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Channel Estimation Using Extended Kalman Filter and Adaptive Maximum Likelihood Estimator in MIMO-OFDM System

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Abstract

Channel estimation is an important issue for wireless communication systems. This paper presents an algorithm for performing effective channel estimation for multiple input multiple output (MIMO) orthogonal frequency division multiplexing (OFDM) systems when they encounter fading environment.However, due to inadequate information and poor estimations of the noise statistics the filter performance may be degraded. In order to reduce the errors and to increase the filter performance, a new extended Kalman filter (EKF) and weightage based adaptive maximum likelihood estimator (AMLE), is proposed in this work**.** The effect of inter carrier interference (ICI) is removed by decomposing the channel matrix, which efficiently leads to estimation of the data symbol. The channel is modeled as multipath parametric Rayleigh and Rician fading. The fading complex amplitudes and carrier frequency offset are jointly estimated for this channel.Simulated results shows that EKF-AMLE has better estimation precision than that of the EKF.

Keywords- MIMO OFDM, Extended Kalman Filter, Channel Estimation, Adaptive maximum likelihood estimator.

1. Introduction

Wireless communications have advanced very quickly. The fast development in the number of new subscribers, the development of different global technologies and wireless standards, the demand in the new, best quality, low cost services and also higher data rates are the primary inspirations for the development in the wireless communications. A general wireless communication system be made up of three fundamental elements: a transmitter, a communication channel and a receiver. The transmitter translates the information bits to signals that can be efficiently transmitted over the channel. The physical medium utilized as the communication channel to send the signal from the transmitter to the receiver. The receiver makes an effort to pull through the transmitted information, as correctly as possible at the receiving end of a digital communication system [1]. Both the transmitter and the receiver could either be fixed or mobile, and they are separate by the channel. The channel can be wire line or wireless [2]. A communication framework is characterized by three parameters: bandwidth efficient, power efficient, or cost efficient. There is a high importance on bandwidth efficiency in the vast majority of the frameworks [1]. Digital communication systems use modulation for avoiding attenuation, to handover a digital bit message stream (lower frequency) over a channel. Modulation is the procedure of fluctuating one or more characteristics of a high-frequency periodic waveform (the carrier signal) with a modulating signal (message signal). A number of modulation approaches are utilized as a part of communication systems and FDM (Frequency Division Multiplexing) is one among them. FDM is a signal multiplexing form where non-overlapping frequency ranges are allotted to diverse signals or to every "user" of a medium [3]. OFDM (Orthogonal Frequency Division Modulation) is a frequency-division multiplexing (FDM) scheme utilized as a digital multi-carrier modulation technique to achieve high data rates and permits digital data to be effectively and consistently transmitted over a radio channel, even in multipath atmospheres [5]. The important objectives of the communication framework are to offer good coverage in a non-line-of-sight (LOS) environment, reliable transmission, high peak data rates and high spectrum efficiency. These framework necessities can be experienced by the combination of two powerful technologies in the physical layer design: multi-input and multi-output (MIMO) antennas and orthogonal frequency division multiplexing (OFDM) modulation [6].

Multiple-input multiple-output (MIMO) utilizes several antenna arrays at both transmitter and receiver and gives enhanced BER, or data rate contrasted with conventional communication frameworks [7]. MIMO has prominent features which offer a noteworthy rise in data throughput and link range without extra bandwidth and increase transmit power [7, 4]. On the other hand, a number of issues face the design of MIMO systems that accomplish the intended improvement of system capacity and/or system performance. One of these at the transmitter of system performance where nonlinear distortion tends to degrade the system signal-to-noise ratio (SNR) and consequently, system influences BER at the recipient side [7]. The key to understanding the impact of nonlinear amplification on system performance is to identify the component of the nonlinear output which is responsible for degradation of system SNR. In light of the orthogonalization of the nonlinear model introduced in [8], the output of nonlinear can be divided into a useful signal component and uncorrelated distortion component which is responsible for degrading the system performance. The uncorrelated distortion comprises of two fundamental components: the first is in-band distortion and the second is out-of-band distortion. In MIMO methods, signal pre coding results in higher PAPR and consequently, nonlinear distortion results in severe degradation of system SNR and BER [7]. MIMO systems utilizing OFDM have been effectively explored for the always-increasing demand of high data rate transmission in recent or future telecommunication frameworks.

In multiple-input–multiple-output (MIMO) communications frameworks, the received signal is made out of the sum of a number of transmitted signals that share the propagation environment and are subject to multipath propagation effects and noise at the receiver. The multipath channel brings about Inter Symbol Interference (ISI), while the non-orthogonality among the signals transmitted provides increment to inter antenna interference (IAI) at the receiver. To lessen the impacts of ISI and IAI that diminish the performance and the capability of MIMO systems, the designer needs to construct a MIMO equalizer [7]. Equalization methods are two types: the linear and the nonlinear. The linear equalizers are simple to implement but in real time transmission it suffer from more noise. Two famous linear equalizers are: the zero-forcing (ZF) equalizer and the minimum mean-square error (MMSE) equalizer. Among nonlinear equalization methods, decision feedback equalization (DFE) is the most well-known in light of the fact that it is simple to implement and generally performs well. On the other hand, the DFE suffers from error propagation, it leads to poor performance. The optimum equalization method is maximum likelihood sequence estimation (MLSE) [8]. Numerous blind channel equalization algorithms for chaotic communication system [9-11] have been suggested. In wireless communication, users transmit signals independently, so the communication system has a multi-input multi-output (MIMO) structure. Thus, these algorithms sometimes fall short for wireless communication. For chaotic MIMO communication frameworks, a dual extended Kalman filter (DEKF) algorithm was proposed to accomplish blind channel equalization, in which DEKF algorithm runs two different EKFs: one for chaotic signals and the other for channel coefficients [12].

2. Related works

There are numerous research works are present in MIMO-OFDM systems. Some of the recent related research methodologies are presented in the following.

Fangqing Jiang *et al.* [13] have discussed ICA based MIMO-OFDM VLC scheme, where ICA was applied to convert the MIMO-OFDM channel into a number of SISO-OFDM channels to decrease computational complexity in channel estimation, without any spectral overhead. In addition, the FM was initially examined to further modulate the OFDM symbols to remove the correlation of the signals, to enhance the separation performance of the ICA algorithm. Khaled M. Gharaibeh [9] have presented, analyzed report of the effect of nonlinear amplification on the performance of a MIMO system. Their performance analysis was in view of relating in-band distortion to a system BER of an M-QAM modulated signals transmitted over a MIMO Rayleigh fading channel. They have shown that transmitter precoding results is increased in-band distortion and subsequently, increased system BER over the case when no precoding was used. Their outcomes is used to derive limit of nonlinearity, which gives energy efficient MIMO systems.

