A New Step Size Control Technique for Blind and Non-Blind Equalization Algorithms

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Abstract. *A new variable step size (VSS) control technique employing cross correlation between channel output and error signal has been proposed as a solution to the problem of slow convergence of blind and non-blind equalization algorithms. The new method resolves the conflict between the convergence rate and low steady state error of the fixed step-size conventional blind and non-blind equalization algorithms, such as Constant Modulus Algorithm (CMA) and Least Mean Squares (LMS) algorithm. Computer simulations have been performed to verify the performance of the proposed method in frequency selective Rayleigh fading channels. The proposed technique has been compared with the popular non-blind equalizers, LMS and Recursive Least Squares (RLS) algorithms, and blind equalizers, the conventional CMA, Zhao's VSS-CMA and Demir's VSS-CMA as benchmarks. The obtained simulation results have demonstrated that the proposed VSS-CMA and VSS-LMS algorithms have considerably better performance than the conventional CMA, Zhao's VSS-CMA and Demir's VSS-CMA blind equalization algorithms, and the conventional LMS non-blind equalization algorithm.*

Keywords

Cross correlation, VSS-CMA, VSS-LMS, blind equalization, adaptive blind and non-blind training.

1. Introduction

Inter symbol interference is one of the greatest impediments of high data rate digital communication systems. In order to overcome the effects of the impairment, several channel estimation and equalization methods have been developed in the last few decades. One of the best ways to cancel the effects is to use an equalizer filter which eliminates the ISI while combining the multi path energy [1]-[3]. In practice, Linear Transversal Equalizers (LTE) and Decision Feedback Equalizers (DFE) are the most common structures used [4], [5]. But, in suppressing the ISI, the LTE inevitably enhances the channel noise. This basic limitation of a LTE's ability to cope with severe ISI has motivated a considerable amount of research into suboptimal nonlinear equalizers with low computational complexity such as the DFE.

The decision feedback equalization is a technique widely used for removing ISI in frequency selective multipath channels. The major problem in DFE is the so called error propagation; a decision error propagating through the feedback filter enhances ISI instead of cancelling it. Thus, a single error may cause a burst of errors in subsequent decisions. As reported in [5], the performance loss due to this phenomenon is approximately 2 dB for some channels. However, the existing blind algorithms, originally designed for transversal equalizers [6], [7], cannot be directly applied with a recursive equalizer, such as a DFE, because of the phenomenon of error propagation that characterizes a decision feedback updating. Namely, the enormous number of errors at the start of equalization restricts the use of blind adaptation to the case of a mild channel. Recently, several authors have presented various approaches to overcome this major defect of decision feedback blind equalizers [7]-[10]. Therefore, the use of soft decisions to mitigate error propagation in a conventional DFE is considered for application to blind equalization in this paper.

In order to achieve high speed reliable communications, channel identification and equalization are necessary to overcome the effects of ISI. Conventionally, channel equalizers are of two types: as blind and non-blind. The non-blind channel equalizers waste bandwidth by their dependence on a training sequence. On the other hand, blind channel equalization is one of the most important process during which an unknown input data sequence is recovered from the output signal of an unknown channel. Unlike the conventional adaptive non-blind channel equalizers, the blind channel equalizers do not require any training sequence. Instead, the statistical properties of the transmitted signals are exploited to carry out the equalization at the receiver without access to the transmitted symbols. Hence, they are capable of saving valuable bandwidth that is wasted by sending training sequence.

The popular constant modulus algorithm (CMA) proposed by Sato [11] in 1975 and the famous least mean squares (LMS) algorithm proposed by Widrow [12] in 1966 are widely employed in communications such as blind and non-blind channel equalization and identification for their low computational complexity and simple structure. However, due to using fixed step size, the CMA and LMS algorithms suffer from a conflict between convergence rate and steady-state error. A larger step size can speed up the convergence rate, but at the same time it increases the steady-state error. A smaller step size can decrease the steady-state error, but the convergence rate will be poor.

