Review on Adaptive Blind Channel Estimation using LMS Based Techniques in OFDM Systems

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Abstract: In communication systems, Multiple Input Multiple Output (MIMO) channel is introduced for achieving good bit rate and high data speed. Usually, the communication systems attain good quality of services, high transmission rates and minimum probability of error, while Orthogonal Frequency Division Multiplexing (OFDM) is combined with MIMO. In MIMO-OFDM, channel estimation shows great importance, which is utilized for estimating the transmitted signal utilizing receiver signal. In MIMO-OFDM, channel capacity is also increased due to channel estimation. In addition, accurate retrieval of channel state information is a challenging process in MIMO-OFDM system. Generally, the channel state information is retrieved utilizing channel estimation, when all the channels between the transmit antenna are accurately known. In this paper, we describe about the basic information of MIMO-OFDM system and also reviews the dissimilar channel estimation techniques used in MIMO-OFDM system with various system parameters.

Index Terms: Channel estimation, wireless communication system, orthogonal frequency division multiplexing, multiple input multiple output.

1. INTRODUCTION

Usually the radio signals are highly dynamic, where the transmitted signals travel to the receiver by experiencing numerous detrimental effects, which corrupts the signals and often lessen the system performance. Channel estimation is utilized to identify the channel state information in order to understand the channel properties. This information gives details about transmitted signal from transmitter to receiver. Channel Estimation (CE) methods estimates the impulse response of the channel and also describes about the channel behavior. The CE methods are utilized to improve SNR, system performance, mobile localization, and channel equalization, and also to reduce inter symbol interference [1], [2]. Generally, CE approaches are sub-divided into two types: blind type and pilot type. CE is carried-out to investigate the channel effect on signal by inserting pilot tones into every OFDM symbol. The existing CE approaches needs probe sequence to occupy reliable bandwidth, but it utilizes only the received data. Though, the blind CE approaches are attractive compared to the trained approaches, due to self-sufficiency in training [3], [4]. The convergence rate of blind channel estimator is very slow, because it requires huge amount of data.

The major problem in OFDM is inter symbol interference. In order to address this concern, many CE approaches are developed to diminish inter-channel interference in 3GPP LTE system [5]. Most of the CE approaches are utilized for minimizing the MSE between the output of noisy received signal and adaptive filter. The wiener filter based iterative CE algorithm [6] is developed to gain accurate information about second order channel data, which is not feasible at a destination. The developed approach needs knowledge about channel correlations and also the computational complexity is high. Hence, the most popular CE algorithm is LMS that includes a few benefits like memory load, low computational complexity and simple in practical implementation [7]. The performance of LMS algorithm is inversely proportional to the convergence speed, step size, and single parameter. The convergence speed of LMS is fast for large step size values. Henceforth, the range of step size is mentioned but the selection of optimal step size is not mentioned properly in order to ensure the algorithm to be convergent. Thus, the existing LMS algorithm does not obtain fast convergence and steady state MSE. In all practical circumstances, one of the major issues is to develop algorithms that delivers good MSE performance and fast convergence [8].Normalized-LMS (NLMS) CE approach is developed for increasing the MSE performance and fast convergence. The developed NLMS algorithm effectively selects the normalized step size parameter and also considers the variations in signal level at the filter input. In addition, the LMSE channel estimator minimizes the MSE between the estimated and actual channels by using winer equation. A major problem in NLMS-CE algorithm are miss adjustments and high computational complexity [9]. There is a trade-off between the convergence speed and steady state error, while a constant scalar step size is utilized in NLMS algorithm that effectively avoids the fast convergence. The step size is varied during adaptation in order to deal with this problem. Variable Step Size (VSS) approaches are used to deliver steady state MSE performance. At the start of iteration, these approaches utilize larger step size in order to speed up the convergence rate [10]. Numerous VSS-LMS type CE methods are developed in the literature section [11], [12].In a non-stationary environment, these algorithms are not adaptive in tracking the optimal step size parameter. The existing (VSS-LMS CE) approach delivers maximum MSE, since it can-not tracks the optimal step size. While the algorithm parameters are not effectively adjusted, it may further lead to worse steady state outcome. Presently, an adaptive LMS algorithm is developed to adjust the step size by utilizing the energy of instantaneous error [13]. The step size update is not an accurate reflection of the state of adaptation before or after convergence, due to the presence of measurement noise and estimation error that degrades the performance of adaptive approaches. In addition, a time varying step size LMS method [14] is developed that delivers better performance related to the standard NLMS and LMS algorithm. These algorithms can-not accurately measure the auto-correlation between the estimation errors, while the channel is fast time varying. In order to combat the channel

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dynamics, the Recursive Least Squares (RLS) based CE algorithms are used utilized rapidly for improving the MSE performance and for fast convergence, but it needs optimal forgetting factor such that the estimator error is minimized.

