ISSN (Online) : 2319 - 8753
ISSN (Print) : 2347 - 6710

International Journal of Innovative Research in Science, Engineering and Technology

Volume 3, Special Issue 3, March 2014

2014 International Conference on Innovations in Engineering and Technology (ICIET'14)

On 21st & 22nd March Organized by

K.L.N. College of Engineering, Madurai, Tamil Nadu, India

Adaptive Feedback Based Normalized Channel Equalizer Using Minimal Symbol-Error-Rate Approach

[1]Saranya V, [2]BabiMol.T.M.

Dept of Electronics & Communication Engineering, PET Engineering College, Tamilnadu, India

ABSTRACT: Inter-symbol Interference (ISI) is well thought-out as a major problem in the wireless communication channel to transfer data. The purpose of the equalizer is to reconstruct the original signal by using filters or other techniques, and remove ISI. There are several methods to solve the problem. One of the methods is adaptive decision feedback equalizer based MSER (ADFEM) is Presented along with the minimum-mean-squared-error (MMSE) criterion and the least-square (LS) criterion, adopt the squared error as the performance measure. The proposed scheme adopts appropriate block floating Point format for the data as well as the filter weights and works out separate update relations for the real and imaginary filter weight. The feed forward and the feedback filter output are used to prevent certain dynamic scaling of the respective input, although overflow in weight update calculations is avoided by imposing certain upper bound on the algorithm step size m which is shown to be less than the convergence bound. The proposed scheme achieves considerable computational gain over its floating point based counterpart.

INDEX TERMS- Multiple input multiple output, Adaptive decision feedback equalizer, Equalization to Remove ISI, Adaptive Equalization, block floating point, minimum mean square error and least square error

I. INTRODUCTION

Equalizer is a filter that compensates the scattering effect of the transmission channel. Indeed the signal suffers from the inter-symbol interference while propagating through the channel and white Gaussian noise is added at the receiver front end. To compensate the effect of the channel, different equalization techniques are used at the receiver end. Decision feedback equalizer uses previously detected decisions to eliminate ISI from the received symbol. The distortion on the current symbol that is caused by the previous symbol is subtracted. An adaptive decision feedback equalizer is designed by using least mean square algorithm.In [34] an iterative approach to solve turbo equalization problem, in which a maximum a posteriori probability (MAP) equalizer and a MAP decoder exchange soft information in the form of prior probabilities over the transmitted symbols. It show that for the turbo equalization application, MMSE based SISO equalizer perform well compared with a MAP equalizer while providing a tremendous complexity reduction. In [29] DFE vastly reduces computational complexity as compared to adaptive equalizer. In [35] inter-symbol interference is the major problem in communication channel, an adaptive equalization algorithm based on the new quasi Newton method is proposed. The proposed algorithm has fast convergence speed and low bit error rate within the large step size. In [18] Linear adaptive channel equalization had mentioned using the least mean square (LMS) algorithm and the recursive least squares (RLS) algorithm for an innovative multi-user (MU) MIMO- OFDM wireless broad band communications system is proposed. It show an improvement of 0.15 in BER when using Adaptive Equalization and RLS algorithm compared to the case in which no equalization is employed.