In order to solve this problem, many variable step size (VSS) algorithms have been proposed [13]-[23]. The principles of these VSS-CMA and VSS-LMS algorithms are: a larger step size is chosen to speed up the convergence at the beginning of the adaptive process, and the step size will get smaller at the steady state region. Xiong and co-workers [13] and Aboulnasr and Mayyas [22] proposed a VSS algorithm based on the lag(1) error autocorrelation function between $\hat{e}(k)$ and $\hat{e}(k-1)$. Here, $\hat{e}(k)$ is the output error of the blind and non-blind identification system. However, lag(1) error autocorrelation is a poor index of convergence closeness and poor noise immunity. Liyi and co-workers [14] proposed an alternative scheme that considers a nonlinear function of instantaneous error for adjusting the step-size parameter. Shahzad and co-workers [15] use two adaptive equalizers that work in parallel to increase the speed of convergence while reducing the tradeoff between the convergence speed and steady state error. Zhao and co-workers [16] derive a new VSS constant modulus blind equalization algorithm, which uses the cross-correlation coefficient estimation between the input signal and the error signal to control the step-size of CMA. However, the above algorithms are based on an assumption that the input is statistically independent. In the case of correlated signal, especially highly correlated signal, these VSS algorithms converge slowly. Additionally, most of these approaches involve significant increases in complexity or computational cost.

On the other hand various kind of successful studies have concentrated on adjusting the step-size of the CMA and LMS algorithm obtaining a better convergence and error performance using analytical or fuzzy logic based approaches [17], [18]. As far as authors' knowledge all these systems were considering an analytic approach to the step size adjustment by doing either considering error variations or obtaining a possible trajectory for the training. However, instead of using an analytic approach, this work, inspired by [16], [20] and [21], aims to design a training trajectory for the simple CMA and LMS algorithm employing cross correlation between channel output and error signal which provides a simple and more deterministic control on the training trajectory. Thus, with the help of proposed technique the performance of the conventional CMA and LMS algorithms have become comparable to other blind adaptive VSS-CMA and non-blind adaptive VSS-LMS training algorithms. Simulation results have shown that the proposed VSS-CMA and VSS-LMS algorithms perform better than the conventional CMA, Zhao's VSS-CMA [16] and Demir's VSS-CMA [21] blind training algorithms, and the conventional LMS non-blind training algorithm found in the literature.

The rest of the paper is organized as follows: The following section summarizes the blind and non-blind channel equalizer trainings. Section 3 explains some of the VSS-CMA algorithms. The proposed VSS-CMA algorithm is introduced in detail in Section 4. Section 5 evaluates the obtained MSE and BER performances to verify the feasibility and robustness of the proposed technique and finally, the paper is concluded in Section 6.

2. Channel Equalization

The received signal of a wideband channel $v(k)$ is given by

$$v(k) = \sum_{i=0}^{L-1} h(i)x(k-i) + \eta(k) \tag{1}$$

where $x(k)$ is the transmit data sequence, $h(i)$ is the ith tap coefficients of the tapped-delay-line filter model of a channel, L is the tap number of the channel, $\eta(k)$ is the additive white Gaussian noise (AWGN) component and k is the time index. The channel is assumed quasi-static in (1), for which the fading channel coefficients are constant over duration of one frame and changed independently from one frame to the next frame. The carrier frequency offset effect is also ignored in (1).

2.1 Non-Blind Equalization

The ISI of (1) is cancelled by a time domain equalizer filter. Linear Transversal Equalizer (LTE) and Decision Feedback Equalizer (DFE) filter can be used for this aim. When LTE filter is employed, its output, $\hat{x}(k)$, is given by [4], [5]

$$\hat{x}(k) = \sum_{i=0}^{N} w(i)v(k-i) \tag{2}$$

where $N + 1$ is the tap number of LTE and $w(i)$ is the ith LTE coefficient. For an ordinary training case, the error function of an equalizer is calculated by

$$\hat{e}(k) = x(k - L_{offset}) - \hat{x}(k) \tag{3}$$

where training is supervised which means the training sequence is known by the receiver. The number indicated by L_{offset} is attained for the adjustment of the center tap of equalizer filter. The coefficient update equation of the LMS algorithm for an equalizer filter is given by

$$w(i+1) = w(i) + \mu_{LMS}(k)\hat{e}(k)v^*(k-i), \quad i = 0, 1, \ldots N\,. \tag{4}$$

In (4), $\mu_{LMS}(k)$ is the step size of the LMS algorithm and $v^*(k-i)$ is the complex conjugate of kth incoming sample $v(k)$ with the shift number i for ith equalizer coefficients.

2.2 Blind Equalization

If a training sequence is not issued in the transmission, one of the blind algorithms has to be applied. For the adaptive blind training, the CMA algorithm is one of the best training techniques, which uses the cost function [6], [24]

$$\bar{J}_{CMA}(w) = E\{(|\hat{x}(k)|^2 - \Delta_2)^2\}\,. \tag{5}$$

Here $E\{\ \}$ is the expectation operator, $\hat{x}(k)$ is the k^{th} estimation of the equalizer filter given by (2), and Δ_2 is a real positive constant calculated by $\Delta_2 = E\{|x(k)|^4\}/E\{|x(k)|^2\}$ using the transmitted data.

