Dual bound Kalman Filter for Signal Estimation in Multipath Fading for MIMO-OFDM Communication system

G Rajender, T Anil Kumar, K Srinivasa Rao

Abstract: In this paper, Signal estimation in MIMO-OFDM communication using enhanced kalman filtration is proposed. Received Signal is passed through estimator unit, where the interference level is estimated and applied over the signal to compensate the error to minimal. Recursive estimators are used for estimation, in the kalman filter model, least mean square (LMS) estimator is used for the error estimation and minimization. In recursive estimation convergence delay is primal factor of estimate and defines the speed of estimation. In the existing process of estimation, errors are propagated in a backward direction to update the weight factor for forward error minimization. However, the error updation in the dynamic channel model is non linear and a backward feed loop in different cases leads to instability and doesn't converge. This problem is solved by introducing dual bound estimation logic, where a forward weight adaptation in parallel with backward weight is monitored to derive a updating weight factor. The error performance, delay and MSIE parameter is validated for different SNR sand step sizes.

Index term: Dual bound coding, Kalman filter, IMO-OFDM Communication system.

I. INTRODUCTION

In order to achieve the increasing demands for wireless communication services, new techniques that allow efficient use of available frequency spectrum, increasing system capacity and speed of communications with accuracy, are in development. These developments were made to improve communication efficiency; however, the issue of channel dynamicity remains a considering issue for current and next generation communication systems. For the estimation of channel parameter, in [1] STBC based coding based on multi antenna MIMO system is developed. The system was developed using BPSK and QPSK modulation, under time variant channel conditions. A STBC coding introduced for the improved format of the iterative Joint Channel Estimation was outlined in [2]. Time and Frequency information correlation has been specified with the use of the cyclic Prefix (CP) coding. Two variants of estimation using CP based on the forwarded back-end assessment approach was presented. In [3], blind channel estimation was developed for STBC broadcasting. This approach was outlined based on the second order statistics (SOS).

The Channel considered for MIMO coding based on the pre-coding to rotation or resonance of transit angles of antenna is defined. Channel estimation was developed for an OFDM / OQAM based on a iterative estimate in [4]. The recurrence approach has been made to improve the channel's analysis by using the recipient's imaginary component. A M-QAM for OFDM was outlined in [5]. A Frequency Flat Modeling has been outlined for the transmitter and relay unit for the joint channel estimation of a OFDM system. Here, the functionality of the channel ratio depends on the channel's impulse response on the MIMO-OFDM system. [6,7] outlined a channel response in goal for estimation based on the interaction of a transmitter antenna. Approach of a wiener filter for channel estimation optimization by improving channel behavior in time and frequency domain is suggested. Based on a number of high speed mobile environments, in [8] a method based on bias Extension Model (BEM) is proposed.

The suggested approach gives a better estimate of the time variant channel condition in propagation. According to effective calculation, a symmetric extension mechanism for the OFDM system has been proposed in [9] to reduce Mean square error (MSE) and power loss. The anticipation of partial frequency reactions and the decrease in the MSE and low power in signaling. A SCM based channel estimation for zero padding to MIMO-OFDM systems is presented in [10] with different representative features. The identifiable condition is very simple, and more optimal than the column reduction technique. This gives better performance in low-moderate SNR through numerical simulation.

In [11] a second approximation ratio for OFDM systems for first order estimation in received signal to detect joint CFO and CIR in OFDM system is presented. An Adaptive Iteration algorithm provides the first order approximation. The second-order is developed as a mapping method, for the frequency tracking range and the channel estimation compatible to the first order estimate. A channel estimator defined for the space-time modeling of the channel's estimation for long-term features (more than multiple OFDM symbols) through a space tracking algorithm was presented in [12]. Objects that affect the speed of the fading magnitude can be observed using LS techniques, which exploit the temporary interaction of the correlation process.

In particular, turbo equalization has been chosen as a benchmark for performance evaluation along the signal propagation in MIMO-OFDM communication system. In [13], a Semi-blind approach using time synchronization for the OFDM systems based on unit vectors was developed for a channel estimation scheme. In [14,15] a

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MIMO-OFDM communication channel estimation for a high-mobility scenario of communications system is presented that is different from the basic evolutionary process of transformation.