In [13] LSER algorithm has a complexity that increases linearly with the equalizer length. This paper considers an MSER approach for the DFE design with the multilevel pulse-amplitude modulation scheme. The proposed LSER algorithm has faster convergence rate than an existing LMS-style stochastic gradient adaptive MSER algorithm known as the AMSER algorithm. In [15] simple stochastic adaptive algorithm is used for realizing the minimum BER equalizer. If the number of equalizer coefficient is sufficient, the minimum mean squared error (MMSE) linear equalizer directly minimizes bit error rate (BER). The drawback of this method is when the number of equalizer coefficient is insufficient; the minimum BER can outperform the MMSE equalizer. In [12] linear multiuser detector is used to minimize the bit error rate. The minimum BER criterion was proposed for combating inter-symbol interference (ISI) in single user communication system. The binary phase shift keying (BPSK) transmission is considered for a channel with additive white Gaussian noise (AWGN) in a direct sequence code division multiple access (DS-CDMA) system. In this paper, least mean square algorithm is used. Least mean squares (LMS) algorithms are a class of adaptive filter used to minimize a desired filter by finding the error signal of the filter coefficients (difference between the desired and the actual signal). LMS algorithm is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time. The LMS algorithm is used in adaptive filtering for several reasons. The main features of LMS algorithm are low computational complexity, proof of convergence in stationary environment, unbiased convergence in the mean to the Wiener solution, and stable behavior when implemented with finite-precision arithmetic. The convergence analysis of the LMS presented here utilizes the independence assumption. The paper further ordered as follows: Section 2 proposes system model. Section 3 Adaptation Algorithms whereas simulation result is given in section 4 and conclusion is defined in section 5

II SYSTEM MODEL

In fig.1, the random integer generates a discrete sequence r_k . Consider a Linear discrete time channel whose output at time instant k is given by

$$r_k = \sum_{i=0}^{L} h_i s_{k-i} + n_k \qquad (1)$$

Wherer_k→ linear discrete time channel

s_k→ Time uncorrelated finite state input sequence

h_i→ Channel impulse response

n_k→ White Gaussian noise

The generated integer value will be fed to BPSK modulation. The main process of the Binary phase shift keying (BPSK) modulation is to calculate the objective function. The objective function is calculated by many steps the first step is to correct symbol detection and then the detected symbol will considered the following constraint. The constraint has the optimization problem and then it will be solved by using Lagrange multiplier for obtaining the objective function. The objective function of BPSK source is

$$J(c_k) = \|c_k - c_{k-1}\|^2 + \lambda\left(\tanh\left(\beta(c_k^T r_k)\right) 1\right) \qquad (2)$$

Where c_k→ equalizer parameter at time instant k

c_{k-1}→ Equalizer at previous instant

λ→ Lagrange multiplier

β→ Sufficiently large number

c_k^T→ Estimated equalizer

r_k→ Linear discrete time channel

In channel modeling the Rayleigh fading type is used. It is defined as

$$h = h_I + h_R \qquad (3)$$

Where h_I→ channel impulse response for imaginary term

h_R→Channel impulse response for real term

ISI channel transmission is $hr_k + n$

In fig.2, an Adaptive Decision Feedback Equalizer (ADFE) is an equalization technique which uses previously detected symbols to remove the ISI form the received symbols. It is implemented using least mean square (LMS) algorithm. ADFE allows a window of ISI to pass from feed-forward filter, while attempts to minimize the rest of ISI. Window of the ISI is then subtracted by means of feedback filter. By using this technique, ADFE does not increase the noise, which results in a distortion less transmission.

At initial stage training symbols are transmitted which are known by the receiver. The recovered symbol is subtracted from the desired symbol and the difference is known as error. This error is used to update the Feed forward filter and feedback filter. In initial stage the error value is large means passing time and error reduces when its value becomes approximately equal to zero. The step-size parameter **m** controls the size of the correction that is applied to the tap-weight vector as it proceeds from one iteration cycle to the next. The basic idea of a DFE is that if the values of the symbols previously detected are known, then ISI contributed by these symbols can be cancelled out exactly at the output of the forward filter by subtracting past symbol values with appropriate weighting. The forward and feedback tap weights can be adjusted simultaneously to fulfill a criterion such as minimizing the MSE.

The advantage of a DFE implementation is the feedback filter, which is additionally working to remove ISI, operates on noiseless quantized levels, and thus its output is free of channel noise.Some entities have been described below, which have been used in the block diagram and in the derivation of ADFE.