The error function to verify CMA criterion is

$$\hat{e}(k) = \hat{x}(k)(\Delta_2 - |\hat{x}(k)|^2)\,. \tag{6}$$

Using a stochastic gradient descent (SGD) algorithm to define the update equation, the coefficient vector is adapted by [6], [24]

$$w(i+1) = w(i) + \mu_{CMA}(k)\hat{e}(k)v^*(k-i), \quad i = 0, 1, ...N \tag{7}$$

where $\mu_{CMA}(k)$ is the step size parameter of CMA, $\hat{e}(k)$ is the k^{th} estimate of error function using CMA criterion. In order to guarantee a stable operation in all VSS-CMA and VSS-LMS algorithms, a sufficient condition for the step size parameter is [4], [5]

$$0 < \mu(k) < \frac{2}{3tr[\mathbf{R}]} \tag{8}$$

where $tr[\boldsymbol{R}]$ is the trace of the input signal $x(k)$ autocorrelation matrix $\boldsymbol{R}$.

3. VSS-CMA Algorithms

VSS-CMA algorithms have been used extensively in blind adaptive filtering to improve the performance of the fixed step size conventional CMA. Common aspects of several VSS-CMA algorithms are summarized in this section. The VSS-LMS algorithms are explained in detail in [19], [20].

3.1 VSS-CMA – 1

Xiong's algorithm [13] uses the autocorrelation between $\hat{e}(k)$ and $\hat{e}(k-1)$ in order to adjust the step size parameter. In this way, the algorithm can effectively maintain a reasonable immunity to uncorrelated additive noise. To update the variable step size Xiong's approach [13] considers the square of the error signal autocorrelation estimate obtained through a low-pass filter given by

$$c(k) = \alpha c(k-1) + (1-\alpha)\hat{e}(k)\hat{e}(k-1) \tag{9}$$

where $c(k)$ is the estimate value of autocorrelation of error signal and α is positive control parameter. The setting of the step size parameter is

$$\mu(k) = \beta c^2(k) \tag{10}$$

where β is a scale factor used for controlling the bounds of the step size $\mu(k)$.

3.2 VSS-CMA – 2

Liyi's algorithm [14] utilizes a nonlinear function of remainder error to control the step size. The remaining errors should be properly transformed, and then control the step size, that is

$$\mu(k) = \beta[1 - \exp(-\alpha|\hat{e}(k)|)] \tag{11}$$

where β is the proportionality factor and α is positive control parameter. It is used to control the value scope of $\mu(k)$. When $0 \le 1 - \exp[-\alpha|\hat{e}(k)|] \le 1$, therefore the value scope of $\mu(k)$ satisfies $0 \le \mu(k) \le \beta$.

3.3 VSS-CMA – 3

Zhao et al. proposed a new VSS-CMA based on cross correlation estimation between the input signal $x(k)$ and error signal $\hat{e}(k)$ to control the step size of CMA [16]. The step size parameter is calculated as in (12) in Zhao's algorithm.

$$\mu(k) = \alpha ACC(k) \tag{12}$$

where α is the step size factor, to guarantee convergence the value of α must make the maximum of $\mu(k)$ is smaller than $\mu_{\max}$. $ACC(k)$ is average cross correlation coefficient estimation between the input signal and the error signal, calculated by

$$ACC(k) = \frac{1}{N}\left[\sum_{i=0}^{N-1}|C_i(k)|\right] \tag{13}$$

where $C_i(k)$ is the cross correlation coefficient estimation between $x(k-1)$ and $\hat{e}(k)$. $C_i(k)$ is decided by the following formulas

$$p_e(k) = \beta p_e(k-1) + (1-\beta)\hat{e}^2(k)\,, \tag{14}$$

$$p_i(k) = \beta p_i(k-1) + (1-\beta)x^2(k-i)\,, \tag{15}$$

$$p_{e,i}(k) = \beta p_{e,i}(k-1) + (1-\beta)\hat{e}(k)x(k-i)\,, \tag{16}$$

$$C_i(k) = \frac{p_{e,i}(k)}{p_e(k)p_i(k)}, \ i = 0,1,..,N-1 \tag{17}$$

where β is the positive control parameter. At first the cross correlation of $x(k)$ and $\hat{e}(k)$ is strong, $ACC(k)$ is large, $\mu(k)$ is large too, the algorithm convergences quickly. After convergence, the cross correlation of $x(k)$ and $\hat{e}(k)$ is weak, $ACC(k)$ is small, $\mu(k)$ is small too. Therefore, $ACC(k)$ can meet the need of the algorithm with variable step size.