Maodong Li [14] have presented QoE-aware video streaming solution to maximize multiuser QoE for Scalable Video Coding (SVC) streaming over multiuser (MU) Multiple-Input Multiple-Output (MIMO)-Orthogonal Frequency Division Multiplexing (OFDM) systems. The researcher succeeded that by integrating novel

QoE-aware video adaptation (QoEVA) and QoE-aware resource allocation (QoERA) methods. They have first studied on QoEVA of SVC by means of a subjective video quality assessment database and have derived QoE-optimized scalability adaptation tracks. A rate-QoE model was then developed to approximate the track and was utilized to outline QoERA. By proving the NP-hardness of the QoERA issue, the paper has also proposed an adaptive solution where resource block assignment, power allocation and modulation selection were jointly optimized to improve multiuser QoE. Their test outcomes shows that the proposed QoEVA significantly performs better than other traditional video adaptation techniques and their proposed QoERA achieved more improved user experience as compared to state-of-the-art solutions.

Neeraj Shrivastava and Aditya Trivedi [15] have presented performance analysis of multiple-input multiple-output orthogonal frequency-division multiplexing (MIMO-OFDM) system utilizing STF Coding and random beam forming. Their proposed approach that joined beam forming with STF code offers enhanced performance than STF in term of bit error rates (BER). That was additionally seen that their proposed method gave better execution as compared to the combined space-time block code (STBC) with beam forming. Additionally, computational complexity of their proposed scheme was calculated.

Yoav Eisenberg and Joseph Tabrikian [16] have presented a bit and a power allocation algorithm for multiple-input multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) systems. The optimum power allocation algorithm in terms of maximum capacity in MIMO-OFDM systems was given by the joint space-frequency water-filling (JSF-WF) algorithm. The algorithm included multiple singular value decompositions and an iterative water-filling calculation over the sub channels, and as a result, has a high computational complexity. The paper has also presented an algorithm with reduced bit and power allocation complexity. The proposed algorithm was in light of a geometric channel model comprising of a number of clusters of sub paths, characterized by a set of physical parameters. It performs beam forming with null-steering towards the clusters directions-of-departure, such that the frequency selective MIMO channel was altered into a flat fading MIMO channel. Hence, constant bit and power allocation over the frequency domain can be performed, which was simple to compute and implement. The performance of the proposed algorithm was assessed and compared to the JSF-WF algorithm in terms of bit-error-rate, for known and mis-specified channel model parameters. That was exhibited that the proposed algorithm performance was somewhat lower than the JSF-WF performance, while it significantly reduced the complexity of the allocation algorithm. The signal-to-noise ratio (SNR) estimation problem was considered for an amplitude modulated known signal is Gaussian noise. The benchmark technique was the maximum-likelihood estimator (MLE).

Efthymios Stathakis *et al.* [17] have discussed on the issue of constructing a finely modified version of the MLE, namely the AMMLE, which was outclassed, in terms of achievable MSE, the MLE for the SNR estimation problem. The primary involvement was based on the actual MSE expressions for the SNR, which characterized performance more accurately. Though, their mathematical analysis was based on diverse methods and they were established the desired estimator in closed-form, thus obviating the need for solving an optimization problem. Subsequently, their examination was done by extending the methodology and researcher were introduced some methods to accommodate the efficient numerical solution of the resulting optimization problem. Additionally, the extension to the multiple-input multiple-output (MIMO) model was discussed and studied. Mathematical results showed that an MSE enhancement over the traditional MLE and the related UCRB for all the scenarios under consideration.

George Ignatius [18] have presented an algorithm for performing efficient channel estimation for multiple input multiple output (MIMO) orthogonal frequency division multiplexing (OFDM) systems when they encounter a fast fading environment. The algorithm models the parameters to be assessed utilizing an auto-regressive model, which was executed utilizing Burg Method. The channel estimation have been performed using an Extended Kalman Filter (EKF). The impact of inter-carrier interference (ICI) was uprooted by QR decomposing the channel matrix, which successfully leads to the estimation of the data symbol. The channel have been modeled as L-path parametric Rayleigh flat fading. The Rayleigh complex amplitudes (CA) and carrier frequency offset both have been computed for this channel. They have assessed their performance utilizing the EKF and equalization was simplified utilizing the QR equalizer. The EKF had the capacity to track the parameters efficiently while the QR equalizer helps lessen the ICI effectively. In this way, the paper has effectively implemented a complete MIMO - OFOM system model with a successful channel estimation adaptive filter.

Weile Zhang and Qinye Yin [19] have presented blind carrier frequency offset (CFO) estimation technique for orthogonal frequency division multiplexing (OFDM) with multi-antenna receiver taking into account the maximum likelihood (ML) criterion. When contrasted with the traditional MUSIC-like CFO searching algorithm, their proposed method not only has the advantage of being applicable to fully loaded systems, additionally can achieve vastly improved performance in the presence of null subcarriers. The theoretical performance analysis and numerical results were given, both of which exhibited that their proposed technique can attain the Cramér–Rao bound (CRB) under the high signal-to-noise ratio (SNR) region. The proposed method was applied to fully loaded systems, and succeeded comparable performance with existing techniques. It was additionally shown that, the simulation results match the theoretical analysis, and can almost approach the CRB under the moderate and high SNR region.

Miin-Jong Hao and Chiu-Hsiung Lai [20] have proposed a ML method for the CFO estimation in the MIMO-OFDM systems with the PAPR reduction precoder. A minimum error probability based precoding matrix have been used to decrease the PAPR of OFDM signals. By using the property of the precoding matrix, a cost function similar to the multiple signal classification (MUSIC) algorithm was established for the CFO estimation. With the pre-coding scheme in the MIMO-OFDM system, the researcher has achieved the advantage in the PAPR reduction of OFDM signals and performed a simple CFO estimation concurrently. The outcome of the simulation has demonstrated that the MSE performance of the MIMO-OFDM was enhanced with the increment in the roll-off factor of the precoder in both the AWGN and multipath fading channel environments. The MSE performance degraded with the increment of the number of the receive antennas. With the precoder in the MIMO-OFDM system, the experiment has also succeeded to lessen the PAPR of OFDM signals and performed simple CFO estimation simultaneously.