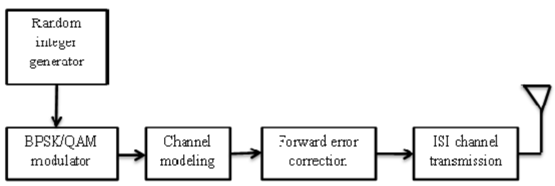

Figure 1: Block diagram of transmitter section

The entities are

m= step size

J = Cost function

y[n] = Input at feed-forward filter at time n

e[n] = Error

W[n] = Current coefficients of feed-forward filter

W[n+1] = Updated coefficients of feed-forward filter

b[n] = Current coefficients of feedback filter

b[n+1] = Updated coefficients of feedback filter

Z[n] = Input at feedback filter at time n

A derivation to update the coefficients of feed forward filter and feedback filter is given below. The coefficients of feed-forward and feedback filter are updated by minimizing the cost. The cost function is used to minimize the mean square error.

$J = E\{e[n]^2\}$(1)

$$e[n] = d[n] - y[n] \quad (4)$$

Where

$$y[n] = [W^H[n]y[n] - b^H[n]z[n]]$$

Putting the value in (2), it becomes

$$e[n] = d[n] - w^H[n]y[n] + b^H[n]z[n] \quad (5)$$

The updated Equation for Feed Forward Filter is

$$w(n+1) = w(n) + my[n]e^*[n] \quad (4)$$

The updated Equation for Feedback Filter is

$$b(n+1) = b(n) + mz[n]e^*[n] \quad (6)$$

ADFE offers many advantages over adaptive equalizer. ADFE has higher computational complexity and better performance meanwhile the computational complexity of the adaptive equalizer is low but it doesn't offer better performance as good as ADFE. In this paper, we propose a different approach to the complexity reduction by adopting suitable data format for the input and the equalizer coefficients. In a practical communication receiver, the received signal level is usually very weak which also fluctuates randomly due to effects like fading. In this paper, we present a BFP treatment to finite precision implementation of the LMS based ADFE. Such a realization is intrinsically more difficult than a BFP based realization of transversal adaptive filters, since, unlike the latter, the ADFE consists of a decision feedback loop with a non-linear decision device. The proposed scheme provides a viable solution to this problem by effectively modifying and extending the framework. For this, first, appropriate BFP formats are adopted for the FFF and the FBF coefficients. Separate update relations for the mantissas as well as the exponents for each set of coefficients are worked out next. For the FFF, the input is block formatted by an efficient block formatting algorithm which also includes certain dynamic scaling of the data for preventing overflow at the FFF output. For the FBF, however, no block processing of the corresponding input (i.e., decisions) is possible, as that makes the system non causal Instead, the data stored in the FBF memory is block formatted at each time index, by appropriately modifying the proposed block formatting algorithm. It is also required to prevent overflow in the weight update