4. The Proposed Variable Step Size Constant Modulus Algorithm

The block diagram of the proposed VSS-CMA algorithm based on cross correlation between channel output $v(k)$ and error signal $\hat{e}(k)$ is given in Fig. 1.

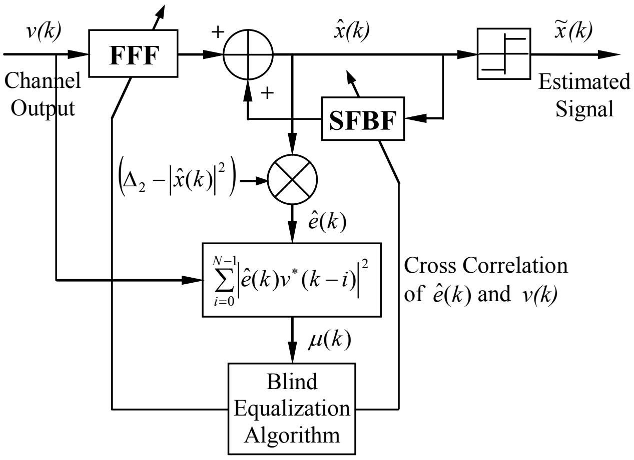

Fig. 1. The proposed VSS-CMA algorithm based on cross correlation of channel output and error signal with soft decision feedback equalizer.

The proposed method, inspired by [16], [20] and [21], considers the cross correlation function between the channel output and error signal, improving the convergence speed and performance. The greatest novelty of this study is different from [16] that the channel output signal is used in cross correlation. Zhao's technique needs the transmitted signal in the receiver. However, since the proposed method employs the channel output signal, it does not require the transmitted signal. Moreover, the proposed VSS method provides both noise and ISI immunity since the channel output signal (1) includes both ISI and noise information. So far there are no any published works on the proposed method, as far as author's concern. Thus, this contribution, inspired by [16], [20] and [21], investigates the proposed technique in the context of blind and non-blind channel equalizations.

Let us consider $Q(k)$ as a smooth estimation of the cross correlation function between error signal, $\hat{e}(k)$ and channel output, $v(k)$ given by

$$Q(k+1) = \lambda Q(k) + (1-\lambda)\sum_{i=0}^{L-1}\left|\hat{e}(k)v^*(k-i)\right|^2 . \tag{18}$$

Thereafter the step-size update equation is calculated by

$$\mu(k+1) = \alpha\mu(k) + \gamma Q(k) \tag{19}$$

where α, λ and γ are positive control parameters.

In order to illustrate the accuracy of the proposed method Soft Decision Feedback Equalizer (SDFE) filter has been employed for simulated communication channels in this study. The output of SDFE filter, $\hat{x}(k)$ is calculated by

$$\hat{x}(k) = \sum_{i=-L_{ff}}^{0} w(i)v(k-i) + \sum_{i=1}^{L_{sfb}} w(i)\hat{x}(k-i) \tag{20}$$

where L_{ff} and L_{sfb} is the number of feed forward filter (FFF) and soft feedback filter (SFBF) taps of the SDFE. The update equations of the CMA algorithm for FFF and SFBF components of the SDFE are given by

$$w(i+1) = w(i) + \mu(k)\hat{e}(k)v^*(k-i), \quad i = -L_{ff}, -L_{ff}+1, \ldots 0\,, \tag{21}$$

$$w(i+1) = w(i) + \mu(k)\hat{e}(k)\hat{x}^*(k-i), \quad i = 1, 2, \ldots L_{sfb}\,. \tag{22}$$

The step size update equations and computational complexities of subjected VSS-CMA algorithms are given by Tab. 1 in simulation studies.

The comparison of the computational complexities of the step size update equations required for per weight update is given by Tab. 1. Here, N is the tap number of the SDFE filter. The greatest advantage of the CMA algorithm is the fact that it requires far less computational complexity as for the other blind algorithms.

