LMS Based Adaptive Channel Estimation for LTE Uplink

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Abstract. *In this paper, a variable step size based least mean squares (LMS) channel estimation (CE) algorithm is presented for a single carrier frequency division multiple access (SC-FDMA) system under the umbrella of the long term evolution (LTE). This unbiased CE method can automatically adapt the weighting coefficients on the channel condition. Therefore, it does not require knowledge of channel, and noise statistics. Furthermore, it uses a phase weighting scheme to eliminate the signal fluctuations due to noise and decision errors. Such approaches can guarantee the convergence towards the true channel coefficient. The mean and mean square behaviors of the proposed CE algorithm are also analyzed. With the help of theoretical analysis and simulation results, we prove that the proposed algorithm outperforms the existing algorithms in terms of mean square error (MSE) and bit error rate (BER) by more than around* $2.5dB$.

Keywords

SC-FDMA, PAPR, LMS, NLMS, VSS-LMS, RLS.

1. Introduction

The further increasing demand on high data rates in wireless communication systems has arisen in order to support broadband services. The 3rd generation partnership project (3GPP) members started a feasibility study on the enhancement of the universal terrestrial radio access (UTRA) in December 2004, to improve the mobile phone standard to cope with future requirements. This project was called long term evolution (LTE) [1], [2]. First 3GPP LTE specification is being finalized within 3GPP release-9. 3GPP LTE uses single carrier frequency division multiple access (SC-FDMA) for uplink transmission and orthogonal frequency division multiplexing access (OFDMA) for downlink transmission [3]. SC-FDMA is a promising technique for high data rate transmission that utilizes single carrier modulation and frequency domain equalization. Single carrier transmitter structure leads to keep the peak to average power ratio (PAPR) as low as possible that will reduce the energy consumption. SC-FDMA combines the desirable characteristics of OFDMA, such as simple implementation, robustness against frequency-selective channels, and relative easiness to employ multiple antenna transmission techniques as well as similar throughput performance [4], [5]. The transmitter of a SC-FDMA system first groups the modulation signals into blocks, then performs a DFT operation to produce a frequency domain representation of the input signals. It then maps each of the DFT outputs to one of the orthogonal subcarriers that can be transmitted. Finally, IDFT transforms the subcarrier amplitudes to a complex time domain signal [6]. Therefore, SC-FDMA is an important technique for broadband multimedia access, anywhere, and anytime wireless communication systems.

Since the radio channel is highly dynamic, the transmitted signal travels to the receiver by undergoing many detrimental effects that corrupt the signal and often place limitations on the performance of the system. Channel estimation (CE) techniques allow the receiver to approximate the impulse response of the channel and explain the behavior of the channel. It can be employed for the purpose of detecting received signal, improve signal to noise ratio (SNR), channel equalization, reduced intersymbol interference (ISI), mobile localization, and improved system performance [7], [8]. In general, CE techniques can be divided into two major categories such as the trained and blind. The former CE algorithm requires probe sequences that occupies valuable bandwidth whereas the latter uses the received data only. Due of course to their self-sufficiency in training, blind CE techniques are considered more attractive than trained based techniques [9], [10]. The training aided CE literature is rich, but, as our most important interest lies with blind CE methods, we will not track its presentation any more.

Several CE techniques have been proposed to mitigate inter-channel interference (ICI) in the uplink direction of 3GPP LTE system [11]. Most of the CE algorithms are derived from the minimization of the mean square error (MSE) between the output of the adaptive filter and noisy received signal. In [12], Wiener filtering based iterative CE has been investigated. But this scheme requires accurate knowledge of second order channel statistics, which is not always feasible at a destination. This scheme also requires high computational complexity and knowledge of channel correlations. Probably the simplest and most popular CE algorithm belonging of adaptive group is the standard least mean squares (LMS) algorithm which has the lead of low computational complexity, memory load, and simplicity of practical implementation [13]. Moreover, its performance and fast convergence speed are inversely related through a single parameter, step size. For large values of step size, the convergence of the LMS filter coefficients is very fast, but the steady state MSE is large and vice versa. In order to ensure the algorithm to be convergent, the range of step size is specified but the choice of optimal step size has not been properly addressed. Therefore, the existing LMS CE algorithm is not possible to obtain fast convergence and small steady state MSE at the same time. One of the important concerns in all practical realistic situations is to develop algorithms which give fast convergence of the filter coefficients and good MSE performance [14]. In order to increase MSE performance as well as fast convergence, normalized LMS (NLMS) CE algorithm is proposed which takes into account the variation in the signal level at the filter input and selects a normalized step size parameter. A drawback of NLMS algorithms is a higher computational complexity and misadjustment i.e., the mismatch between the true and estimated coefficients [15]. When a constant scalar step size is used in the LMS/NLMS algorithm, there is a trade off between the steady state error and the convergence speed, which prevents a fast convergence when the step size is chosen to be small for small output estimation error. In order to deal with this problem, one important idea is to use varying step size during adaptation.

Variable step size (VSS) methods are commonly sought after to provide steady state MSE performance. This method uses larger step size at the start of the iteration to speed up the convergence rate of the algorithm, and smaller step size when the algorithm is convergent [16]. Several VSS-LMS type CE techniques have been proposed in the literature [17], [18], [19]. But these algorithms are not adaptive to track the optimum step size parameter in a nonstationary environment. The existing VSS-LMS CE algorithms [20] cannot provide the minimum MSE in the tracking problem, since they cannot acquire and track the optimum step size. They may even cause worse steady state results, when the algorithm parameters are not appropriately adjusted. In [21], an adaptive time-varying step size LMS is proposed where the step size is adjusted using the energy of the instantaneous error. But due to the presence of the estimation error and measurement noise, the step size update is not an accurate reflection of the state of adaptation before or after convergence. This degrades the significant performance of these adaptive approaches. Furthermore, in [19], [22] proposed a time-varying step size LMS method that gives improved performance compared with standard LMS and NLMS algorithm. But when the channel is fast time-varying then this algorithm cannot accurately measure the autocorrelation between estimation error to control step size update. Therefore, the performance is reduced significantly. To combat the channel dynamics, the recursive least squares (RLS) based CE algorithm is frequently used for rapid convergence and improved MSE performance [9]. But it requires optimum forgetting factor such that the estimator error is minimized. Although a lot of modified CE algorithms have been studied on employing adaptive forgetting factor and parallel forgetting factor, the CE performance is severely degraded in highly dynamic fading channel even when the forgetting factor is well optimized [23]. However, this scheme also requires high computational complexity that is the major obstacle for practical base station (BS) as well as tiny mobile terminal implementation. Therefore, an efficient CE algorithm superior to the existing methods is necessary which provides both rapid convergence to the true channel coefficient and smallest steady state MSE.