In [16] the channel estimation following the channel's bit error rate (BER), and with the help of a GNU Radio, the synchronization of the OFDM system was developed. This estimation illustrates a lower BER performance in signal propagation. A generalized analysis was performed on the OFDM system in [17] using a low-complex channel estimate, without the cancellation of the iterative estimation that is suitable for the SISO / MISO communication system, and compatible to a OFDM system with the time domain synchronization. The MSE and BER were observed to be decreased in this case.

An average method used by the inter-frame used as a channel-coordinate for a common orthogonal frequency-division multiplexing was defined in [18]. The weight inter-frame average method was more efficient at channel analysis than average frame adjustments. The method improves channel estimation by combining the time and frequency components. In an OFDM system, for the estimation of channel a fast linear minimum mean square error (LMMSSE) was outlined in [19].

A widely linear mean square error (WLMMSE) for multiband Orthogonal Frequency Division Multiplexing in Ultra Wide Band system was outlined in [20,21]. This method reduces computational complexity and cost based on singular value decomposition (SVD) of the received signal. [22, 23] develop, a method for channel estimation using the iterative filtering for the MIMO-OFDM system, where the channel improves the lower complexity of the channel using the Jake's training method.

The past developments in the enhancement of signal estimation are bound to a specified channel propagation model and the diversity in interference under multipath fading giving phase and magnitude deviation gives high convergence delay and lower estimation accuracy. To achieve the objective of signal estimation under a multipath scenario in MIMO-OFDM communication under diverse channel condition, a new dual bound estimation for a recursive estimator following kalman filtration approach is proposed in this paper. This paper is outlined in 7 sections. The communication model following OFDM-MIMO communication system is outlined in section 2. Section 3 presents the signal propagation under multipath scenario. Section 4 presents the approach of existing signal estimation in MIMO-OFDM communication system. The approach of proposed dual bounded estimation in kalman filtration is outlined in section 5. Section 6 outlines the simulation results and the conclusions for the developed approach are covered in section 7.

II. MIMO-OFDM COMMUNICATION SYSTEM

In a MIMO communication, Information data are divided into sub-streams of M-bits, where each of which is transmitted on a sub channel for a given bandwidth. This is obtained by using the filters which is used to switch the sub-stream spectrums to the corresponding sub-band region. Therefore, there is a subset of multi carriers modulation that transfers a R modulated bits with a filter that provides R/M distinct carrier channels over the available bandwidth for M parallel sub-bands used for the Broadcasting operation. Multi-carrier communication are most suitable for MIMO based communication systems. Multiple Input Multiple Output (MIMO) Wireless communication units contains multiple antennas on the transmitter and multiple-antenna mapped for receiving the signals at the receiver. The combination of MIMO and OFDM give a much higher throughput and much easier receiving process at the receiver. The main advantage of a MIMO-OFDM communication system is the offered throughput. Due to a multi carrier communication model with frequency division, the offered throughput is very high. However, the channel effect is considered to be effective. A basic transmission model of a MIMO-OFDM communication system is presented in Figure 1.

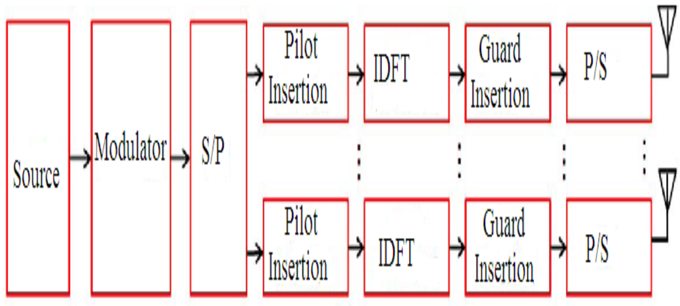

Figure 1. MIMO-OFDM transmission model

Mapping the character stream to a serial bit stream as symbols is made by the modulator at the transmitter side. The serial symbols are processed for parallel sub stream conversion. Pilot symbols for channel evaluation are added to these parallel sub-streams in the frequency domain. A OFDM modulation is then applied over the encoded stream using a inverse discrete Fourier transformation (IDFT) coding.

