: fuzzy membership, fuzzification, normalization, defuzzification, and output [7] , [8]. The number of nodes in the fuzzification layer represents the number of fuzzy rules. Nodes of the same layer have similar functions. In general, ANFIS is trained by supervised training methods. The training set consists of inputs xi (i = 1,2, …, N), and their expected targets yi, where xi denotes an input vector with n variables, and N denotes the number of samples. A typical j-th fuzzy rule in a Sugeno model with n-dimensional input vector xi has the following:

If xi1 is Uj1 and … and xik is Ujk and … and xin is Ujn, then output is $f_j(x_i) = \alpha_{j0} + \sum_{k=1}^{n} \alpha_{jk}\, x_{ik}$ where Ujk represents the fuzzy set of the j-th rule, and the k-th input variable in the antecedent layer are defined separately for each rule and each input variable; , $f_j(x_i)$ represents the output function of the fuzzy rule as a crisp function in the consequent layer. Furthermore, ajk represents the linear parameter of the output function $f_j(x_i)$ belonging to the j-th rule and the k-th input variable. Usually, $f_j(x_i)$ is a polynomial of the input variable x_i. The working regions of the fuzzy rules are defined by the membership functions of the antecedent layer. The overall output of the system is obtained from the weighted sum of the fuzzy rule outputs.

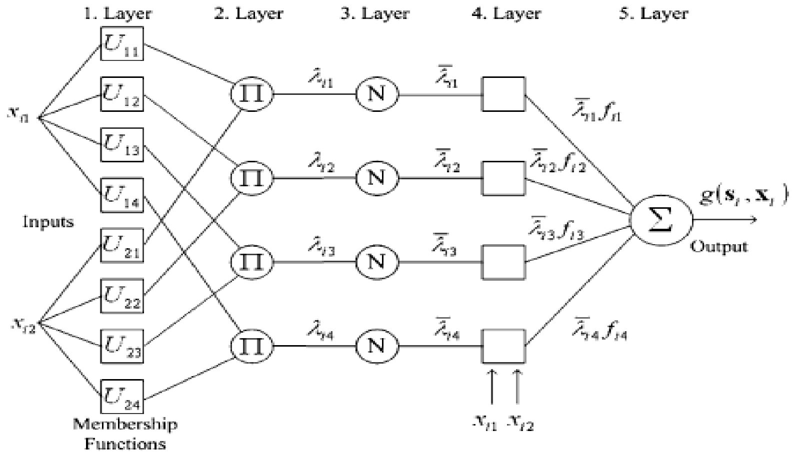

Fig. 2: ANFIS architecture.

Figure 2 illustrates the first-order Sugeno fuzzy inference system that has two rules and two input variables:

Rule 1: If xi1 is U11 and xi2 is U12, then $f_1(x_i) = \alpha_{10} + \alpha_{11}x_{i1} + \alpha_{12}x_{i2}$

Rule 2: If xi1 is U21 and xi2 is U22, then $f_2(x_i) = \alpha_{20} + \alpha_{21}x_{i1} + \alpha_{22}x_{i2}$

3.1. Layer 1 (Fuzzy membership layer)

Each node in this layer generates membership grades of inputs for fuzzy sets. The output of the j-th rule and the k-th input variable node are generated by different membership functions, such as the generalized bell, sigmoidal, and Gaussian membership functions [8]. The Gaussian membership function has continuous derivatives relating to the

cost function. Here, we derive the expressions by including the Gaussian membership function:

$$\beta_{ijk} = \exp\left(-0.5\left(\frac{x_{ik} - \mu_{jk}}{\sigma_{jk}}\right)^2\right)$$

Where xik represents the k-th variable of the i-th input sample; and, the mean μjk and the variance σjk are the nonlinear parameters of the membership function βijk. These are referred to as the antecedent (premise) parameters of the ANFIS and are adjusted in the training process.

3.2. Layer 2 (uzzification layer)

The firing strengths of each rule are obtained from the product of the membership grades of the fuzzy sets.

Thus, the output of the j-th rule for i-th input vector is given by

$$\lambda_{ij} = \prod_{k=1}^{n} \beta_{ijk}$$

where λij denotes the firing strength of the i-th input vector and the j-th rule.

3.3. Layer 3 (Normalization layer)

ANFIS is essentially based on the Sugeno model, which makes use of the weighted average de-fuzzification method. At times, the sum of the firing strengths of the rules in layer 2 may be greater than 1 or close to 0. If the sum of the firing strengths is not close to unity, the meaning of membership functions could be lost .To prevent such a loss, the firing strength kij is normalized with the sum of the firing strengths. In this layer, the output of each node is given as:

$$\overline{\lambda_{ij}} = \frac{\lambda_{ij}}{\sum_j \lambda_{ij}} \qquad j = 1, 2,\ldots\ldots\ldots\ldots r.$$

where r represents the number of rules, and $\overline{\lambda_{ij}}$ represents the normalized firing strength of the j-th rule.