In this paper, we propose an adaptive algorithm in the uplink direction of LTE systems which estimates the channel impulse response (CIR) from received block of data without any prior knowledge of the channel. To the best of the author's knowledge, this is the first time such scheme is proposed for LTE uplink systems. Specifically, we are going to develop recursive LMS type variable step size algorithm that can automatically adapt the optimum weighting coefficients on the channel condition. This time-varying step size method is re-selected at each iteration to minimize the sum of the squares of the prior estimation errors up to that current time point. Next, the mean and mean square behaviors as well as complexity of the proposed CE algorithm are presented. The following advantages are gained by using this proposed scheme. Firstly, this CE algorithm uses phase weighting scheme such that the algorithm is less vulnerable to signal variations owing to noise as well as estimation errors. With such approaches, convergence towards the true channel vector is guaranteed. Secondly, the proposed CE uses time-varying step size parameter such that larger step size at the beginning of the iteration to accelerate the convergence rate of the algorithm, and uses smaller step size when the algorithm is convergent. Hence, this CE algorithm does not have the convergence speed toward the true channel coefficients-MSE trade off problem. Thirdly, the proposed estimate $\mathbf{h}(m)$ is an unbiased estimate of the tap weight vector $\mathbf{w}$(m). An unbiased estimate indicates that its mean value is identical to the true parameter value. Consequently, as the number of observation increases, the estimate is assured to converge to the true parameter. Ideally, we would like our estimator to be unbiased and to have the smallest possible error variance. Fourthly, the proposed method does not require measurements of the relevant channel correlation functions, nor does it require matrix inversion. Finally, the proposed scheme outperforms conventional methods with respect to the MSE and bit error rate (BER) of the estimated channel by more than 2.5 dB.

The following notations are adopted throughout the paper: bold face lower and upper case letters are used to represent vectors and matrices respectively. Superscripts $\mathbf{x}^T$ denote the transpose of the $\mathbf{x}$, $tr[\mathbf{X}]$ denote the trace of the matrix $\mathbf{X}$, $\mathbf{I}$ is the identity matrix, and the symbol $E(.)$ denote expectation.

The rest of the paper is organized as follows. In Sec. 2, we describe the system model of the LTE uplink channel. In Sec. 3, the iterative CE method is reviewed for the convenience of the introduction of the proposed method. The proposed CE scheme is presented in Sec. 4. In Sec. 5, we compare the proposed method with the existing CE schemes via simulations. Finally, conclusions are made in Sec. 6.

2. LTE Uplink System Description

In this Section, we briefly explain LTE SC-FDMA system model, subcarrier mapping, fading channel statistics, and received signal model which is really imperative for designing efficient channel estimator.

2.1 Baseband System Model

An equivalent baseband block diagram for the communication system under investigation is shown in Fig. 1.

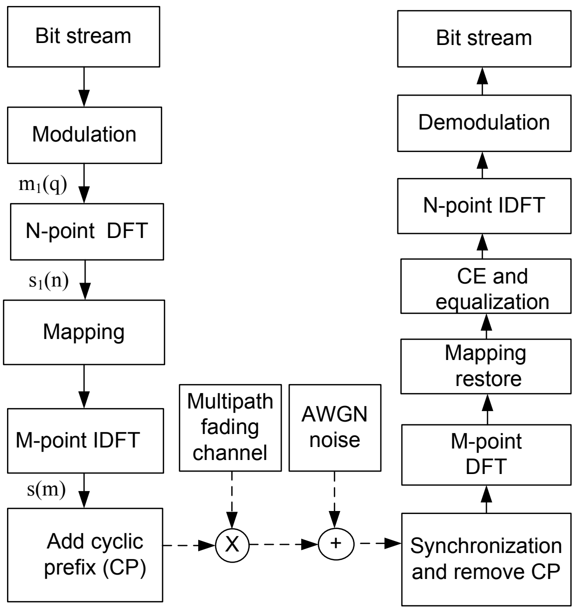

Fig. 1. Simplified block diagram of a LTE SC-FDMA wireless system.

At the transmitter side, a baseband modulator transmits the binary input to a multilevel sequences of complex numbers $m_1(q)$ in one of several possible modulation formats including binary phase shift keying (BPSK), quaternary PSK (QPSK), 8 level PSK (8-PSK), 16-QAM, and 64-QAM. These modulated symbols perform an N-point discrete Fourier transform (DFT) to produce a frequency domain representation [1]. The DFT followed by IDFT in a distribution-FDMA (DFDMA) or localization-FDMA (LFDMA) subcarrier mapping setup operates as efficient implementation to an interpolation filter. In distributed subcarrier mode, the outputs are allocated equally spaced subcarriers, with zeros occupying the unused subcarrier in between. While in localized subcarrier mode, the outputs are confined to a continuous spectrum of subcarriers. Except the above two modes, interleaved subcarrier mapping mode of FDMA (IFDMA) is another special subcarrier mapping mode [24], [25]. The difference between DFDMA and IFDMA is that the outputs of IFDMA are allocated over the entire bandwidth, whereas the DFDMA's outputs are allocated every several subcarriers. An example of SC-FDMA transmit symbols in the frequency domain for 2 users, 3 subcarriers per user and 6 subcarriers in total is illustrated in Fig. 2.