Rajendra Prasad K *et al.* [21] have proposed the Extended Kalman Filter (EKF) in view of the probability theory, has been to assess the time varying channel for multiple-input multiple-output (MIMO) orthogonal frequency division multiplexing (OFDM) non-linear systems. Because of insufficient information and poor estimations of the noise statistics the filter performance may be degraded. In order to lessen the errors and to increase the filter performance, a fuzzy extended Kalman filter (FEKF), based on the priori estimation was proposed in this work. The originality of this paper was that the paper was prepared from the fact that by the use of possibility distribution techniques, rather than Gaussian distribution techniques, a fuzzy description of the expected state and measurement was adequate to get a decent estimation. Compared with the EKF, the proposed algorithm was utilized to manage fuzzy uncertainty, as well as to handle asymmetries and to estimate the states more accurately. Simulated outcomes have demonstrated that FEKF has improved estimation precision over the EKF.

Bor-Sen Chen *et al.* [22] have proposed a robust fuzzy MIMO-OFDM channel estimation method with time-varying mobile velocity. The channel was model defined by a nonlinear state-space dynamic equation. The states of the nonlinear channel parameter system incorporated the time-varying channel gains and the dynamics of the channel. The proposed technique was assessed the channel state by interpolating three linear parameter model at low, medium, and high mobile speeds to approximate the nonlinear channel parameter system. The decision-directed channel-tracking technique through a fuzzy-based Kalman filter has been outlined to avoid occupation of the available bandwidth because it does not need pilot help. The inherent delay issue of the decision-directed scheme also be solved by the prediction capability of the proposed technique. Additionally, the robust MMSE equalizer was proposed to enhanced symbol detection performance while factoring in the channel prediction error. Simulation outcomes showed that the proposed technique was more precisely track the channel than existing approaches. As a result, the decision-directed channel tracking of the proposed technique for MIMO-OFDM systems were effective for a mobile station with time-varying velocity over a fast multipath fading channel.

Kefei Liu *et al.* [23] have proposed two semi-blind receivers, namely, the least squares Khatri-Rao factorization (LSKRF) and simplified closed-form PARAFAC decomposition (S-CFP) coupled with a pairing algorithm, for joint symbol and channel estimation. The LS-KRF receiver was a closed-form solution that delivered performance stability as well as lower computational complexity compared to the alternating least squares (ALS) based algorithm, whereas the S-CFP with pairing receiver takes into consideration for higher transmission efficiency since it does not require the utilization of pilot symbols for symbol detection. The uniqueness conditions, spectral efficiency and computational complexity of the LS-KRF and S-CFP with pairing receivers were analyzed and compared with the ALS receiver algorithm. It was demonstrated that the S-CFP with pairing receiver was the same order of computational complexity as the ALS receiver. Additionally, simulation outcomes demonstrated that our S-CFP with pairing receiver achieves almost the same performance as the ALS and training based receivers with extra pilot overhead at sufficiently high signal-to-noise ratio conditions.

3. Proposed methodology for Channel Estimation Using Extended Kalman Filter and Adaptive Maximum Likelihood Estimator in MIMO-OFDM System

In wireless communication, the arrangement of multiple-input multiple-output (MIMO) wireless technology with orthogonal frequency division multiplexing (OFDM) has been perceived as a standout amongst the most encouraging techniques to support high data rate and performance. Specifically, coding over the space, time, and frequency domains delivered by MIMO-OFDM will empower a much more reliable and robust transmission over the harsh wireless environment. Multiple input multiple output (MIMO) can be utilized to enhance information carrying capability in orthogonal frequency division multiplexing (OFDM). In MIMO-OFDM, system channel estimation task turns out to be tougher because of the change in channel parameter. From now on, to discover a suitable channel estimation technique, which has the capacity to follow changes at the moment, is a matter of high importance. In the present research paper, an adaptive algorithm is proposed for channel estimation in MIMO-OFDM system has been discussed. This paper has proposed adaptive minimum likelihood estimation (AMLE) and Extended Kalman filter (EKF) is used as adaptive filter.

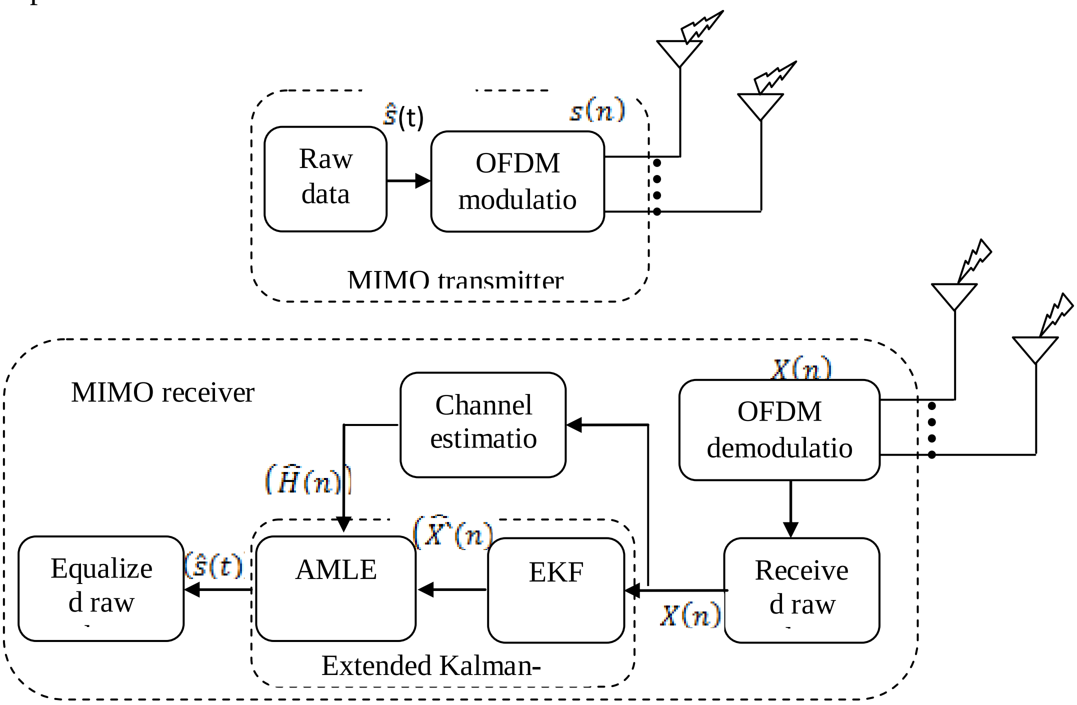

Figure 1: Block Diagram of EKF-AMLE channel Estimation method

3.1 Channel Selection and Channel Estimation

Signal multipath happens when the transmitted signal reaches at the receiver by means of multiple propagation paths. Each of these paths may have a different phase, attenuation, delay and Doppler frequency connected with it. Because of the arbitrary phase shift connected with each received signal, they may include destructively, resulting in a phenomenon called *Fading*.