Algorithms	Step Size Update Equations	Multip.	Add.
VSS-CMA [16]	$\mu(k) = \alpha\frac{1}{N}\left[\sum_{i=0}^{N-1}\left\lvert C_i(k)\right\rvert\right]$	$5N$+12	N+2
VSS-CMA [21]	$\Delta(k+1) = \beta\Delta(k) + (1-\beta)\sum_{i=0}^{L-1}\left\lvert\hat{e}(k)\hat{e}^*(k-i)\right\rvert^2$ $\mu(k+1) = \alpha\mu(k) + \gamma\Delta(k)$	$2N$+7	N+2
Proposed VSS-CMA	$Q(k+1) = \lambda Q(k) + (1-\lambda)\sum_{i=0}^{L-1}\left\lvert\hat{e}(k)v^*(k-i)\right\rvert^2$ $\mu(k+1) = \alpha\mu(k) + \gamma Q(k)$	$2N$+7	N+2

Tab. 1. The step size update equations and computational complexities of VSS-CMA algorithms.

The total computational complexity of the conventional CMA algorithm is $8N+6$ multiplications and $8N$ additions at each iteration [18]. The additional computational complexity brought by the proposed VSS-CMA method to the CMA algorithm is $2N+7$ multiplications and $2N+2$ additions. The complexity incurred by the proposed technique does not prevent its application. However, the proposed method requires $3N+5$ multiplications and N additions less computational complexity than whom is using the VSS-CMA [16], proposed by Zhao et al. On the other hand, it can be seen from Tab. 1 that the computational complexity of the proposed method is the same as our prior work [21]. Although these complexities are the same, the proposed technique is more successful than our prior work [21] since the proposed VSS method provides both noise and ISI immunity. Thus, a more robust version of CMA algorithm is developed with a very small complexity concern.

5. Computer Simulation Results

In this section, simulation results are illustrated to verify the performance of the proposed VSS-CMA and

VSS-LMS algorithms in frequency selective Rayleigh fading channels.

The simulation studies have composed of two stages. In the first stage of the studies are performed using the blind channel equalization. In the second stage of the studies are implemented employing the non-blind channel equalization.

5.1 Simulation Results of the Blind Channel Equalization

The simulation studies of the blind channel equalizers are performed via 1000 Monte Carlo type iterations using the QPSK modulation. In this simulation, a three taps channel profile with average coefficient amplitudes given by (0.407, 0.815, 0.407), which is defined by Proakis and corresponds to an RMS delay spread of approximately 42 ns, is used [5]. A nine taps SDFE filter, composed of a feed forward filter (FFF) of five taps and soft feedback filter (SFBF) of four taps, is used in both blind and non-blind channel equalization. The proposed method is compared with Zhao's VSS-CMA [16], Demir's VSS-CMA [21] and fixed step size conventional CMA for blind equalization, and conventional LMS algorithm for non-blind equalization. The step size parameter for conventional CMA was equal to 0.005. The step size factor α was equal to 0.63 and the positive control parameter β was equal to 0.75 for Zhao's VSS-CMA. Positive control parameters, α was equal to 0.978, β was equal to 0.996 and γ was equal to 0.85 for Demir's VSS-CMA. The step size parameter was equal to 0.045 for conventional LMS algorithm. Positive control parameters, α was equal to 0.995, λ was equal to 0.822 and γ was equal to 0.984 for the proposed VSS-CMA. Maximum and minimum step size values are limited to 0.01 and 5E-7 respectively for all simulated VSS-CMA algorithms. Equalizer coefficients are initialized to zero value, except the central tap which is set to unit value before blind adaptation.

Two performance criteria were used to assess the convergence rate of blind and non-blind equalizers in simulation studies. The first criterion was a decision-based estimated mean square error (MSE) metric and the second criterion was the bit error rate (BER) metric in this study.

Blind learning curves of the conventional CMA, Zhao's VSS-CMA [16], Demir's VSS-CMA [21] and the proposed VSS-CMA equalizers are obtained in the value of Signal to Noise Ratio (SNR) of 20 dB illustrated in Fig. 2 for a stationary environment. The length of iteration is 4096 QPSK symbols for the MSE performance comparisons in all simulated algorithms.

Fig. 2 shows that Zhao's VSS-CMA [16] algorithm has faster convergence speed and lower MSE floor than the conventional CMA. It is observed that the performance of the VSS-CMA [21] is exceeding to the performance of the conventional CMA and VSS-CMA [16] and converges to the lower MSE floor. However, the proposed technique outperforms the performance of all blind equalization algorithms and converges to the lowest steady state MSE floor.