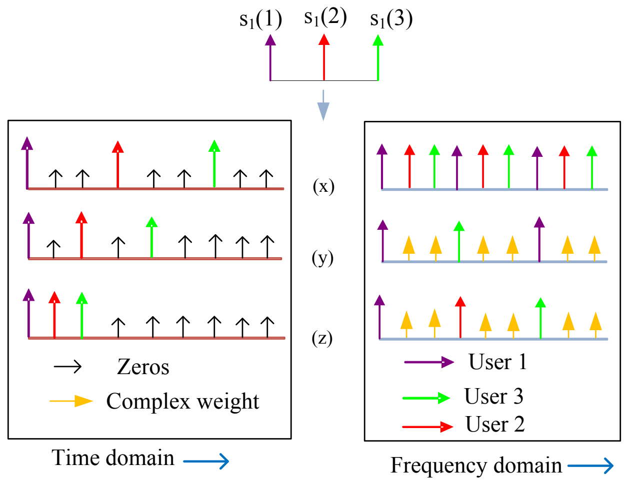

Fig. 2. Multiple access scheme of SC-FDMA: (x) IFDMA mode, (y) DFDMA mode and (z) LFDMA.

Finally, the IDFT module output is followed by a cyclic prefix (CP) insertion that completes the digital stage of the signal flow. A cyclic extension is used to eliminate ISI and preserve the orthogonality of the tones. Assume that the channel length of CP is larger than the channel delay spread.

2.2 Channel Model

Channel model is a mathematical representation of the transfer characteristics of the physical medium. These models are formulated by observing the characteristics of the received signal. According to the documents from 3GPP, in the mobile environment, a radio wave propagation can be described by multipaths which arise from reflection and scattering. If there are l distinct paths from transmitter to the receiver, the impulse response of the wide-sense stationary uncorrelated scattering (WSSUS) fading channel can be represented as [26]:

$$w(\tau,t) = \sum_{j=0}^{l-1} w_j(t)\delta(\tau-\tau_j) \tag{1}$$

where fading channel coefficients $w_j(t)$ are the wide sense stationary i.e. $w_j(t) = w(m,j)$, uncorrelated complex Gaussian random paths gains at time instant t with their respective delays τ_j, where $w(m,j)$ is the sample spaced channel response of the lth path during the time m, and $\delta(.)$ is the Dirac delta function. Based on the WSSUS assumption, the fading channel coefficients in different delay taps are statistically independent. In time domain, fading coefficients are correlated and have Doppler power spectrum density modeled in Jakes and has an autocorrelation function given by [27]:

$$E[w(m,j)w^T(n,j)] = \sigma_w^2(j)J_0[2\pi f_d T_f(m-n)] \quad (2)$$

where $w(n,j)$ is a response of the l^{th} propagation path measured at time n, $\sigma_w^2(j)$ denotes the power of the channel coefficients, f_d is the Doppler frequency in Hertz, T_f is the symbol duration in seconds, and $J_0(.)$ is the zero order Bessel function of the first kind [26].

2.3 Received Signal Model

The transmitted symbols propagating through the radio channel can be modeled as a circular convolution between the channel impulse response (CIR) and the transmitted data block i.e., $[s(m) * w(\tau,t)]$. Since the channel coefficient is usually unknown to the receiver, it needs to be efficiently estimated while maintain little computational complexity. At the receiver, the opposite set of the operation is performed. After synchronization, cyclic prefix samples are discarded and the remaining N samples are processed by the DFT to retrieve the complex constellation symbols transmitted over the orthogonal sub-channels. The received signals are demapped and equalizer is used to compensate for the radio channel frequency selectivity. After IDFT operation, these received signals are demodulated and soft or hard values of the corresponding bits are passed to the decoder. The decoder analyzes the structure of received bit pattern and tries to reconstruct the original signal. In order to achieve good performance the receiver has to know the impact of the channel. Thus, an accurate and efficient CE algorithm is necessary to coherently demodulate the received data [28].

3. A Review of the CE Algorithms

Adaptive CE is one the most important current research interests in the wireless communications where the channel is rapidly time-varying. An adaptive algorithm is a process that changes its parameter as it gains more information of its possibly changing environment. This method tries to adjust the filter parameter in such a way that minimizes the MSE between the output of the filter and the desired signal. Therefore, the adaptive filter parameters are entirely known, replicates the system in question whose parameters are unknown. In other words, the parameters of the adaptive filter give a good approximation of the parameters of the unknown scheme. The performance of this type CE algorithm is dependent on the convergence towards the true channel coefficients , computational complexity as well as minimum MSE performance [29].

3.1 Least Mean Squares (LMS) Algorithm

The LMS algorithm is based on the stochastic gradient and is given by [13]

$$\begin{aligned}\mathbf{e}(m) &= \mathbf{S}^T(m)\mathbf{w}(m) + \mathbf{z}(m) - \mathbf{S}^T(m)\mathbf{h}(m)\\ \mathbf{h}(m+1) &= \mathbf{h}(m) + \eta\mathbf{S}(m)\mathbf{e}(m)\end{aligned}$$

where η is step size, $\mathbf{S}(m)$ is the transmitted diagonal matrix at sampling time m, $\mathbf{h}$(m) is the adaptive filter coefficient, and $\mathbf{e}(m)$ is the estimation error. The filter coefficients are updated using an estimate of the cost function gradient, $[\eta\mathbf{S}(m)\mathbf{e}(m)]$. In all practical applications, the signals involved might be corrupted by noise. When the noise is present in the received sequence, interference will also in the coefficients adaption process through the term $[\eta\mathbf{S}(m)\mathbf{e}(m)]$. As a result, where the distribution of the noise is highly impulsive, the LMS scheme might have low convergence and lower steady state MSE performance. The step size parameter, η determines the convergence rate of the algorithm and higher value provides faster convergence. However, if η exceeds certain bound then the algorithm will diverge. As the bound on η is not known a priori and is dependent on the various statistics. In practice, a somewhat conservative scalar value of η is used. Also a higher value of η results in higher variations in the tap weight vector estimate after the initial convergence phase. Such variations result in increased distortion in the combiner output which in turn results in an increased MSE and BER [9], [13].