The guard insertion is used to differentiate two transmitting packets. The processed data bits are then passed into a parallel to serial converter, where the serial stream is transmitted to the receiver unit. The receiver unit shown in Figure 2, performs a channel estimation and derive the equalization parameter to compensate the channel interference observed on the channel.

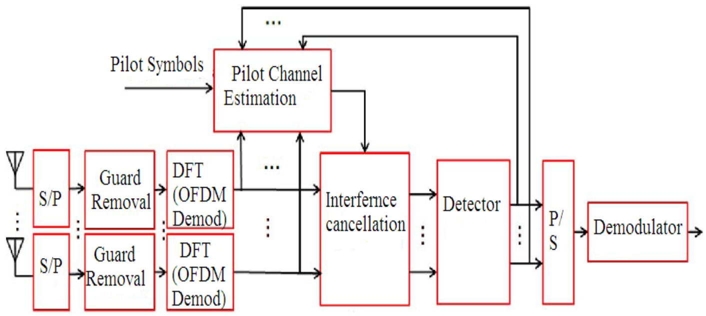

Figure 2 MIMO-OFDM receiver unit

The unit performs a serial to parallel operation, and removes the guard bits from the received information bits. The demodulation process, extract the carrier data and performs the interference cancellation based on the estimated channel parameter. The channel estimation logic carries out the estimation process using a recursive algorithm to minimize the signal error.

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III. MULTIPATH PROPAGATION MODEL

In signal propagation, the wireless channel model with the diverse effect of time-varying parameters with multipath fading effect is observed. In a multipath channel, the receiver from different angles receives many copies of the original signal. Each of them has different Doppler shift and phase offset having different angle-of-arrival and time delays. These paths are combined as constructive or destructive based on the various stages of interference in the signal strength that change over the communication medium. This multipath factor defines the gains or fade of the signal strength. The farther the distance (usually the wavelength of up to half a wavelength) the signal experience the fading faster. The Rayleigh distribution is used to differentiate the varying strength in the difference of signal strength received.

a) Rayleigh Fading

In MIMO system, for i[th] path signal, with an amplitude of a_i and phase φ_i the received signal r(t) is defined as,

$$r(t) = \sum_{i=1}^{N} a_i \cos(\omega_c t + \phi_i) \qquad (1)$$

Where, N is the number of travelling paths. phase ϕ_i depends on the length of different paths which varies by 2π for a path length variation of a wavelength. Thus, these phases are distributed in the uniform manner for a period of $[0, 2\pi]$. On the relative motion between the transmitter and receiver, the received signal is developed in consideration of the motion induced frequency and the phase shift. For a wavelength reflected by an amplitude a_i and phase ϕ_i the signal received from an angle Ψ_i in reference to the direction of the moving direction of the antenna, the Doppler shift of the wave is given by,

$$\omega_{di} = \frac{v}{c} \cos \Psi_i \qquad (2)$$

Where v is the speed of the device, c is the speed of light ($3\text{x}10^8$ m/s), Ψ_i is linearly scattered over $[0, 2\pi]$. The received signal $r(t)$ is given by,

$$r(t) = \sum_{i=1}^{N} a_i \cos(\omega_c t + \omega_{di} t + \phi_i) \qquad (3)$$

The in-phase and quadrature component of the received signal are given by equation (3) as, the in-phase and the quadrature component is given by,

$$I(t) = \sum_{i=1}^{N} a_i \cos(\omega_{di} t + \phi_i) \qquad (4)$$

$$Q(t) = \sum_{i=1}^{N} a_i \sin(\omega_{di} t + \phi_i) \qquad (5)$$

and

$$r(t) = I(t) cos\omega_c t - Q(t) sin\omega_c t \qquad (6)$$

The region R is defined by,

$$R = \sqrt{[I(t)]^2 + [Q(t)]^2} \qquad (7)$$

The Probability Density Function (PDF) of Signal Envelope, $f(r)$, for a channel with Rayleigh fading is given by,