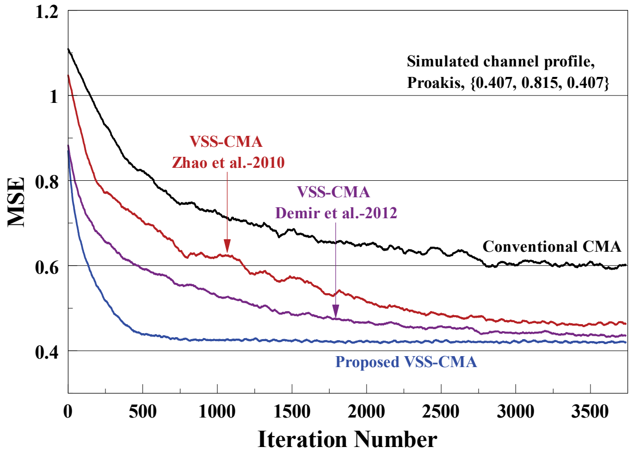

Fig. 2. Comparison of the MSE convergence performances of the blind adaptive channel equalizers for a stationary environment.

Performances of the blind learning curves of the four equalizers, namely, the conventional CMA, VSS-CMA [16], [21] and the proposed VSS-CMA, are compared in Fig. 3 in the value of SNR of 20 dB for a non-stationary environment. In this study, a three taps channel profile with average coefficient amplitudes given by (0.407, 0.815, 0.407), which is defined by Proakis, is used [5] in the first region as can be seen in Fig. 3. When the iteration number is 2000, channel profile abruptly changes to an exponential decay in the second region.

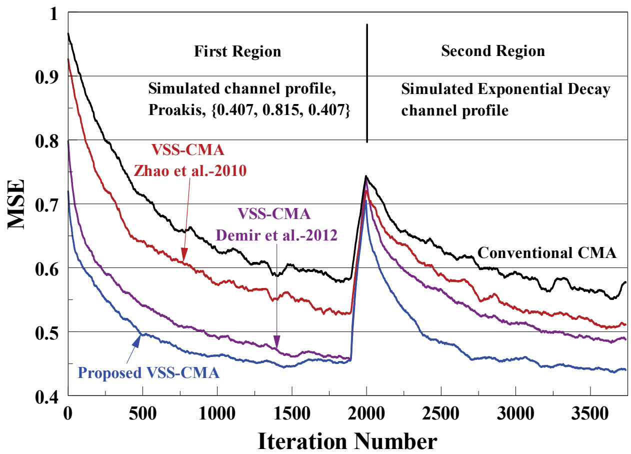

Fig. 3. Comparison of the MSE convergence performances of the blind adaptive channel equalizers for a non-stationary environment.

Fig. 3 shows that Zhao's VSS-CMA [16] algorithm has faster convergence and tracking speed than the conventional CMA in both regions. It can be easily seen that Demir's VSS-CMA [21] performs better performance than the conventional CMA and VSS-CMA [16] in both regions. However, the proposed technique outperforms the performance of the three blind equalization algorithms and converges to the lowest steady state MSE floor in both regions.

The obtained comparative BER performances of non-blind training, the conventional LMS algorithm, and blind trainings, the conventional CMA, the VSS-CMA [16], [21] and the proposed VSS-CMA are given in Fig. 4. In this simulation, the same conditions are valid as in Fig. 2 for all blind training algorithms, except the length of the payload data after blind training was 4096 symbols of QPSK modulation. It should be mentioned here that the BER performance samples are obtained after 4096 iterations of blind training and 450 iterations of non-blind training.

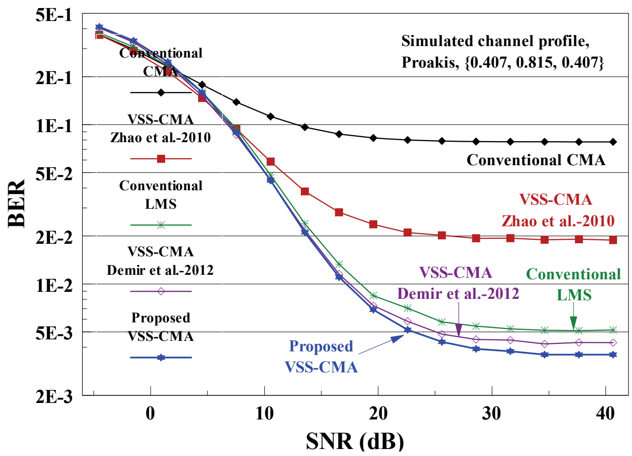

Fig. 4. Comparison of the BER performances of the blind and non-blind adaptive channel equalizers.