3.2 Normalized LMS (NLMS) Algorithm

The main problem of the LMS CE algorithm is that it is sensitive to the scaling of its input signals. This makes it very hard to choose η that guarantees stability of the algorithm. The NLMS is a variant of the LMS algorithm that solves this problem by normalizing with the power of the input signal. The NLMS algorithm can be summarized as [29]:

$$\begin{aligned}\mathbf{e}(m) &= \mathbf{S}^T(m)\mathbf{w}(m) + \mathbf{z}(m) - \mathbf{S}^T(m)\mathbf{h}(m)\\ \mathbf{h}(m+1) &= \mathbf{h}(m) + \eta\mathbf{e}(m)[\mathbf{S}^T(m)\mathbf{S}(m)]^{-1}\mathbf{S}(m) \quad (3)\end{aligned}$$

when a constant scalar step size is employed in the LMS/NLMS algorithm, there is a trade off among the steady state error-convergence towards the true channel coefficients, which avoids a fast convergence when the step size is preferred to be small for small output estimation error. In order to guarantee the algorithm to be convergent, the range of step size is specified but the choice of optimal learning step size has not been appropriately addressed. In order to deal with these troubles, one key idea is to exploit varying step size during adaptation.

3.3 Variable Step Size (VSS)-LMS Algorithm

The VSS-LMS algorithm involves one additional step size update equation compared with the standard LMS algorithm. The VSS algorithm is [30], [19]

$$\begin{aligned}\eta(m+1) &= \alpha\eta(m) + \gamma p^2(m)\\ p(m) &= \beta p(m) + (1-\beta)\mathbf{e}^T(m)\mathbf{e}(m-1) \quad (4)\end{aligned}$$

where $0 < \alpha < 1$, $0 < \beta < 1$, and $\gamma > 0$. When the channel is fast time-varying then algorithm cannot accurately measure the autocorrelation between estimation error to control step size update. So, this CE algorithm cannot provide the minimum MSE in the tracking problem, since it cannot acquire and track the optimum step size. It may even cause worse steady state results, when the algorithm parameters are not appropriately adjusted. In addition, control parameters α and β need to be adjusted for a better performance. As can be seen here, a general characteristic of these VSS CE methods is that predetermined control parameters are necessary to improve the performance. Though, in most of them, rules to choose control parameters are not specified. Those parameters are always selected from extensive simulations, or from experience. It is clear that the choice of parameters would significantly influence the performance of these schemes.

3.4 Recursive Least Squares (RLS) Algorithm

To combat the channel dynamics, the RLS based CE algorithm is frequently used for rapid convergence and improved MSE performance [9]. The standard RLS algorithm is

$$\begin{aligned}
\mathbf{e}(m) &= \mathbf{S}^T(m)\mathbf{w}(m) + \mathbf{z}(m) - \mathbf{S}^T(m)\mathbf{h}(m)\\
\mathbf{R}(m) &= \mathbf{B}(m-1)\mathbf{S}(m)[\lambda + \mathbf{S}^T(m)\mathbf{B}(m-1)\mathbf{S}(m)]^{-1}\\
\mathbf{B}(m) &= \lambda^{-1}\mathbf{B}(m-1) - \lambda^{-1}\mathbf{R}(m)\mathbf{S}^T(m)\mathbf{R}(m-1)\\
\mathbf{h}(m+1) &= \mathbf{h}(m) + \mathbf{S}(m)\mathbf{e}(m)\mathbf{R}(m)
\end{aligned} \tag{5}$$

where λ is the exponential forgetting factor with $0 < \lambda < 1$. The smaller value of λ leads to faster convergence rate as well as larger fluctuations in the weight signal after the initial convergence. On the other hand, too small λ value makes this algorithm unstable. Subsequently, it requires best possible forgetting factor such that the estimator error is decreased. Although a lot of modified CE algorithm has been studied on employing adaptive forgetting factor and parallel forgetting factor, the CE performance is severely degraded in highly dynamic fading channel even when the forgetting factor is well optimized [23]. However, this scheme also has computational complexity-performance trade off problem that is the major obstacle for practical mobile terminal as well as base station (BS) implementation [31], [32]. Consequently, an efficient CE algorithm better than existing algorithms is required which gives both fast convergence and minimum steady state MSE.

4. Proposed Adaptive CE Algorithm

The simplified block diagram of a proposed CE algorithm in LTE SC-FDMA system is illustrated in Fig. 3 and its linear transversal filter in Fig. 4.

The signal **S(m)** is transmitted via a time-varying channel $\mathbf{w}(m)$, and corrupted by an observation noise $\mathbf{z}(m)$ before being detected in a receiver. The reference signal $\mathbf{h}(m)$ is estimated by using any kind of CE algorithm such as LMS, NLMS, RLS. The noisy observation at time index m is

$$\begin{aligned}
\mathbf{r}(m) &= s_1(m-1)w_1(m) + \ldots.. + s_l(m-l)w_l(m) + \mathbf{z}(m)\\
&= \sum_{j=1}^{l} s_j(m-j)w_j(m) + \mathbf{z}(m)\\
&= \mathbf{S}^T(m)\mathbf{w}(m) + \mathbf{z}(m),
\end{aligned} \tag{6}$$

where $s_j(m-j), j = 1,2,\ldots..,l$ are transmitted signal vectors at time m, $\mathbf{S}(m) = diag[s_1(m-1), s_2(m-2), \ldots\ldots, s_l(m-l)]$, l is the distinct paths from transmitter to the receiver, $\mathbf{w}(m)$ is the channel coefficients at time m, and $\mathbf{z}(m)$ is the observation noise with zero mean and variance σ^2. After processing some intermediate steps (synchronization, remove CP, DFT, and demapping), the decision block reconstructs the detected signal to an approximate modulated signal and its phase. The output $\mathbf{y}(m)$ of the adaptive filter is expressed as

$$\begin{aligned}
\mathbf{y}(m) &= d_1(m-1)h_1(m) + \ldots.. + d_l(m-l)h_l(m)\\
&= \sum_{j=1}^{l} d_j(m-j)h_j(m)\\
&= \mathbf{D}^T(m)\mathbf{h}(m)
\end{aligned} \tag{7}$$

where $d_j(m-j), j = 1,2,\ldots..,l$ are detected signal vectors at time m, $\mathbf{D}(m) = diag[d_1(m-1), d_2(m-2), \ldots\ldots, d_l(m-l)]$. In this problem formulation, the ideal adaptation procedure would adjust $w_j(m)$ such that $w_j(m) = h_j(m)$ as $m \to \infty$. In practice, the adaptive filter can only adjust $\mathbf{w}(m)$ such that $\mathbf{y}(m)$ closely approximates desired signal over time. Therefore, the instantaneous estimated error signal needed to update the weights of the adaptive filter is

$$\begin{aligned}
\mathbf{e}(m) &= \mathbf{r}(m) - \mathbf{y}(m)\\
&= \mathbf{r}(m) - \mathbf{D}^T(m)\mathbf{h}(m).
\end{aligned} \tag{8}$$