3.4. Layr 4 (Defuzzification layer)

This layer combines the normalized firing strengths of the rules and the values of the linear polynomials fj(xi). The output of each node is given by:

$$\overline{\lambda_{ij}} f_j(x_i) = \overline{\lambda_{ij}}\left(\alpha_{j0} + \sum_{k=1}^{n} \alpha_{jk} x_{ik}\right)$$

3.5. Layer 5 (Output layer)

This layer has one node supplying the overall output. The overall output g(μ,σ,α,x) is given by the sum of each weighted rule's outputs and depends on the ANFIS parameters s={ μ,σ and α} and the input vector xi; hence:

$$g(s,x_i) = \sum_{j=1}^{r}\left(\overline{\lambda_{ij}}\, f_j(x_i)\right)$$

4. Simulation Results

The bit error rate (BER) and mean square error (MSE) performances of our proposed channel estimator are compared to LMS and LS algorithms. To train ANFIS, 1200 training symbols and 100 epochs are used. The bit error rate performance of channel estimators versus signal to noise ratio is shown in Fig.4. It indicates that the performance of our proposed channel estimator based on ANFIS is better than other algorithms. Not only at low SNR values but also at high SNR values BER performance of ANFIS is better than LS and LMS algorithms considerably. The performance of estimators is also measured by mean square error (MSE) in Fig.5. As it is seen from Fig.5, estimation error of ANFIS is less than LS and LMS algorithms.

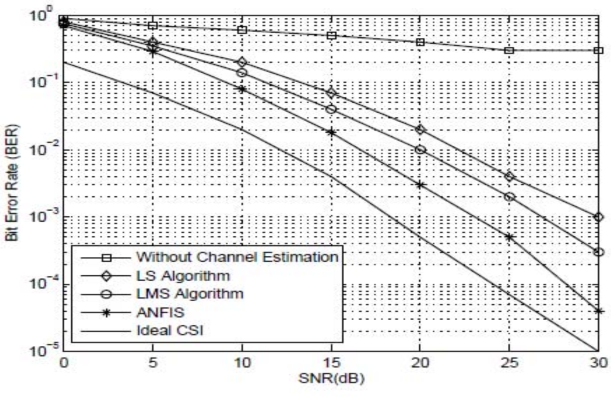

Fig. 3. BER performances of channel estimators.

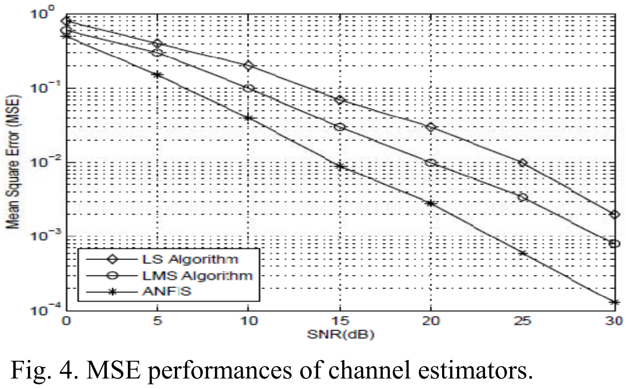

Fig. 4. MSE performances of channel estimators.

5. Conclusion

An Enhanced Channel Estimation Technique for MIMO-OFDM Based Communications Using Neuro Fuzzy Approach has been proposed in this paper. The channel model has been described by a nonlinear state-space dynamic equation. The states of the nonlinear channel parameter system include the time-varying channel gains and the dynamics of the channel. In our proposal, by using learning capability of ANFIS the network is trained by correct channel state information; then we use this trained network as a channel estimator. Our proposed estimator performs better than the LS and LMS algorithms.

6. References

[1] G. L. Stuber, J. R. Barry, S. W. McLaughlin, Y. Li, M. A. Ingram, and T. G. Pratt, "Broadband MIMO-OFDM wireless communications," *Proceedings of the IEEE,* 92(2): 271–294, Feb. 2004.

[2] Y. Hongwei, "A road to future broadband wireless access: MIMO-OFDM based air interface," *IEEE Commun. Mag.*.43(1): 53–60, Jan. 2005.

[3] H. Sampath, S. Talwar, J. Tellado, V. Erceg, and A. Paulraj, "A fourth generation MIMO-OFDM broadband wireless system design, performance, and field trial results," *IEEE Commun. Mag.*, pp. 143–149, Sept. 2005.

[4] A. J. Paulraj, D. A. Gore, R. U. Nabar, and H. Bolcskei, "An overview of MIMO communications - a key to gigabit wireless," *Proceedings of the IEEE,* 92(2): 198–218, Febuary 2004.

[5] Y. Li, N. Seshadri, and L. Ariyavisitakul, "Channel estimation for OFDM systems with transmitter diveristy in mobile wireless channel," *IEEE J. Sel. Areas Commun.*, vol. 17, pp. 461-471, March 1999.

[6] W. G. Song and J. T. Lim, "Pilot-symbol aided channel estimation for OFDM with fast fading channels," *IEEE Trans. Broadcast.*, vol. 49, pp.398-402, December 2003.

[7] Jang JSR (1993) ANFIS: adaptive network based fuzzy inference systems. IEEE Trans Syst Man Cybern 23:665–685.

[8] J. S. R. Jang, C. T. Sun, E. Mizutani, Neuro-fuzzy and soft computing. Prentice Hall, Upper Saddle River, 1997.

[9] M. Shin, H. Lee, and C. Lee, "Enhanced channel-estimation technique for MIMO-OFDM systems," *IEEE Trans. Veh. Technol.*, 53(1): 261–265, January 2004.

[10] Y. Qiao, S. Yu, P. Su, and L. Zhang, "Research on an iterative algorithm of LS channel estimation in MIMO OFDM systems," *IEEE Trans Broadcasting,* 51(1):149–153, March 2005.

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