The obtained BER performances agree with the MSE performances given in Fig. 2. It is observed that the VSS-CMA [16], proposed by Zhao et al., performs better than the conventional CMA and it also converges to the lower BER floor. On the other hand, the VSS-CMA [21], proposed by Demir et al., has more superior performance than the conventional CMA, VSS-CMA [16] and conventional LMS algorithm. However, the BER performance of the proposed VSS-CMA algorithm outperforms the performance of the three blind equalizers, the conventional CMA and the VSS-CMA [16], [21], and conventional LMS non-blind equalizer. While the LMS algorithm converges to 5E-3 BER floor, the proposed method converges to 3E-3 BER floor. Thus, the proposed method improves the performance of the conventional CMA algorithm significantly. The controlled training by the proposed technique has become faster, very accurate and more stable.

5.2 Simulation Results of the Non-Blind Channel Equalization

The simulation studies of the non-blind channel equalizers are performed via 1000 Monte Carlo type iterations using the QPSK modulation. In this simulation, a five taps channel profile with average coefficient amplitudes given by (0.227, 0.46, 0.688, 0.46, 0.227), which is defined by Proakis and corresponds to an RMS delay spread of approximately 42 ns, is used [5]. A thirteen taps SDFE filter, composed of a FFF of nine taps and a SFBF of four taps, is used in non-blind channel equalization. The proposed method is compared with Zhao's VSS-LMS [16], Demir's VSS-LMS [21], fixed step size conventional LMS and conventional RLS algorithm for non-blind equalization. The step size parameter for conventional LMS algorithm was equal to 0.045 and the forgetting factor for conventional RLS algorithm was equal to 0.999. The step size factor α was equal to 0.8 and the positive control parameter β was equal to 0.968 for Zhao's VSS-LMS algorithm. Positive control parameters, α was equal to 0.896, β was equal to 0.955 and γ was equal to 0.832 for Demir's VSS-LMS algorithm. Positive control parameters, α was equal to 0.988, λ was equal to 0.725 and γ was equal to 0.996 for the proposed VSS-LMS algorithm. Maximum and minimum step size values are limited to 0.1 and 5E-5 respectively for all simulated VSS-LMS algorithms. Equalizer coefficients are initialized to zero value before non-blind adaptation.

Non-blind learning curves of the conventional LMS, conventional RLS, Zhao's VSS-LMS [16], Demir's VSS-LMS [21] and the proposed VSS-LMS equalizers are obtained in the value of SNR of 15 dB demonstrated in Fig. 5 for a stationary environment. The length of iteration is 450 QPSK symbols for the MSE performance comparisons in all simulated algorithms.

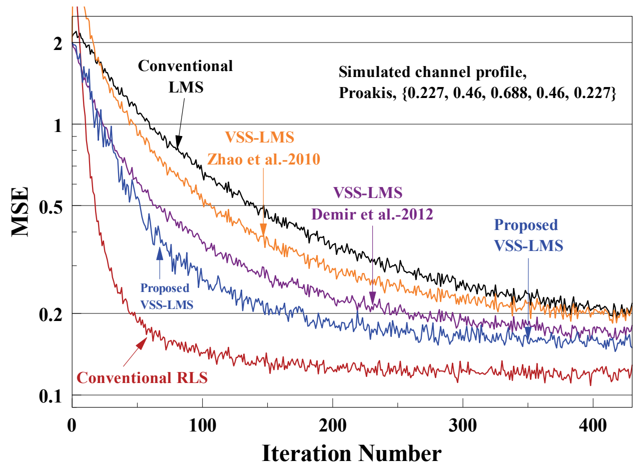

Fig. 5. Comparison of the MSE convergence performances of the non-blind adaptive channel equalizers for a stationary environment.

It is shown in Fig. 5 that Zhao's VSS-LMS algorithm little accelerates the LMS, but it converges to the LMS algorithm at the end of the training. It is observed that the performance of the proposed VSS-LMS algorithm outperforms to the performance of the conventional LMS, VSS-LMS algorithm published by Zhao et al. [16] and Demir's VSS-LMS [21] algorithm and converges to the lower MSE floor and comes closer to the performance obtained by the conventional RLS algorithm.