This priori error signal, $\mathbf{e}(m)$ is used for tuning the adaptive filter weights to minimize the estimator error. The error signal is fed into a procedure which alters or adapts the parameters of the filter from time m to time $(m+1)$ in a well-defined manner. As the time index m is incremented, it is hoped that the output of the adaptive filter becomes a better and better match to the desired response signal through this adaptation process, such that the magnitude of $\mathbf{e}(m)$ decreases over time as shown in Fig. 5.

Now define the proposed cost function $j(m)$ for the adaptive filter structure that minimizes the square distance between the received signal and its estimate. This object function also includes a phase discriminate weighting sequence $p(m)$ such that algorithm is less vulnerable to signals variations owing to noise as well as estimation errors. The weighting sequence $p(m)$ is the distance between the initial modulated carrier phase α and carrier synchronization phase β i.e.,

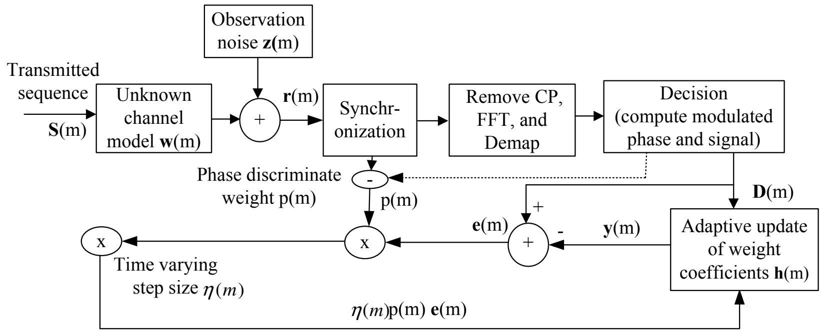

Fig. 3. Modeling an unknown time-varying system.

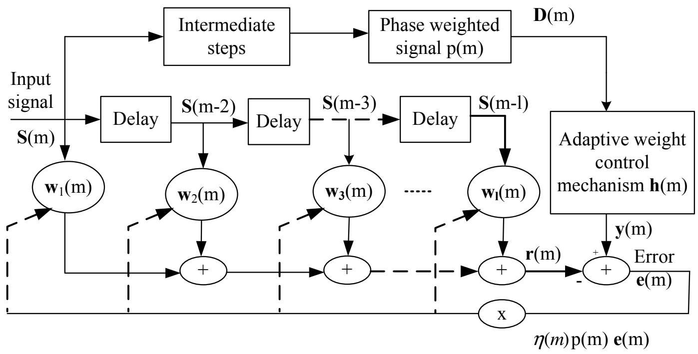

Fig. 4. Transversal adaptive filter with time-varying tap weights.

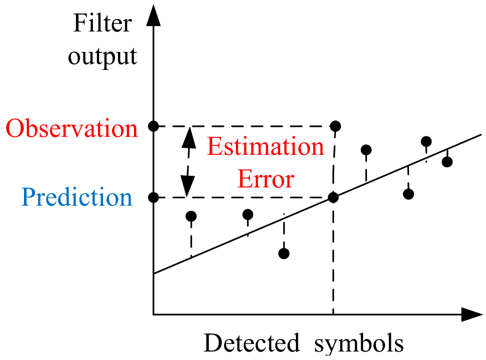

Fig. 5. Residual error.

$$p_1(m) = \frac{min|\alpha(m) - \beta(m)|}{\pi/M}$$
$$p(m) = p_1(m)p_1(m-1).........p_1(m-l) \quad (9)$$

where M is the alphabet size i.e. $M = 2$ for BPSK, $M = 16$ for 16-QAM etc, (π/M) is the normalized factor. So, the proposed cost function $j(m)$ is

$$\begin{aligned} j(m) &= p(m)\mathbf{e}^T(m)\mathbf{e}(m) \\ &= p(m)[\mathbf{r}^T(m)\mathbf{r}(m) - \mathbf{r}^T(m)\mathbf{D}^T(m)\mathbf{h}(m) - \\ &\quad \mathbf{r}(m)\mathbf{h}^T(m)\mathbf{D}(m) + \mathbf{D}^T(m)\mathbf{D}(m)\mathbf{h}^T(m)\mathbf{h}(m)]. \end{aligned} \quad (10)$$

To minimize the cost function in (10), we take the gradient with respect to filter coefficient which yields

$$\Delta_{\mathbf{h}} j(m) = p(m)[-2\mathbf{r}(m)\mathbf{D}(m) + 2\mathbf{D}(m)\mathbf{D}^T(m)\mathbf{h}(m)]. \quad (11)$$

The steepest descent method is used to adjust adaptive parameters in order to search the quadratic MSE performance function for its minimum. According to this method, a sequence of change is made to the weight vector along the direction of the negative gradient. Therefore, the next weight vector, $\mathbf{h}(m+1)$, is made equal to the present weight vector, $\mathbf{h}(m)$, plus a change proportional to the negative gradient at the m^{th} iteration:

$$\begin{aligned} \mathbf{h}(m+1) &= \mathbf{h}(m) - 1/2\eta(m)\Delta_{\mathbf{h}} j(m) \\ &= \mathbf{h}(m) + p(m)\eta(m)\mathbf{D}(m)[\mathbf{r}(m) - \mathbf{D}^T(m)\mathbf{h}(m)] \\ &= \mathbf{h}(m) + p(m)\eta(m)\mathbf{D}(m)\mathbf{e}(m) \end{aligned} \quad (12)$$

where $\mathbf{h}(m+1)$ denotes the weight vector to be computed at iteration $(m+1)$, and $\eta(m)$ is the time-varying step size parameter which is related to the rate of convergence and control stability. The term $[\eta(m)p(m)\mathbf{D}(m)\mathbf{e}(m)]$ represents the correction factor or adjustment that is applied to the current estimate of the tap weight vector. Its observed that coefficients of the adaptive filter are update using an estimate cost function gradient, priori error $\mathbf{e}(m)$, phase discriminate weighting sequence $p(m)$, and time-varying step size parameter $\eta(m)$. Using this phase weighting scheme to eliminate the signal fluctuations more due to noise and decision errors.