Depending on the nature of the multiple paths received, there are two types of Multipath channels:

- Discrete Multipath
- Diffuse Multipath

Here we are considering a discrete multipath channel estimation for estimating signal which already exists in channel.

3.1.1 Discrete Multipath

When the paths between the transmitter and the receiver are discrete, each with a different attenuation and delay, the channel is called a discrete multipath channel.

As shown in the figure above, the discrete multipath channel can be modeled as follows:

$$X(t) = \sum_{i=1}^{N} \alpha_i s(t - \tau_i(t)) \qquad (1)$$

Where

N is the number of rays impinging on the receiver.

$s(t)$ is the input signal

α_i is the path attenuation

τ_i is the path delay.

It can be seen that a natural representation of the discrete multipath channel is a tapped delay line with time varying coefficients and possibly time varying tap spacing. If we express *s (t)* as:

$$s(t) = \mathrm{Re}\,al\ part\,of\ \{\tilde{s}(t)e^{j2\pi f_C t}$$

We can express the complex channel output as:

$$\tilde{X}(t) = \sum_{i=1}^{N} \tilde{\alpha}_i \tilde{s}(t - \tau_i(t)) \qquad (2)$$

Where:

f_c : The frequency of the carrier

$\tilde{\alpha}_i = \alpha_i e^{j2\pi f_C t}$

Thus we see that we can describe the time varying discrete multipath channel by a time varying complex impulse response:

$$\tilde{h}(\tau : t) = \sum_{i=1}^{N} \tilde{\alpha}\delta(t - \tau_i(t)) \quad (3)$$

Where $\tilde{\alpha}$ is the time varying complex attenuation of each path. We can already see that for a fixed number of paths, *(N)* and path delays τ_i, if we were to specify the properties of the complex attenuation $\tilde{\alpha}_i$, for each path, we would be able to characterize the time varying channel.

3.1.2 Channel estimation

Before approaching towards the problem of predicting and analyzing the observable properties of transmission, it should be first defined what is mean by a channel. In its most general sense, a channel can describe everything from the source to the sink of a radio signal. This incorporates the physical medium (free space, fiber, waveguides etc.) between the transmitter and the receiver through which the signal transmits. The word channel states to this physical medium throughout this work. A vital element of any physical medium is, that the transmitted signal is received at the receiver, corrupted in a variety of ways by frequency and phase-distortion, inter symbol interference and thermal noise.

Then again, a channel model can be considered as a numerical representation of the transfer features of this physical medium. This model could be based on some known basic physical phenomenon or it could be framed by fitting the best mathematical / statistical model of the observed channel behavior. Most channel models are developed by observing the characteristics of the received signals for every particular environment. Diverse scientific models that clarify the received signal are then fitted over the gathered data. Typically the particular case that best describes the behavior of the received signal is utilized to model the given physical channel. Channel estimation is basically characterized as the procedure of characterizing the impact of the physical channel on the input sequence. If the channel is thought to be linear, the channel estimate is basically the estimate of the impulse response of the system. It must be focused once more that channel estimation is just a scientific representation of what is really happening. A “good” channel estimate is one where some sort of error minimization criteria are satisfied (e.g. MMSE).

The procedure of channel estimation has been described. There are two approaches for channel estimation. These are: training sequence / pilot based channel estimation and blind channel estimation. The estimation algorithms purpose is to minimize the mean squared error. An attempt has been made to estimate h in the presence of noise and model mismatch, through observing the channel output X (n): $\hat{X(n)} = H(n) * s(n) + \eta(n)$. In the figure 1, η(n) is the estimation error. The objective of most channel estimation algorithms is to minimize the mean squared error (MMSE), E [η2 (n)] while using as little computational resources as possible in the estimation process.

The one of the primary tasks of MIMO-OFDM systems is how to achieve the channel state information correctly for coherent detection of information symbols. The channel state data can be acquired through different types of estimation algorithms. In a wireless communication link, channel state information (CSI) delivers the known channel properties of the link. This CSI should be estimated at the receiver and usually fed back to the transmitter. Consequently, the transmitter and receiver can have distinctive CSI. The Channel State data may be instantaneous or statistical. In Instantaneous CSI, the present channel conditions are known, which can be observed by knowing the impulse response of the transmitted sequence. However, Statistical CSI contains the statistical characteristics, for example, fading distribution, channel gain, spatial correlation, etc. The CSI acquisition is basically restricted by how fast the channel conditions are changing. In fast fading systems where channel conditions vary quickly under the transmission of a single information symbol, only statistical CSI is reasonable. However, in slow fading systems, instantaneous CSI can be assessed with reasonable accuracy. So, the channel estimation method is introduced to increase accuracy of the received signal. The radio channels in mobile communication systems are typically multi path fading channels, which are bringing about inter symbol interference (ISI) in the received signal. To eliminate ISI from the signal, much sort of detection algorithms are utilized at the receiver side. These detectors should have the knowledge of the channel impulse response (CIR) which can be delivered by the separate channel estimator.

The Kalman estimator combines the two independent estimates of the channel into a LMMSE estimate. The current data estimate of the channel is combined with the predicted (from the model) estimate. This current estimate is then projected through the channel model to predict the next state of the channel. Both these steps are combined into a concise form by using the Kalman filter. As a result of using the Jakes model in conjunction with the data estimates, the Kalman filter based channel estimation procedure drastically improves on the performance of the data-only estimator. We are also able to predict the next state of the channel with some accuracy before the availability of the data-estimate. Lastly, as a consequence of using the Kalman filter, we can also improve on previous estimates, as more data are available. As, Kalman integrated with LMMSE is already existing, hence an Extentded Kalman with Adaptive MLE is proposed to optimize channel.