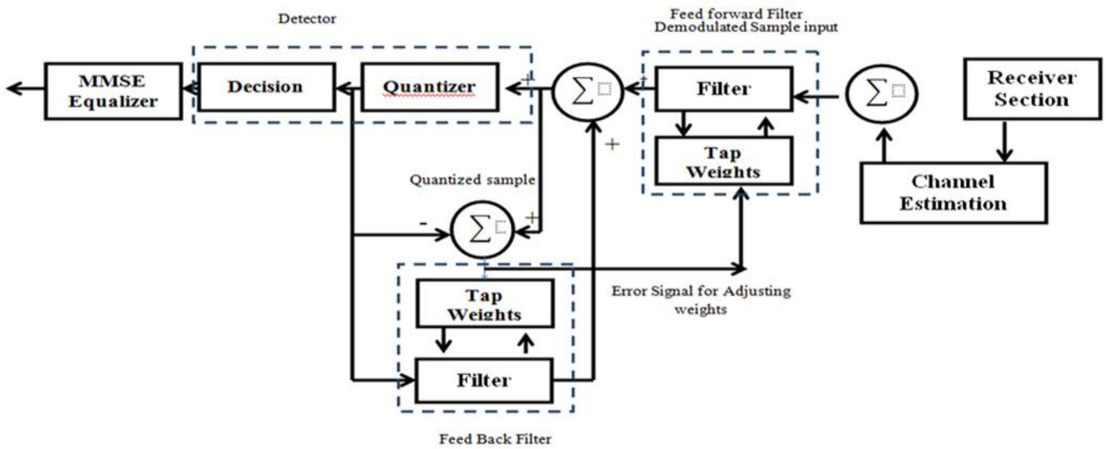

Figure 2: Block diagram of receiver section

computations of the FFF and the FBF. This gives rise to two upper bounds for the step size m, one coming from the FFF and the other from the FBF considerations. The two bounds are related by a simple constant and the lesser of them is used as an upper limit of m, which is interestingly seen to be less than 2=tr R, i.e., upper bound of m for convergence of the LMS iteration. The proposed scheme relies largely on simple FxP operations and thus achieves considerable speed up over a direct FP based realization. Also, simulation results show no appreciable degrading effect on the ADFE performance due to block formatting of data and filter coefficients in finite precision.

III ADAPTATION ALGORITHMS

There are two main adaptation algorithms one is least mean square (LMS) and other is Recursive least square filter (RLS).

3.1. Least Mean Squares Algorithm (LMS)

Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the error signal of the filter coefficients (difference between the desired and the actual signal). LMS algorithm is a stochastic gradient descent method. It is used to adapt based on the error at the current time. LMS filter is built around a transversal (i.e. tapped delay line) structure. Two practical features, simple to design, yet highly effective in performance have made it highly popular in various application. LMS filter employ, small step size statistical theory, which provides a fairly accurate description of the transient behavior. It also includes H∞ theory which provides the mathematical basis for the deterministic robustness of the LMS filters. As mentioned before LMS algorithm is built around a transversal filter, which is responsible for performing the filtering process. A weight control mechanism responsible for performing the adaptive control process on the tape weight of the transversal filter

i. LMS is the most well-known adaptive algorithms by a value that is proportional to the product of input to the equalizer and output error.

ii. LMS algorithms execute quickly but converge slowly, and its complexity grows linearly with the no of weights.

iii. Computational simplicity

iv. In which channel parameter don't vary very rapidly

- ➢ LMS algorithm steps
- Filter output

$$y[n] = \sum_{k=0}^{M-1} u[n-k]w_k^*[n] \qquad (7)$$

- Estimation error

$$e[n] = d[n] - y[n] \qquad (8)$$

- Tap-weight adaptation

$$w[n+1] = w_k[n] + mu[nk]e^*[n] \qquad (9)$$

3.2. Recursive Least Square Algorithm (RLS)

The Recursive least squares (RLS) adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals. These contrast other algorithms such as the least mean squares (LMS) that aim to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS and similar algorithm they are considered stochastic. Compared to most of its competitors, the RLS exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity, and potentially poor tracking performance when the filter to be estimated changes. The RLS algorithm has the same to procedures as LMS algorithm, except that it provides a tracking rate sufficient for fast fading channel, moreover RLS algorithm is known to have the stability issues due to the covariance update formula p(n)

IV SIMULATION RESULTS

In figure 3, the proposed scheme developed the effects of block formatting data and the equalizer coefficients in finite precision. It is based on the ADFE performance and FP based realization. The ADFE was operated in training mode for the first 100 iterations and then, switched over to the decision directed mode for the subsequent iterations. The corresponding learning curve is obtained by plotting the MSE (dB) versus the number of iterations

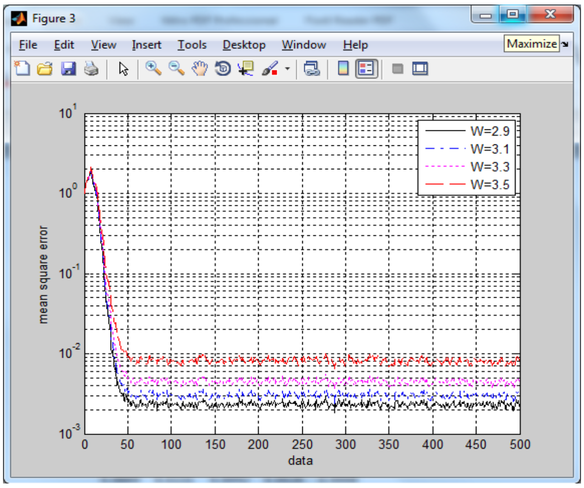

Figure 3: Training mode for Adaptive decision feedback equalizer

In figure 4 channel estimation for minimum mean squared error will be obtained for symbol error rate and signal to noise ratio in dB. Symbol error rate for MMSE is $10^{-1.2}$ and its SNR is 30dB