In order to accelerate the convergence rate to the true channel coefficient, we now derive the expression of time-varying step size for the proposed LMS algorithm. For doing this, taking the gradient in (10) with respect to $\eta(m)$ as

$$\begin{aligned}\Delta_\eta j(m) &= p(m)[\frac{\partial \mathbf{e}^T(m)}{\partial \eta(m)}\mathbf{e}(m) + \frac{\partial \mathbf{e}(m)}{\partial \eta(m)}\mathbf{e}^T(m)] \\ &= -p(m)[\mathbf{D}^T(m)\mathbf{c}(m)\mathbf{e}(m) + \mathbf{D}^T(m)\mathbf{c}(m)\mathbf{e}(m)] \\ &= -2p(m)\mathbf{e}(m)\mathbf{D}^T(m)\mathbf{c}(m), \qquad (13)\end{aligned}$$

for the sake of simplicity, assume that $\mathbf{c}(m) = \frac{\partial \mathbf{h}(m)}{\partial \eta(m)}$. From (12), differentiating $\mathbf{h}(m)$ with respect to $\eta(m)$, we obtain

$$\begin{aligned}\mathbf{c}(m+1) &= \mathbf{c}(m) + \mathbf{b}(m)\frac{\partial \eta(m)}{\partial \eta(m)} + \eta(m)p(m)\mathbf{D}(m)\frac{\partial \mathbf{e}(m)}{\partial \eta(m)} \\ &= \mathbf{c}(m) + \mathbf{b}(m) + \eta(m)p(m)\mathbf{D}(m)\frac{\partial \mathbf{e}(m)}{\partial \eta(m)} \\ &= \mathbf{c}(m) + \mathbf{b}(m) + \eta(m)p(m)\mathbf{D}(m)[-\mathbf{D}^T(m)\mathbf{c}(m)] \\ &= \mathbf{b}(m) + [\mathbf{I} - \eta(m)p(m)\mathbf{D}^T(m)\mathbf{D}(m)]\mathbf{c}(m) \\ &= \mathbf{b}(m) + \xi\mathbf{c}(m), \qquad (14)\end{aligned}$$

for the sake of simplicity, assume that $\mathbf{b}(m) = p(m)\mathbf{D}(m)\mathbf{e}(m)$, and $\xi = [\mathbf{I} - \eta(m)p(m)\mathbf{D}^T(m)\mathbf{D}(m)]$. To decrease the computational complexity without sacrificing convergence speed and MSE performance, assume ξ is a scalar positive constant close to, but less than unity, and $\mathbf{c}(m)$ is initial zeros vector. Similar to (12), the gradient time-varying adaptive step size update equation can be written as

$$\begin{aligned}\eta(m+1) &= \eta(m) - 1/2\varphi\Delta_\eta j(m) \\ &= \eta(m) + \varphi(m)\mathbf{D}^T(m)\mathbf{e}(m)\mathbf{c}(m) \qquad (15)\end{aligned}$$

where φ is the learning rate parameter. This time-varying step size is re-selected at each iteration to minimize the sum of the squares of the prior estimation errors up to that recent time point. So, this algorithm is able to sense the convergence rate at which the best possible tap weight coefficients are changing. At the beginning of our CE algorithm an initial CIR and step size is given to start the iteration process. The algorithm is kept on iterative until the channel estimator converges towards the true channel vectors. The detailed steps of this proposed algorithm is shown in Fig.6. A significant feature of this iterative algorithm is its simplicity; it does not require measurements of the relevant correlation functions, nor does it require matrix inversion, and avoids convergence speed-MSE trade off problem. Next, we compute the mean and mean square behaviors as well as valid range of step-size to achieve convergence of the proposed algorithm.

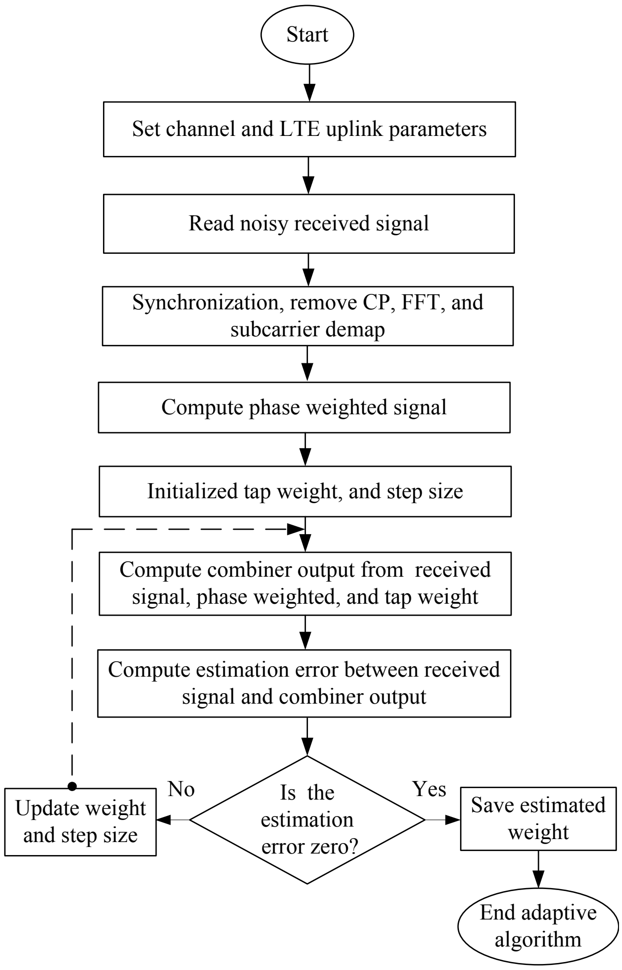

Fig. 6. Flow chart of the proposed CE technique for LTE SC-FDMA system.