4. Proposed Extended Kalman-AMLE filter for channel estimation

In this proposed approach, the channel estimated value of a signal which already exists in transmission medium using Extended Kalman Filter and Adaptive Maximum

Likelihood Estimator (EKF-AMLE) method, is going to be predicted

4.1 Extended Kalman – AMLE

In this research work, the Kalman filter and adaptive maximum likelihood estimation combined together for effective channel estimation. With a specific end goal in utilizing extended Kalman filtering to track or Estimate channel instantly, the channel estimation proposed in this paper utilizes the least adaptive maximum frequency likelihood (AMLE) algorithm. Hence, it can achieve the channel transfer functions in frequency domain very easily. Considering a MIMO-OFDM system with N^T, antennas, the relationship between transmit and receive signals can be expressed as follows

To utilize extended Kalman filtering to track or estimate channel instantly, the channel estimation proposed in this paper utilizes the least sequences (LS) algorithm. Subsequently, the channel transfer functions in frequency domain very easily achievable. Considering a MIMO-OFDM system with NT antennas, the relation between transmit and receive signals can be be expressed as

$$X[n,k] = \hat{H}[n,k]s[n,k] + \hat{\eta}[n,k] \quad (4)$$

Here $\boldsymbol{X}$ [*n*, *k]*, $\boldsymbol{H}$ˆ [*n*, *k*] and $\boldsymbol{\eta}$ˆ [*n*, *k*] are all *NR*×*NT* matrixes, and $\boldsymbol{s}$ [*n*, *k*] is *NT*×*NT* matrix. *n* denotes OFDM symbols with *k* subcarriers. Based on Doppler law number of transmitted data *m* is equal to OFDM symbol *n* (n = m).The channel matrix $\boldsymbol{H}$ˆ [*n*, *k*] can be obtained by the channel estimation method based on EKF which is described as follows.

Let's consider $\boldsymbol{P}$ is the pilot matrix which consists of the pilot sequences from each antenna. $\boldsymbol{P}$ = [$P_1 \ldots\ldots P_{N_T}$] here *n* $\boldsymbol{P}$ is a pilot sequence of an antenna and a cyclic sequence whose period is N_T ,

$$PP^H = P^H P = N_T I \quad (5)$$

P matrix is input of the other signal which is going with the pilot symbol matrix

$$X[n,k] = P[n,k]H[n,k] + \eta[n,k] \quad (6)$$

Where $P[n,k]$ denotes the pilot symbols which is another form of $a[n,k]$ as equation (4) shows. Apply the LS channel estimation method; we can conclude equation (7).

$$\tilde{H}[n,k] = P^{-1}[n,k]X[n,k] \quad (7)$$

Thus the channel state information $\tilde{h}_l[n]$ can be achieved by applying an inverse fast Fourier transform (IFFT) to the transfer function $\tilde{H}[n,k]$. And it can be concluded (8)

$$\tilde{h}_l[n] = h_l[n] + z_l[n] \tag{8}$$

Here $z_l[n]$ is a zero-mean complex Gaussian vector whose distribution is $N(0,\sigma_z^2)$.

The Kalman filtering method exploits the state space model in time/delay domain as (9) shows:

$$h_l[n+1] = Fh_l[n] + \omega_l[n] \tag{9}$$

Here F is $M \times M$ matrix, $M = N_T \times N_R$ and $\omega_l[n]$ is the $M \times 1$ innovation noise vector. If $F, \sigma_z^2, \sigma_\omega^2$ are known in advance, the estimated channel state parameter $\tilde{h}_l[n]$ can be obtained by exploiting Kalman filtering from (8) and (9). But it is not possible to know the key parameter in advance, so estimated Kalman filtering has been utilized to estimate channel estimate parameter.

Considering that wireless channels have some nonlinear characteristics, the channel estimation based on EKF is in essence a linear method which can do with nonlinear problems by the exploiting approximate linear method. So, the augmented state space equation (10) and the measurement equation (11) have been developed.

$$x[n+1] = G(x[n]) + \omega[n] \tag{10}$$

$$\tilde{h}[n] = Qx[n] + z[n]$$

Here, $x[n] = \begin{bmatrix} h_0[n] \\ . \\ . \\ . \\ h_{L-1}[n] \\ vec\{F\} \end{bmatrix}$ and $G(x[n]) = \begin{bmatrix} Fh_0[n] \\ . \\ . \\ . \\ Fh_{L-1}[n] \\ vec\{F\} \end{bmatrix}$ (11)

And we define the $LM \times 1$ measurement vectors $\hat{h}[n] \overset{\Delta}{=} [\tilde{h}_0^T[n] \ldots\ldots \tilde{h}_{L-1}^T[n]]^T$, $z[n] \overset{\Delta}{=} [z_0^T[n] \ldots\ldots z_{L-1}^T[n]]$ and $LM \times (L+M)M$ matrix $Q \overset{\Delta}{=} [I_{LM} \ \ 0_{LM \times M^2}]$.

$$\hat{x}[n+1|n] = G(\hat{x}[n|n]) = \begin{bmatrix} \hat{F}[n|n]\hat{h}_0[n|n] \\ . \\ . \\ . \\ \hat{F}[n|n]\hat{h}_{L-1}[n|n] \\ vec\{\hat{F}[n|n]\} \end{bmatrix} \tag{12}$$

Here, equation (12) updates the time parameter.

$$\hat{x}[n|n] = \hat{x}[n|n-1] + K[n](\tilde{h}[n] - \tilde{h}[n|n-1]) \tag{13}$$

Here the equation (13) updates the measurement equation.

$$K[n\} = \Omega[n|n-1]Q^H (Q\Omega[n|n-1]Q^H + \sigma_z^2 I_{LM})^{-1} \tag{14}$$

$$\Omega[n|n] = (I_{(L+M)M} - K[n]Q)\Omega[n|n-1] \tag{15}$$

$$\Omega[n+1]|n] = U[n]\Omega[n|n]U^H[n] + \sigma_\omega^2 \begin{bmatrix} I_{LM} & 0_{LM\times M^2} \\ 0_{M^2\times M} & 0_{M^2\times M^2} \end{bmatrix} \tag{16}$$

Where U[n] is defined as (17),

$$U[n] = \frac{G(x)}{x}\Big|_{x=x[n|n]}$$

$$= \begin{bmatrix} F[n|n] & 0_{M\times M} \ldots\ldots\ldots\ldots\ldots\ldots 0_{M\times M} & h_0^T[n|n]\otimes I_M \\ 0_{M\times M} & F[n|n] \ldots\ldots\ldots\ldots\ldots 0_{M\times M} & h_0^T[n|n]\otimes I_M \\ . & . \quad\quad . & . \\ . & . \quad\quad . & . \\ . & . \quad\quad . & . \\ 0_{M\times M} & 0_{M\times M} \ \ldots\ldots\ldots \ F[n|n] & h_0^T[n|n]\otimes I_M \\ 0_{M^2\times M} & 0_{M^2\times M} \ldots\ldots\ldots\ldots 0_{M^2\times M} & I_{M^2} \end{bmatrix} \tag{17}$$

Here $\otimes$ denotes the kronecker product.