2 MIMO-OFDM SYSTEM

In wireless communication system, the MIMO channels are combined with OFDM system for delivering high spectral efficiency [16], and robustness [15]. The MIMO-OFDM system plays an emerging role in future and current wireless communications [17]. The graphical depiction of MIMO-OFDM is expressed in figure 1.

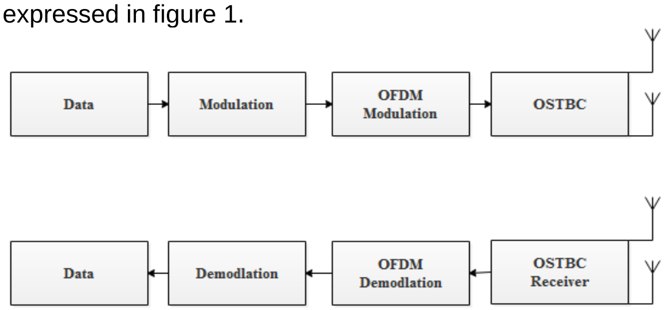

Fig.1. *Graphical depiction of MIMO-OFDM system*

Generally, MIMO transmits dissimilar signals over multiple antennas and OFDM sub-divides the channels into spaced sub-channels to deliver consistent communication at high speed. In addition, MIMO-OFDM system attains high data throughput and capacity related to the existing systems. MIMO is a significant technique that is utilized for enhancing the signal to noise ratio in wireless technologies. OFDM is combined with MIMO systems for ensuring the signals that are transmitted orthogonally with each other. OFDM requires frequency and time synchronization for sustaining the sub-carries and also resistive to frequency offset which is caused by Doppler shift, due to relative motion or difference between the frequencies of local oscillator at the transmitter and receiver [18]. MIMO-OFDM is a base for wireless communication system, which is a future of 4G and 5G broad-band communications.

3 ADAPTIVE CE ALGORITHMS

Adaptive CE is the most important current research in wireless communication. Adaptive algorithm effectively changes its parameter that gains more information of the possibly changing environment. The adaptive algorithm adjusts the filter parameter in such a way that minimizes the MSE between the output of the filter and the desired signal. Thus, the adaptive filter parameters are entirely known that replicates the system in question whose parameters are unknown. Besides, the parameters of the adaptive filter give better approximation of the parameters of the unknown scheme. The performance of CE algorithm depends on the convergence towards the computational complexity, minimum MSE performance, and true channel coefficients [19].

3.1 Least Mean Squares (LMS) algorithm

LMS algorithm is based on the stochastic gradient [20] and is given by Eq (1) and (2).

$$e(m) = S^{T}(m)w(m) + z(m) - S^{T}(m)h(m) \quad (1)$$

$$h(m+1) = h(m) + \eta S(m)e(m) \quad (2)$$

Where, η is stated as step size, $S(m)$ is denoted s transmitted diagonal matrix at sampling time m, $h(m)$ is indicated as adaptive filter coefficient, and $e(m)$ is represented as estimation error. Hence, the filter coefficients are updated utilizing an estimate of the cost function gradient $\eta S(m)e(m)$. In practical applications, the involved signals are corrupted with noise. When the noise is present in the received sequence, interference is also in the coefficients adaption process through the term $\eta S(m)e(m)$. As an outcome, the LMS approach has low steady state MSE performance, and low convergence, while the distribution of the noise is highly impulsive. Step size parameter finds the algorithms convergence rate and the higher value provides faster convergence. If η exceeds, then the LMS algorithm will diverge. Practically, the higher value of η results in higher variations in the tap weight vector after the initial convergence phase. Such variations result in increased distortion in the combined output, which results in increased MSE and BER.

3.2 Normalized LMS (NLMS) algorithm

The conventional LMS algorithm is very sensitive to input signals, so it is very hard to select η. To address this issue, a new algorithm (NLMS) is developed to solve the above mentioned problems by normalizing the power of input signal. Mathematically the NLMS algorithm [20] is summarized in Eq. (3) and (4).

$$e(m) = S^{T}w(m) + z(m) - S^{T}(m)h(m) \quad (3)$$

$$h(m+1) = h(m) + \eta e(m)\left[S^{T}(m)h(m)\right]^{-1} s(m) \quad (4)$$

There is a trade-off among the steady state error convergence, while a scalar step size is utilized in NLMS algorithm that avoids fast convergence. 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 [21]. The VSS algorithm is defined in Eq (5).

$$\eta(m+1) = \alpha\eta(m) + \gamma p^{2}(m)$$

$$p(m) = \beta p(m) + (1-\beta)e^{T}(m)e(m-1) \quad (5)$$

Where, $0 < \alpha < 1, 0 < \beta < 1\, and\, \gamma > 0$.