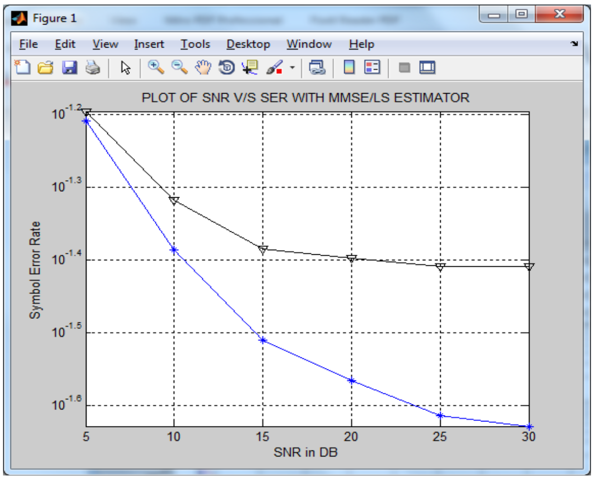

Fig. 4: channel estimation for Minimum mean squared error(MMSE)

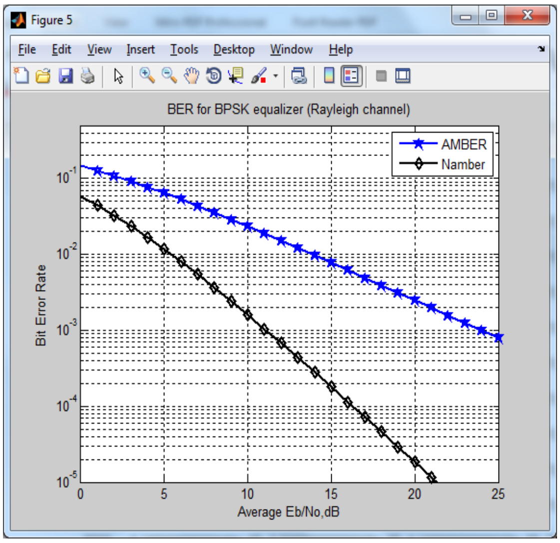

Figure 5: BER for BPSK equalizer

In figure 5, the BPSK equalizer bit error rate is $10^{-0.9}$ for adaptive minimum bit error rate and the BPSK (binary phase shift keying) equalizer bit error rate is $10^{-1.5}$ for normalized adaptive minimum bit error rate.

mmse_mse =

0.0208	0.0111	0.0035	0.0010	0.0004
0.0265	0.0089	0.0047	0.0014	0.0004
0.0261	0.0080	0.0033	0.0011	0.0004
0.0211	0.0099	0.0033	0.0013	0.0003
0.0179	0.0112	0.0036	0.0011	0.0004
0.0257	0.0105	0.0032	0.0011	0.0003
0.0220	0.0082	0.0028	0.0014	0.0003
0.0168	0.0059	0.0038	0.0008	0.0004
0.0153	0.0110	0.0033	0.0011	0.0006
0.0262	0.0120	0.0037	0.0013	0.0004
0.0213	0.0086	0.0040	0.0010	0.0005
0.0228	0.0094	0.0039	0.0015	0.0004

V. CONCLUSION

An efficient scheme to implement the LMS-based ADFE in finite precision using BFP arithmetic is presented. The proposed scheme adopts appropriate BFP format for both data and filter coefficients and recasts the ADFE equations in terms of the respective mantissas and exponents. Block processing is applied to the input which is block formatted by an efficient algorithm. For the FBF, however, no block processing of its input is possible as that leads to non-causality. Instead, the FBF data is block formatted at every index by a suitable modification of the proposed block formatting algorithm. Overflows at the FFF and the FBF output are prevented by certain dynamic scaling of the respective data. Prevention of overflow in weight update calculations, however, imposes an upper bound on the step size m which is shown to be less than the upper bound for convergence of the algorithm. The proposed realization deploys mostly simple FxP operations are largely free from usual FP operations like shift, exponent comparison, exponent addition, etc., resulting in considerable speed up over their FP based counterpart.