Because the measurement and time update equations are a recursive process for estimating the channel state parameters in time/delay domain, we must initialize the vectors as

$$\hat{x}[1|0]=[\hat{h}_0[0]......\hat{h}_{L-1}[0] \quad vec\{I_M\}]^T \ \ and \ \ \Omega[1|10]=I_{(L+M)M}$$

As the equations (14) and (16) show, the innovations noise variance and the measurement noise variance are necessary for EKF filtering. But the innovations noise variance cannot be estimated directly due to $\omega_l[n]$ not being observed. So we construct an equation (18) to estimate $\omega_l[n]$ [11-12].

$$\hat{\omega}_l[n]=\hat{h}_l[n|n]-\hat{F}[n|n]\hat{h}[n-1|n-1] \tag{18}$$

Herein, since $\hat{h}_l[n|n]$ and $\hat{F}[n|n]$ can be obtained by the equations mentioned above, we can conclude the innovations noise variance $\hat{\sigma}^2_{\omega}[n]$ which can be expressed as:

$$\hat{\sigma}^2_{\omega}[n]=\frac{1}{LnM}\sum_{l=0}^{L-1}\sum_{m=1}^{n}\|\hat{\omega}_l[m]\|^2$$

The measurement noise variance also cannot be observed, but estimated. And we attain it as below

$$\hat{z}_l[n]=\hat{h}_l[n]-\hat{h}_l[n|n-1] \tag{19}$$

Here, $\hat{h}_l[n|n-1]=\hat{F}[n-1|n-1]\hat{h}[n-1|n-1]$. So the measurement noise variance can be expressed as:

$$\hat{\sigma}^2_{z}[n]=\frac{1}{LnM}\sum_{l=0}^{L-1}\sum_{m=1}^{n}\|\hat{z}_l[m]\|^2$$

Because $\hat{h}_l[n]$ can be drawn, we can obtain the channel transfer functions in time/frequency domain by FFT as

$$\hat{H}[n,k]=\frac{1}{N_T}\sum_{l=0}^{L-1}\hat{h}_l[n]e^{-j2kl/K} \tag{20}$$

The ideal technique for the joint data discovery and channel estimation is the ML methodology. For an asynchronous channel, the complexity of this sort of estimator depends exponentially on both the number of users and transmitted symbols because only one transmitted symbol and optimization approach cannot be utilized any longer. The estimated channel matrix is going to improve by adaptive maximum likelihood estimation in view of weight with channel matrix. There is a possibility to get an optimized channel matrix from the extended kalman filter,

From the equation (4), Recalling that the entries of η are independent Gaussian random variables with zero mean and variance, the log-likelihood function for the unknown parameters and takes the form

$$\wedge(\tilde{n},\tilde{\xi}) = -N\ln(\pi\sigma_\eta^2) - \frac{1}{\sigma_\eta^2}\| X - s(\tilde{n})\tilde{\xi}\|^2 \tag{21}$$

Where $\tilde{n}\, and\, \tilde{\xi}$ are trial values of $n\, and\, \xi$ respectively, while $\|x\|$ is the Euclidean norm of the enclosed vector x. The joint ML estimates of $n\, and\, \xi$ are obtained y searching for the maximum of $\wedge(\tilde{n},\tilde{\xi})$. To do so, we keep $\tilde{n}$ fixed and let $\tilde{\xi}$ vary in the 2K N_g-dimensional space C^{KN_g}. Then, we see that $\wedge(\tilde{n},\tilde{\xi})$. is maximum when,

$$\hat{\xi}(\hat{n}) = [s^H(\tilde{n})s(\tilde{n})]^{-1} s^H(\tilde{n})X \tag{22}$$

Next substituting (21) back into (22) and minimizing with respect to $\tilde{n}$, we obtain

$$\tilde{n} = \arg\min_{\tilde{n}}\{\| P_Q(\tilde{n})y \|\}^2 \tag{23}$$

Where

$$P_Q(\tilde{n}) = S(\tilde{n})[S^H(\tilde{n})S(\tilde{n})]^{-1} S^H(\tilde{n})$$

Here, minimum symbol value is obtained for given input signal, and channel matrix replaced based on index value as given in equation (24):

$$\hat{H}(n,k) = \hat{H}(n,k) - \tilde{n} \tag{24}$$

5. Results and Discussions

In this segment, a detailed analysis of the proposed system has done and makes use of Bit Error Rate curves to prove the validity and study the system in a detailed manner. Curves are plotted for Traditional Extended kalman filter (EKF) and EKF-AMLE for different cases. The sub-section 5.1 describes the overall experimental set-up and the simulation used. In the section 5.1.1 and 5.1.2, a detailed analysis of the system has been made.

5.1 Experimental Set up and Simulation:

The proposed channel estimation of MIMO-OFDM system based on EKF-AMLE is implemented in MATLAB Version 8.1.0.604 (R2013a). The system on which the technique was simulated was having 4 GB RAM with 64 bit operating systems having i5 Processor. For assessment of the proposed method, randomly generated signals has been used.

The Bit Error occurs when the received bits of the data stream over a communication channel differs from the transmitted signals. This occurs because of alteration of the signal which may occur due to the interference of unwanted signals, noise effects, distortions or bit synchronization errors, multipath fading, attenuation. The bit error rate or bit error ratio (BER) is the ratio of bit errors to the total transferred bits during the specified time interval. BER is performance measure used for evaluating the performance or the functionality of various methods and systems. BER vs. E_b/N_o graphs from which, it can be infer the performance of the system, has been plotted. $\frac{E_b}{N_o}$ is the energy per bit (E_b) to noise power spectral density (N_o) ratio of the received signal. E_b/N_o is basically a normalized signal-to-noise ratio (SNR) measure of the signal. The system for both the Rayleigh and Rician channel independently and plot BER curves for both has been considered.