5. Simulation Results and Discussion

The error performance of the aforementioned iterative estimation algorithms is explored by performing extensive computer simulations. A Rayleigh fading channel is considered for this purpose. More specifically, we use a Jakes-like model, proposed in [27], to simulate fading. All simulation parameters of the LTE SC-FDMA system are summarized in Tab. 1.

Recall that the CE weight update recursion of the proposed algorithm is given in (12), where $\mathbf{e}(m)$ is illustrated in equation (8), and $\eta(m)$ is described in (15). The performance of the proposed CE algorithm is compared with the fixed step size LMS algorithm [14], NLMS algorithm [29], Aboulnasr VSS-LMS algorithm [22], and RLS algorithm [9]. In practice, the ideal channel coefficient $\mathbf{w}$ is unavailable, so estimated reference signal $\mathbf{h}$ must be used instead. The more accurate $\mathbf{h}$ is, the better MSE performance of the CE will achieve. The performance is measured using MSE between the actual and the estimated channel response. MSE versus SNR for different recursive CE techniques in slow (Doppler frequency, $f_d = 100$ Hz), medium ($f_d = 500$ Hz), and fast

System parameters	Assumptions
System bandwidth	5 MHz
Sampling frequency	7.68 MHz
Subcarrier spacing	9.765 kHz (5 MHz/512)
Modulation data type	BPSK
FFT size	16
Subcarrier mapping schemes	IFDMA
IFFT size	512
Data block size	32 (512/16)
Cyclic prefix	4 μ or 20 samples
Channel	Rayleigh fading
Forgetting factor	0.99
LMS gain	0.4
Equalization	ZF
Doppler frequency	100, 500, and 1000 Hz
Number of iteration	300

Tab. 1. The major system parameters used for simulations.

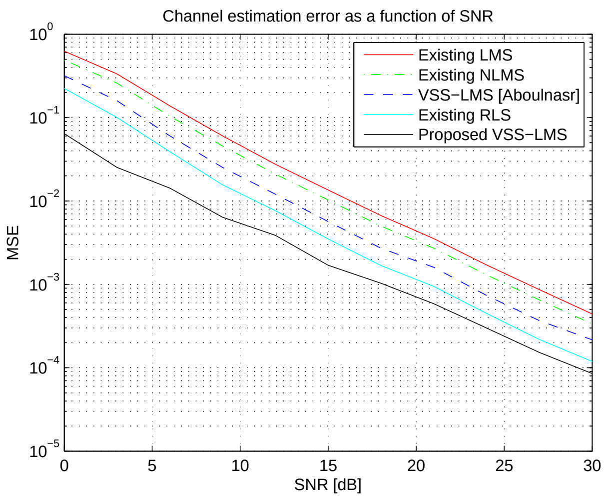

Fig. 7. Comparison of MSE behaviors of all CE algorithms for $f_d = 100$ Hz.

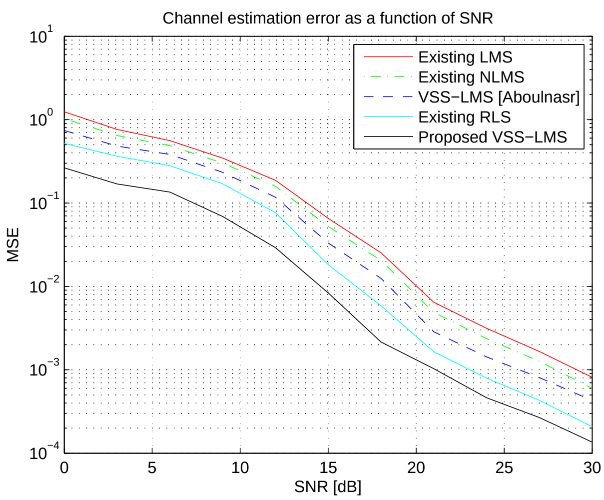

Fig. 8. Comparison of MSE behaviors of all CE algorithms for $f_d = 500$ Hz.

($f_d = 1000$ Hz) time-varying channels are presented in Figs. 7, 8, and 9, respectively.

From the Figs. one can see that proposed adaptive CE can always achieve better performance than other existing LMS, NLMS, Aboulnasr, and RLS method. It is inevitable that the MSE performance gets inferior as the fading increases i.e., f_d increases from 100 Hz to 1000 Hz. The proposed CE algorithm outperforms the RLS and Aboulnasr estimator by approximately 2.5 dB and 4.5 dB in the range of the tested SNRs. This proposed CE algorithm uses phase weighting scheme such that algorithm is less susceptible to both signals fluctuations due to noise and decision errors. Furthermore, the presence of the estimation error and measurement noise, the step size update is an accurate reflection of the state of adaptation before or after convergence. This is due to the drastic decrease in noise level which increases the performance of this algorithm. Moreover, the proposed CE adapt optimal time varying step size parameter such that larger step size at the beginning of the iteration to accelerate the convergence rate of the algorithm, and uses the smaller step size when the algorithm is convergent. So, proposed algorithm has a better anti-nose as well as tracking ability. Therefore, by modified LMS with time-varying step size CE algorithm, we can obtain relatively exact reference signal. The BER is an another important performance parameter in wireless communication system for quality measurement of recovered data. Next, we evaluate the effect of the proposed CE in terms of BER performance. In Figs. 10, 11, and 12, we compare the BER performance of the several channel estimators. BER of the adaptive schemes is computed after the algorithms have converged to their steady state. It is observed that the proposed CE algorithm is the best choice among the others under all scenarios. The error performance degrades with the increased Doppler frequency, i.e., when f_d increases from 100 Hz to 1000 Hz, as expected. The robustness of the estimation algorithms under consideration are