ACKNOWLEDGMENT

Apart from the efforts of me, the success of any work depends largely on the encouragement and guidelines of many others. I take this opportunity to express my gratitude to the people who have been instrumental in the successful completion of this work. I would like to extend my sincere thanks to all of them. I owe a sincere prayer to the LORD ALMIGHTY for his kind blessings and giving me full support to do this work, without which this would have not been possible. I wish to take this opportunity to express our gratitude to all, who helped me directly or indirectly to complete this paper.

REFERENCES

[1] Aaron M Rand Tufts D W (1966) "Intersymbol interference and error probability, IEEE Trans. Inf. Theory, vol.12, no.1,pp.26–34.

[2] Ahmad N N, Chen S, and Hanzo L(2005)" Adaptive minimum bit-errorrate beamforming," IEEE Trans. Wireless Commun.,vol.4, no.2, pp.341–348.

[3] Ahmed Q Z, Chen S, andYang LL(2011) "Reduced-rank adaptive least bit- error-rate detection in hybrid direct-sequence time-hopping ultra wide bandwidth systems, "IEEETrans. Veh. Technol., vol.60, no.3.

[4] Antomiou A,Lu WS, andWang X (2000) "Constrained minimum-BER Multiuser detection," IEEE Trans. Signal Process, vol.48,no.10, pp.2903–2909.

[5] Anastasopoulos A, Chugg K M, and Colavolpe G (2007)"Iterative Detection for channels with memory,"Proc.IEEE, vol.95, no.6,pp.1272–1294.

[6] Barry J R, andYeh CC(2000) " Adaptive minimum bit error rate equalization for binary signaling," IEEE Trans. Commun. , vol.48, pp.1226–1236.

[7] Barry J R, and Yeh CC (2003) "Adaptive minimum symbolerror rate equalization for quadrature amplitude modulation," IEEE Trans. SignalProcess., vol.51, no.12, pp.3263–3269.

[8] Barbieri A, Colavolpe G, andCaire G (2005)" Algorithmsfor iterative decoding in the presence of strong phase noise," IEEE J.Sel. Areas Commun.,vol.23, pp.1748–1757.

[9] Batalama S N, Psaromiligkos I N, and Pados D A (1999)"On adaptive minimum probability of error linear filter receivers for DS-CDMA channels," IEEE Trans. Commun., vol.47,no.7, pp.1092– 1102.

[10] Blostein SD, andWang N (2005) "Comparison of CP based single carrier and OFDM with power allocation," IEEE Trans. Commun., vol.53, no.3, pp.391–394.

[11] Chen S, Hanzoa L, Tana S, and Xua L (2008)" Adaptive minimum error-rate filtering design: a review," Signal Process., vol.88,no.7, pp.1671– 1697.

[12] Chen S, Hanzo L, and Livingstone A (2006)" MBER space-time decision feedback equalization assisted multiuser detection for multiple antenna aided SDMA systems," IEEE Trans. Signal Process.,vol.54,no.8,pp.3090–3098.

[13] Chen S, Hanzo L, and Mulgrew B (2004) "Adaptive minimum symbol-error-rate decision feedback equalization for multi-level pulse-amplitude modulation," IEEE Trans. Signal Process., vol.52, no.7, pp.2092–2101.

[14] Chen FJ, Li J Y, and Wei G (2007) " On minimum-BER linear multi user detection for DS-CDMA channels," IEEE Trans. Signal Process., vol.55, no.3 , pp.1093–1103.