$$f(r) = \frac{r}{\sigma^2} exp\left\{\frac{-r^2}{\sigma^2}\right\}, r \geq 0 \qquad (8)$$

b) Rician Fading

In addition to the multipath components, distribution of interference is also observed when there is a direct path between the transmitter and the receiver. In presence of this path interference, the transmitted signal is given by,

$$r(t) = \sum_{i=1}^{N} a_i \cos(\omega_c t + \omega_{di} t + \phi_i) + k_d \cos(\omega_c t + \omega_d t) \qquad (9)$$

Where k_d defines constant of the direct element , ω_d is the Doppler shift, observed over the LOS path and ω_{di} is the observed doppler effect for indirect path line. The Rician envelop of this channel is given by,

$$f(r) = \frac{r}{\sigma^2} exp\left\{\frac{-r^2 + k_d^2}{2\sigma^2}\right\} I_0\left(\frac{r k_d}{\sigma^2}\right) \qquad (10)$$

$I_0\left(\frac{r k_d}{\sigma^2}\right)$ is the zeroth order Bessel function.

'K' is defined as the ratio between Dynamic Signal Power (direct line) and added signal power (from indirect paths). The distribution factor in decibel is defined as,

$$K(dB) = 10log_{10}\left(\frac{k_d^2}{2\sigma^2}\right) \qquad (11)$$

The signal component adopted to monitor the presence of a direct component is illustrated as a signal that causes the fading due to the two specified channel effect. The outage probability measured as a quality of transmission is defined as an integral factor of received signal $p(t)$ given by,

$$P_{out} = \int_0^{P_{th}} p(t) dt \qquad (12)$$

Where, P_{th} is the threshold power.

These effects of Gaussian noise and fading channels are considered in the communication model. With the stated channel effect a MIMO-OFDM based communication system is developed, where is defined by the channel effect of fading, Gaussian noise and Doppler shift effect.

IV. DUAL BOUND KALMAN FILTER SIGNAL ESTIMATION

In the estimation process of a MIMO-OFDM communication, to estimate the original signal back, adaptive filters were applied. Adaptive filters are designed with adjustable filter coefficients. It adapts to the changes within the input It shows the nature of modifications or adjustments to improve the performance of certain criteria for allowing filtering

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to change input properties. The operating principle of an adaptive filtration system is its time variable self-adjusting performance. The adaptive systems are required to have a time variable and nonlinear characteristic. This characteristic relies on the input signals. If a signal is applied to the input of an adaptive system, to check its response characteristics, the system adapts to the current specific input and thereby changes its filtration value. The operations of such filters are hence dependent on the input data and optimizes error. Kalman filter (KF) is for adaptation used in this approach.

Kalman filter is iterative algorithm for calculating the random signal with a computation method based on a short distance spacing error. The state space model of signal and noise is adopted for estimating state values updated with the measurement of previous value and current measuring value. Therefore, the filtration process can be divided into two parts: Time Update and Measurement Update. The time specification can be calculated to compute the trend of prediction, and the recursion can be considered as the equivalent correction referenced in the prediction of the actual measurement-correcting order. The quantity value measured is used to avoid random interference and to update the system status. The kalman estimate parameters are given by,

$$G(i) = \alpha(i)K(i,i-1)S^H(i)[s(i)K(i,i-1)S^H(i) + \sigma_w^2]^{-1} \tag{13}$$