The performances of the non-blind learning curves of the five equalizers, namely, the conventional LMS, conventional RLS, VSS-LMS [16], [21] and the proposed VSS-LMS, are compared in Fig. 6 in the value of SNR of 15 dB for a non-stationary environment. In this study, a five taps channel profile with average coefficient amplitudes given by (0.227, 0.46, 0.688, 0.46, 0.227), which is defined by Proakis, is used [5] in the first region as can be seen from Fig. 6. When the iteration number is 450, channel profile abruptly changes to an exponential decay in the second region.

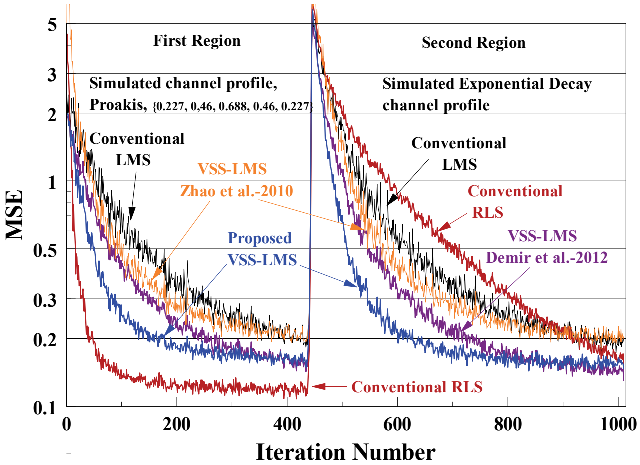

Fig. 6. Comparison of the MSE convergence performances of the non-blind adaptive channel equalizers for a non-stationary environment.

The performances of the aforementioned algorithms are the same as stationary environment performances (Fig. 5) in the first region as can be seen from Fig. 6. However, the proposed technique outperforms the performance of the four non-blind equalization algorithms and converges to the lowest steady state MSE floor in the second regions.

The obtained BER performances of non-blind training, the conventional LMS, conventional RLS, normalized LMS (N-LMS) [25], the VSS-LMS [16], [21] and the proposed VSS-LMS are given in Fig. 7. In this simulation, the same conditions are valid as in Fig. 5 for all non-blind training algorithms, except the length of the payload data after non-blind training was 450 symbols of QPSK modulation. It should be mentioned here that the BER performance samples are obtained after 450 iterations of non-blind training.

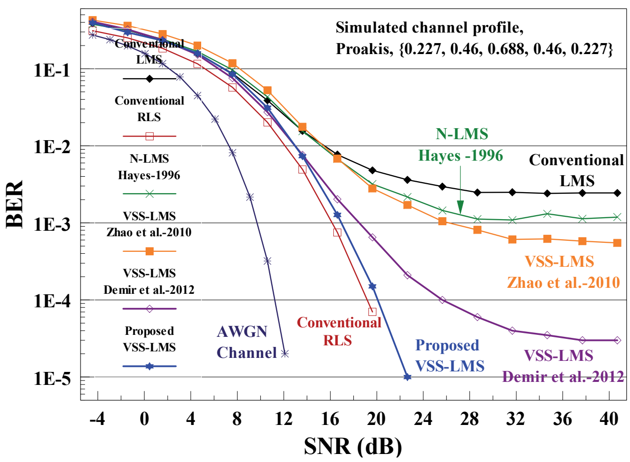

Fig. 7. Comparison of the BER performances of the non-blind adaptive channel equalizers.

The obtained BER performances agree with the MSE performances given in Fig. . It can be easily seen that the proposed technique outperforms the performances of four non-blind equalization algorithms and comes closer to the performance obtained by the RLS algorithm. The performance of the proposed technique has also reduced approximately till 1 dB performance difference with RLS algorithm and also cancelled the error floor. Thus, the proposed method improves the performance of the conventional LMS algorithm significantly.

6. Conclusions

In this paper, a new VSS-CMA blind and VSS-LMS non-blind equalizer based on cross correlation of channel output and error signal has been proposed as a solution to the problem of slow convergence of the fixed step size conventional CMA blind and LMS non-blind equalizer. Thus, the conflict is removed between the convergence rate and low steady state error of the fixed step-size conventional CMA and LMS algorithm. Compared with a state of art low complexity blind and non-blind training schemes, the proposed method has simpler in computational requirements, faster convergence and lower steady state error. It has been shown that a combination of conventional CMA and LMS with the proposed VSS technique provides an effective and robust way for adaptive blind and non-blind equalization. So, the simple CMA and LMS has become with a high performance blind and non-blind adaptive channel equalizer technique. The results of this study show that the proposed VSS-CMA and VSS-LMS is also demonstrated to be very suitable for high speed blind and non-blind trainings and channel tracking.

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