[15] Chen S , andMulgrew B (2001) "Adaptive minimum BER

decision feedback equalizers for binary signalling," Signal Process., vol.81, no.7,pp.1479–1489.

[16] Collings I B, McKay M R, and Tulino AM (2010) " Achievable sum rate of MIMO MMSE receivers: a general analytic framework," IEEE Trans .Inf. Theory, vol.56,no.1,pp.396–410.

[17] Dai L, Yao Y,Zhuang HR, andZhou SD (2003) "Low complexity per-antenna rate and power control approach for closed-loop V-BLAST," IEEE Trans. Commun., vol.51,no.11,pp.1783–1787.

[18] DeLamare RCand Sampaio-Neto R (2003) "Adaptive MBER decision feedback multiuser receivers in frequency selective fading channels," IEEE Commun. Lett.,vol.7, no.2,pp.73–75.

[19] DeLamare RCand Sampaio-Neto R (2009)"Adaptive reduced-rank processing based on joint and iterative interpolation, decimation and filtering," IEEE Trans. Signal Process., vol.57,no.7, pp.2503–2514.

[20] Deneire L and Vandenameele P(2003) " A low complexity ML channel estimator for OFDM,"IEEE Trans. Commun., vol.51,no.2,pp.135–140.

[21] Diniz PS R, andHjoungnesA (2005)"Minimum BER pre filter transform for communications systems with binary signaling and known FIR MIMO channel," IEEE Signal Process. Lett.,vo..3, no.12, pp. 234–237.

[22] Elnoubi S, Elnashar A, and Samir T A (2008)" Block shanno mimimum bit error rate beamforming," IEEE Trans. Veh. Technol.,vol.57,no.5, pp.2981–2990.

[23] Farhang-Boroujeny B, and Rao HIK (2009)"Fast LMS/Newton algorithms for stereophonic acoustic echo cancelation," IEEE Trans. Signal Process, vol.57,no.8, pp.2919-2930.

[24] Gershman A B, Sarmadi N, and Shahbazpanahi S (2009) "Blind channel estimation in orthogonally coded MIMO-OFDM systems: a semi definite relaxation approach," IEEE Trans. Signal Process., vol.57, no.6, pp.2354–2364

[25] Goldstein J S, and Honig M L(2002) "Adaptive reduced rank interference suppression based on the multistage Wiener filter," IEEE Trans. Commun., vol.50, no.6,pp.986–994.

[26] Gunther J and Moon T (2009)"Minimum symbol error rate carrier phase recovery of QPSK,"IEEE Trans. Signal Process., vol. 57,no.8,pp.3101–3107.

[27] Haykin S (2002) Adaptive Filter Theory, 4th editionPrentice Hall.

[28] Jayaraj N B (2010)"Minimum symbol error rate timing recovery system," thesis, Utah State University.

[29] Jerry M and Qilian Liang (2000) " Equalization of nonlinear time varying channels using type 2 fuzzy adaptive filters" IEEE Trans. Signal processing, vol.8, no.5

[30] Nowlan SJ(1993) "A soft decision-directed LMS algorithm for blind equalization," IEEE Trans. Commun., vol.41, no.2, pp.275–279.

[31] Papadias C B and Slock D T M (1997)"Normalized sliding window constant modulus and decision directed algorithms : a link between blind equalization and classical adaptive filtering," IEEE Trans. Signal Process., vol.45,no.1,pp. 231– 235.

[32] Prlja A, and Rusek F (2012)"Optimal hannel shortening for MIMO and ISI channels," IEEE Trans. Wireless Commun., vol.11, no.2,pp.810–818.

[33] SayedA H (2003)"Fundamentals of Adaptive Filtering". JohnWiley&Sons.

[34*] Tuchler (2002)" minimum mean squared error equalization using a priori information" IEEE Trans. Signal processing, vol. 50, no.3.*

[35] Weishi et al (2012) " Investigation of New Quasi Newton adaptive equalization algorithm for communication channel" Journal of information and computational science, vol 9, no. 11, pp 3151-3160.