$$e(i) = y(i) - s(i)\ \hat{h}(i) \tag{14}$$

$$\hat{h}(i+1) = \alpha(i)\hat{h}(i) + G(i)e(i) \tag{15}$$

$$P(i) = [1 - \alpha^{-1}(i)G(i)s(i)]K(i) \tag{16}$$

$$K(i+1) = \alpha(i)P(i)\alpha^H(i) + \sigma_v^2 \tag{17}$$

Here *G*(*i*) is the Kalman Filter gain, *e*(*i*) is the computed error, *h^* is the modified channel for one step estimation, *P(i)* is the permanent state covariance of the updated channel measure, and *s(i)* is the information predicted for the transmitted bits. The calculation of the initial value *h^(0)*, channel transfer parameter *a(i)*, observed coefficient *y(i)*, estimated transmitted data *s(i)*, processed noise variance σ^2 and the measured noise variable σw^2. These parameters are unknown. Hence, these components need to be calculated for the estimation in prior. The estimation in this case is performed based on the pilot signal estimates for a time varying channel. In ideal conditions, the lowest difference in linear measuring is the minimum estimated variance. However, the state estimate is basically biased. The difference of evaluation error is probably larger, much larger than the theoretical differences. This phenomenon is termed as divergence and limits the kalman filtration method application in various domains. Filter diversity occur for a variety of reasons, such as the wrong mathematical modelling reflecting the physical computation and erroneous predication. Since noise is present, the time-sized channels pilots cannot be only observed in estimation. If the noise level is dense, the signal to noise ratio (SNR) will be low, but here as the error is high, which affects the filtering operation. The estimation approach using the least mean square computation is given by,

1. Initialization of each weight w(i) to an arbitrary fixed value
2. Computing filter output
   $\widetilde{n_k} = \sum wk(i)\, x_{k-i}$
3. Computing error estimate
   $e_k = n_k - \widetilde{n_k}$
4. Updating the next filter weights
   $w_{k+1}(i) = w_k(i) + 2\mu e_k x_{k-1}$

In the LMS operation for an N-tap filter, the input to the LMS system is the signal vector $s(k)$ represented as [21],

$$s(k) = [s(k), s(k-1), \ldots\ldots, s(k-N+1)]^T \tag{18}$$

Here, s(k) is the input vector for a period of k, T indicating the transpose operator. The processed filter output due to adaptive coding is given by,

$$y(k) = s^T(k)w(k) \tag{19}$$

Here, w(k) is the updation vector defined by,

$$w(k) = [w_1(k), w_2(k), \ldots, w_{n-1}(k)]^T \tag{20}$$

$w_i(k)$is the i[th] coefficient for the filter adaptive parameter, this factor is updated using least mean square (LMS) estimation given by,

$$w(k+1) = w(k) + 2\mu e(k)S(k) \tag{21}$$

e(k), μ, and *d(k)* denote the error computed, updating step size, and the required signal. Step size parameter defines the convergence rate and accuracy of computation. The Error computed is given by,

$$e(k) = d(k) - r(k) \tag{22}$$

The LMS operation is depicted by a given input signal with noise coefficient. The noise coefficient is compared with a reference value to interpret the error. It is required to lower this error to a relative limiting value given by the user. The limiting value governs the tolerance of the estimation logic. In this filter, the error is propagated back to update a weight value to update the input parameter. The receiver computes a new output based on the input signal and the given weight. The value is constrained for an limited error tolerance. The LMS approach is appropriate in this case for the measurement of error in a linear channel model. However, under dynamic channel condition, signals are affected by a non-linear noise format. In such a case the linear LMS model is unable to converge at a faster rate.

The convergence issue was derived by optimizing the derived cost function. In practice the q[th] power of input value following the QPSK modulation is observed constant. Therefore, the cost function for measuring the equalization to the original data is given by,

$$J = E\{|y - d|^2\} \tag{23}$$

The cost function in a QPSK modulation is an alphabet polynomial fittings method that matches the source value input by the complex elements of a characterized complex roots polynomial equation. Here, the feedback errors are introduced with a gradient vector. The error is then defined as, the feedback error in forward and backward directions defined by,

$$f_{k+1} = f_k - \mu \nabla J(f_k), \quad k = 0,1 \dots N \tag{24}$$

Where, $\nabla J(f_k)$ is the gradient of the feedback error. The conventional stochastic model used in LMS logic is one-sample estimate. This leads to the removal of the noise in the distribution, so leads to a slower convergence and improper weight adjustment.