The developed algorithm cannot accurately measure the auto-correlation between the estimation error in order to control the step size, while the channel is fast time varying. In the tracking problem, CE algorithm cannot deliver minimum MSE, since it cannot track the optimal step size. When the CE algorithm parameters are not properly adjusted, it may lead to worse steady state results. In addition, control parameters α and β need to be adjust for a better performance. Here, a general property of the VSS CE methods is that predetermined control parameters are necessary to improve the performance. Though, in most of algorithms the 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 significantly influences 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 [22]. The standard RLS algorithm is defined in Eq. (6).

$$
\begin{aligned}
&e(m) = S^T(m)w(m) + z(m) - S^T(m)h(m) \\
&RB(m) = B(m)S(m)\left[\lambda + S^T(m)R(m-1)\right] \\
&B(m) = \lambda^{-1}B(m-1) - \lambda^{-1}R(m)S^T(m)R(m-1) \\
&h(m) = h(m) + S(m)e(m)R(m) \qquad (6)
\end{aligned}
$$

Where, λ is denoted as exponential forgetting factor with $0 < \lambda < 1$. The smaller value of λ leads to faster convergence rate and larger fluctuations in the weight signal after the initial convergence. Besides, small λ value makes the RLS algorithm unstable. Subsequently, it requires best possible forgetting factor such that the estimator error is decreased. However, a lot of new CE algorithms are developed by utilizing parallel and adaptive forgetting factor. In high dynamic fading channel, the CE performance are severely diminished, while the forgetting factor is optimized [23]. Though, the RLS scheme has computational complexity-performance, which is the major obstacle for practical mobile terminal and base station implementation [24-25]. Subsequently, an efficient CE algorithm is better than the existing algorithms, which gives fast convergence and minimum steady state MSE.For time varying channels, best estimation method is blind estimation, which is further classified into two sub categories full blind and semi blind estimation techniques. In this scenario, best methods to estimate the channel are LMS based methods, because these methods give best estimation under noisy environment and also have less complexity and easy to design. The LMS algorithms are further classified into four types, where each type has their own advantages and disadvantages. Still, the LMS algorithm has some issues due to easy design and less complexity. For adaptive filter, if we preferred only LMS algorithm it creates problem in identifying the step size, since if step size is big or small it increases the error and decreases the processing speed.To mitigate this problem, an optimization technique is combined with LMS algorithm to solve the issues occurred in step size selection. Presently, there are several optimization approaches are available for step size selection like adaptive greedy algorithm, adaptive bussgang algorithm, sparse multipath channel estimation, subspace pursuit algorithm, etc. In order to work with channel estimation, adaptive technique along with LMS algorithm is employed.

Author	Methodology	Advantage	Limitations
Karami, et al,[26]	Compressed Sampling Matching Pursuit (CoSaMP) combined with NLMS algorithm	The combination of NLMS algorithm with CoSaMP performs better compared to the existing algorithms in blind channel estimation.	The obtained result shows a limited improvement in bit error rate compared to fixed transmission schemes.
Kapoor, et al, [27]	Combination of GVSS-LMS and MKF algorithms for the robust channel estimation. In addition, NVFF-RLS algorithm are combined for effective channel prediction.	Higher convergence and the lower tracking error	The wireless channels under the impulsive environment needs to be investigated.
Sedighi, et al, [28]	Estimating the channel vector coefficient by using three different techniques such as RR-LMS, RR-RLS algorithm and RR-Kalman filter.	MSE performance and the channel capacity performance is good.	RR-LMS, RR-RLS algorithm are very large complexity compared to other algorithms.
Sahoo, et al, [29]	Adaptive filtering model is developed with l0-norm penalty.	Due to sparse modeling, some of the weight coefficients tend to zero, which leads to substantial reduction in computational complexity.	The bit error rate performance of the system is average.
Gui, et al, [30]	Stable sign function with LMS algorithm.	Delivers better performance in light of gain.	The bit error rate performance of the system is average.
Tian, et al, [31]	Complex norm constraint algorithms termed as complex-valued ZA-LMS (CZA-LMS), RZA-LMS (CRZA-LMS), l 0-LMS (C0L0 -LMS), and Adaption penalized LMS (CAP-LMS).	Fastest convergence rate compared to other complex sparse LMSs.	The estimation bias decreases, when the speed of convergence increases.
Wang, et al, [32]	Improved Norm-Constrained Set Membership (INCSM-NLMS) algorithm	LPSM-NLMS algorithm attained low effect on the sparseness measure, which is very effective in sparse channel estimation applications.	The estimation behavior of the system is average.
Gui, et al, [33]	Sparse LMF algorithm	Sparse LMF gives low SNR, while sparse LMS performs better in high	Slow convergence speed in high SNR

		SNR region	region.
Li, et al, [34]	Reweighted NA-LMS/F (RNA-LMS/F) algorithm is also developed.	Steady state behavior and the convergence speed is normal in various stages.	Large complexity compared to other algorithms.

4 CONCLUSION

In this paper, a survey on various Channel Estimation Techniques used in MIMO-OFDM systems is presented. The performance of the system can be improved, if channel state information of MIMO channels is estimated by channel estimation schemes. From the survey, it is concluded that further modification in channel estimation techniques will make the system better. Thus, the future work can be conducted on the further improvement in channel estimation technique for MIMO-OFDM systems.

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