Rayleigh fading is basically a statistical model for the effect of a propagation environment on transmitted signal. Rayleigh fading model agrees that magnitude of a signal that has gone through channel will vary randomly, or fade, based on Rayleigh distribution the radial component of the sum of two uncorrelated Gaussian Random variables. Rician fading is mainly a stochastic model for radio for radio propagation anomaly initiated by partial cancellation of radio signal by itself and the signal arrives at the receiver by several different paths and at least one of the path is varying. Rician fading occurs in all the existing paths, usually a line of sight signal is much stronger than others. In Rician fading, the amplitude gain is described by Rician distribution.

5.1.1 Effects on the performance of the proposed system by varying the length of the user input signal:

In this section, the length of the user input data MC has been varied, in order to assess the performance of the system. The Rayleigh and Rician fading channels have been considered and in all cases, BER curves for both the EKF and EKF-AMLE have been plotted. The OFDM parameters are fixed for nFFT = 64, and size of the signal constellation M = 16.

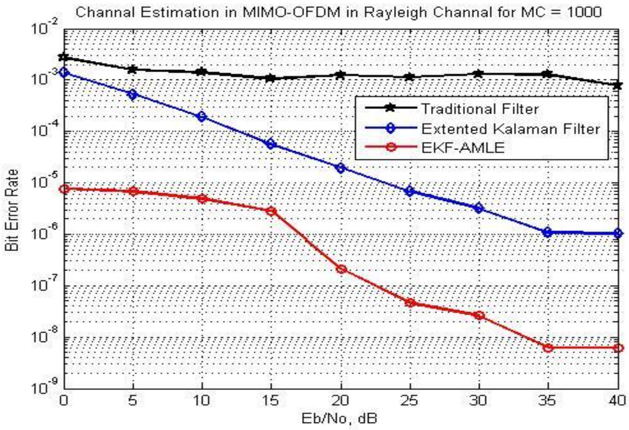

Figure 2:Bit Error Rate Vs Eb/N_0 Rayleigh channel for MC=1000

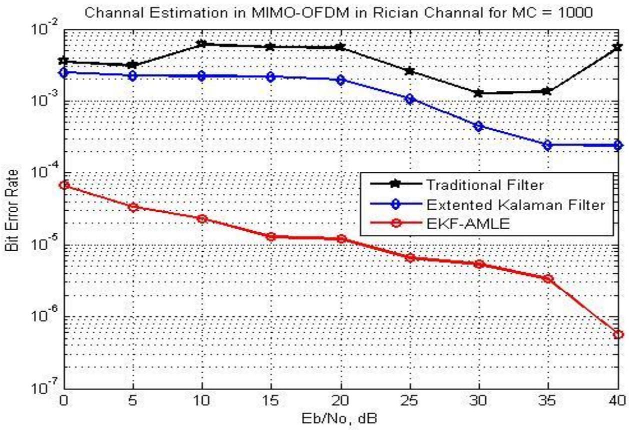

Figure 3: Bit Error Rate Vs Eb/N_0 Rician channel for MC=1000

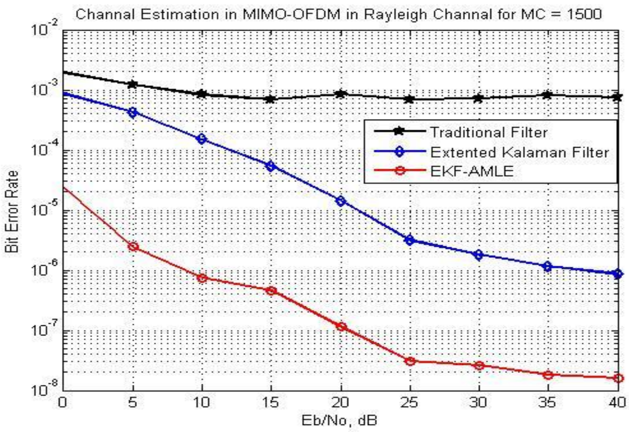

Figure 4: Bit Error Rate Vs Eb/N_0 Rayleigh channel for MC=1500

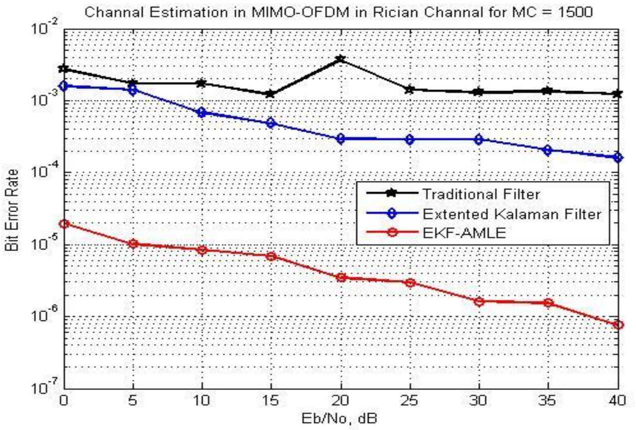

Figure 5: Bit Error Rate Vs Eb/N_0 Rician channel for MC=1500

Inferences form the BER graphs from figure 9-12 (varying length of input user signal):

- The BER curves are obtained by varying the length of the user input data MC. The Rayleigh and Rician fading channels have considered for the experiment and in all cases, BER curves have plotted for both the EKF and EKF-AMLE.
- Figure 9 and 10 give BER curves for Rayleigh channel when user input is at 1000 and 1500 respectively.
- Figure 11-14 give BER curve for Rician channel when user input is at 1000 and 1500 respectively.
- From analysing the results, we can infer that all the cases gave good results. Among the BER curves, Rayleigh channel gave better results. We can also infer that the best result was obtained for MC = 1500;
- EKF-AMLE gave better results than EKF and Traditional filter in all cases.

5.1.2 Effects on the performance of the proposed system by varying the OFDM parameters:

In this section, the performance of the system has been evaluated by varying the some OFDM parameters like size of FFT and size of signal constellation. Two cases have been considered of nFFT = 64 and nFFT=128 and signal constellation size M=16 and M=32, where nFFT stands for size of FFT in modulation and M stands for the Size of signal constellation. In all cases, BER curves for both the EKF and EKF-AMLE have been plotted. The number of user signal input and channel is fixed for 1000 in Rayleigh channel for nFFT=64, nFFT =128 and M=16, M=32.