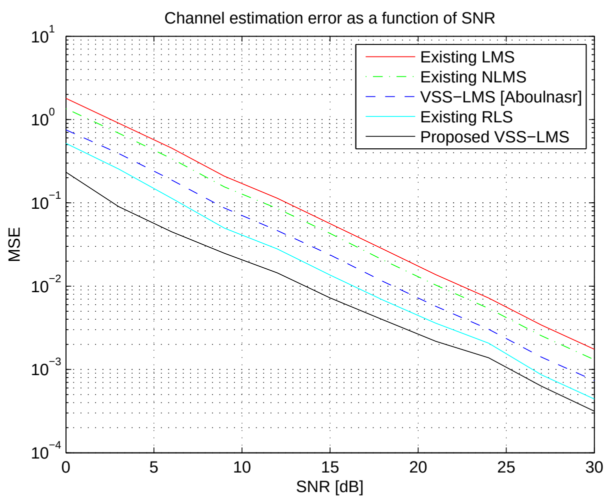

Fig. 9. Comparison of MSE behaviors of all CE algorithms for $f_d = 1000$ Hz.

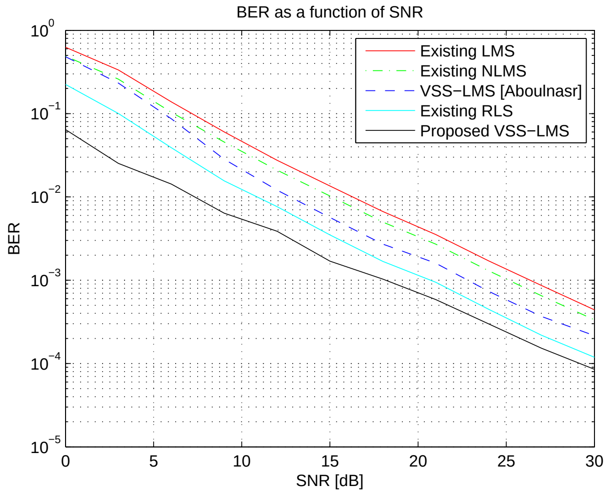

Fig. 10. BER performance of five algorithms as a function of SNR in Rayleigh fading channel with $f_d = 100$ Hz.

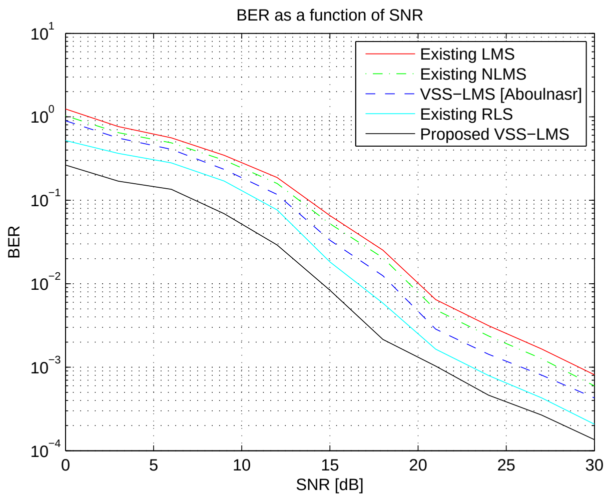

Fig. 11. BER performance of five algorithms as a function of SNR in Rayleigh fading channel with $f_d = 500$ Hz.

different with respect to the increase in Doppler frequency. It concludes that the proposed CE algorithm outperforms RLS and Aboulnasr estimator by around 2.5 dB and 4.5 dB in the range of the tested SNRs. Finally, we conclude that proposed CE technique provides the best results among all considered estimators in both simulated scenarios.

We estimated the number of arithmetic operations by taking into account the number of additions and multiplications. It is clear that the simplest estimator are the LMS [14] and Aboulnasr method [22] while proposed algorithm requires slightly few more operations than LMS and Aboulnasr method. On the other hand, NLMS [29] algorithm requires one real division but proposed approach doesn't require matrix inversion for implementation. Furthermore, the RLS algorithm [9] requires one matrix inversion as well as higher computational complexity than all others schemes.

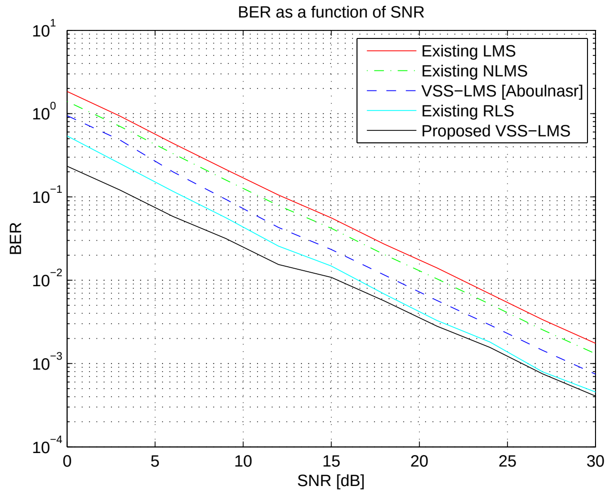

Fig. 12. BER performance of five algorithms as a function of SNR in Rayleigh fading channel with $f_d = 10000$ Hz.

However, the proposed scheme requires slightly more arithmetic complexity that is minor problem for practical base station (BS) implementation because the SC-FDMA CE is done by the information received by the BS. In BS, CE accuracy and data estimation is the most important.

6. Conclusion

An accurate CE is one of the most important issues for reliable future wireless communication systems such as LTE. To combat the channel dynamics and support broadband multimedia access, we proposed a time-varying step size LMS CE scheme for wireless systems. This estimator automatically adapts the weighting coefficients on the channel condition so that information of channel, and noise statistics are not essential. The proposed algorithm is exploited to further eliminate signals fluctuations due to noise decision errors by the phase weighting scheme. With such approaches, convergence towards the true channel vector is assured. The mean, mean square behaviors, unbiased estimator, and computational complexities of the proposed CE algorithm are analyzed. Even though, the proposed CE technique requires little bit high computational complexity, the advantage in the MSE and convergence towards true channel coefficient as well as BER performance may be significant useful for future mobile communications which allow broadband multimedia access, anywhere, and anytime wireless communication.

Acknowledgment

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2010- 0017118).

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