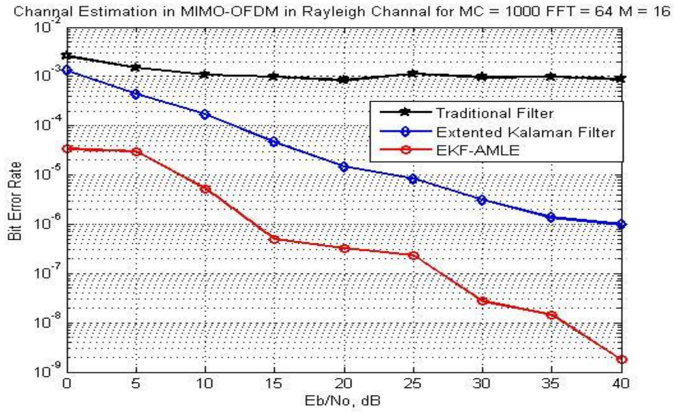

Figure 6: Bit Error Rate Vs Eb/N_0 Rayleigh channel for MC=1000, FFT = 64, M=16

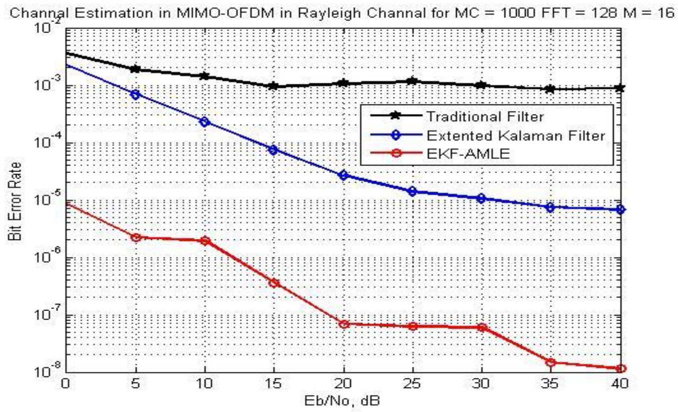

Figure 7: Bit Error Rate Vs Eb/N_0 Rayleigh channel for MC=1000, FFT = 128, M=16

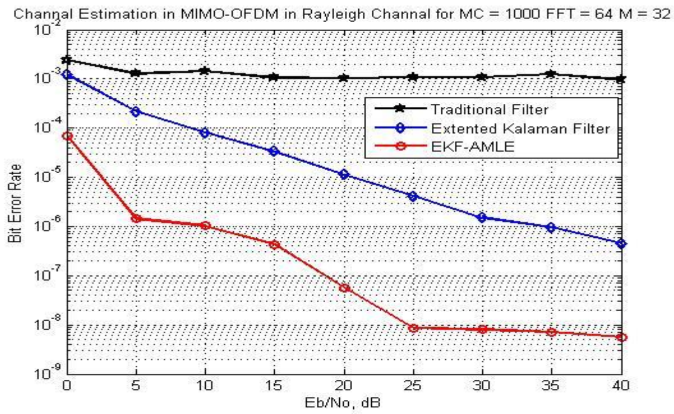

Figure 8: Bit Error Rate Vs Eb/N_0 Rayleigh channel for MC=1000, FFT = 64, M=32

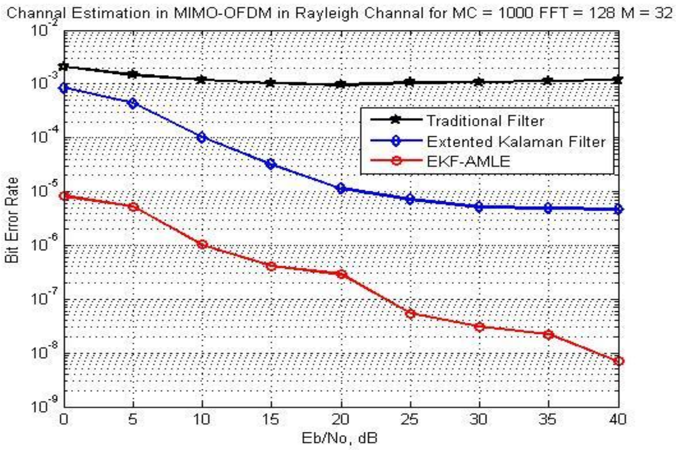

Figure 9: Bit Error Rate Vs Eb/N_0 Rayleigh channel for MC=1000, FFT = 64, M=32

Inferences form the BER graphs for the four plots (varying OFDM parameters):

- BER curves are plotted for varying the size of the FFT (nFFT = 64, 128) for both the Rayleigh and Rician fading channels. nFFT = 64 indicates the size of Fast Fourier Transform (FFT).
- BER curves are plotted for varying the size of signal constellation (M=16, 32) for both the Rayleigh and Rician fading channels. nFFT = 64 indicates the size of OFDM modulator and demodulator.
- BER curves are plotted for both the EKF and EKF-AMLE. The number of user signal input is fixed for 1500.
- Figure 13 and figure 14 shows the BER graph obtained for nFFT = 64 and nFFT=128 respectively, when Rayleigh channel and M = 16 was used.
- Figure 15 and figure 16 shows the BER graph obtained for nFFT=64 and nFFT = 128 respectively, when Rayleigh channel and M = 32 was used.
- From analysing the results, we can infer that all the cases gave good results. Among the BER curves, Rayleigh channel gave better results. We can also infer that the best result was obtained for N=2.
- EKF-AMLE gave better results than EKF and traditional filter in all cases.

Conclusion

The paper talks about a multiple-input multiple-output (MIMO) system which utilizes OFDM. User signals are transmitted utilizing OFDM where the user data are separated into parallel streams. The transmitted signals are received by the antenna array after propagating through the fading channel. The received signals are assessed utilizing the Extended Kalman Filter with Adaptive Maximum Likelihood Estimator (EKF-AMLE). Adaptive weights are figured out in light of the minimum error value utilizing the iterative process in MLE. Various curves are found by varying the fading channel, number of user signals, FFT size and size of signal constellation. The fading channel considered are the Rayleigh and the Rician fading channel. Also, the research work has carried out experimentation for user signal MC = 1000 and MC = 1500. BER curves are drawn for both EKF and EKF-AMLE for all the cases. All the BER curves achieved good results and from the analysis, it is found that system performs better when Rayleigh channel was considered.

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