The specific gradient method is used by its approximates from a single block of channel output sample through sample estimate, and by repeatedly using a data block in each frequency. This precise gradient estimates improve the speed and accuracy of convergence. The estimator is given with an error tracking capability to train the variation in feedback error over a block length. This is used to optimize the cost function for a period of observation, and hence minimizes the local extrema convergence delay.

The proposed approach looks for an optimal step size for the minimization of cost function in the direction of search given as,

$$\mu_{opt} = \arg\min \mu \nabla J(f - \mu g) \tag{25}$$

The optimal search of step size optimizes the convergence performance by monitoring the variation in the computed error values in forward and backward direction, processed over a block data.

The updated errors are then defined by

$$f_{k+1}^{\wedge f} = f_k^{\wedge f} + 2\mu_{opt}{}^{f} e_k^f a_k \tag{26}$$

$$f_{k-1}^{\wedge b} = f_k^{\wedge b} + 2\mu_{opt}{}^{b} e_k^b a_k \tag{27}$$

Here the iterations terminated when,

$$\frac{\| f_{k+1} - f_k \|}{\| f_k \|} < \frac{\eta}{N} \tag{28}$$

Where η is a small positive constant defining the error tolerance limit of the system. The proposed dual bound KF approach leads to an observing factor in forward and backward direction hence leads to a optimal cost function optimization which results in faster convergence. As the approach, include the forward and backward factor simultaneously, the updation of error is achieved in both the directions.

V. SIMULATION RESULTS

For the evaluation of the suggested system, a MIMO-OFDM communication system is developed by considering a MIMO-OFDM communication having 2 set of transmission and reception antennas. For the encoding, a block size of N=128 and a cyclic prefix(CP) for 16 bit length and FFT size of 256 is chosen. 50 active sub carriers are considered. Channel bandwidth of 3.5GHz is considered in compliance to IEEE 802.11n standard for MIMO-OFDM model. The sampling rate is taken at 2.28MHz, and symbol duration (Ts) is taken as 0.112ms. A QPSK modulation is used. The observations of mean square identification error (MSIE) for different SNR and step size are computed and the obtained results for the developed system are as shown below.

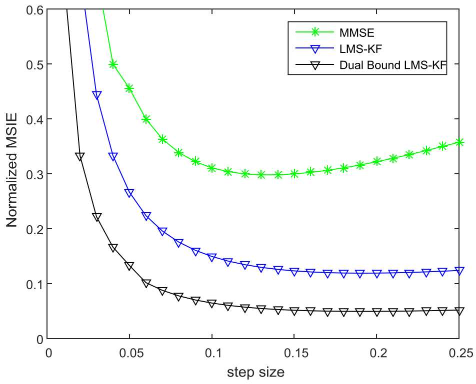

Figure 3. MSIE performance of the developed approach compared with conventional estimation approach

Table 1. Normalized MSIE for Doppler spread of 0.01 for MMSE, LMS-KF, and Dual bound LMS-KF

Step size	MMSE	LMS-KF	Dual bound LMS-KF
0	0.5008	0.4233	0.3333
0.05	0.4002	0.2993	0.2000
0.1	0.3111	0.2456	0.1556
0.15	0.3015	0.2400	0.1500
0.2	0.3222	0.2511	0.1611
0.25	0.3522	0.2655	0.1755

Table 2 Normalized MSIE for Doppler spread of 0.02 for MMSE, LMS-KF Dual bound LMS-KF

Step size	MMSE	LMS-KF	Dual bound LMS-KF
0	0.6015	0.5322	0.4221
0.05	0.5032	0.3399	0.2652
0.1	0.4231	0.3548	0.2123
0.15	0.4021	0.3420	0.2003
0.2	0.4154	0.3552	0.2658
0.25	0.4336	0.3615	0.2985

Figure 3 compares the proposed Dual bound LMS-KF with the LMS-KF, and MMSE approach. When compared to LMS-KF the performance of proposed is observed to be improved and obtain an optimized error value with the increase in the step-size at Doppler spread F_dT_s=0.01 and 0.02. The proposed approach has low error value nearer to that of MMSE. The result illustrates that, when there is an increase in step-size, there is a gradual decrease in MSIE and becomes linear at higher step size.

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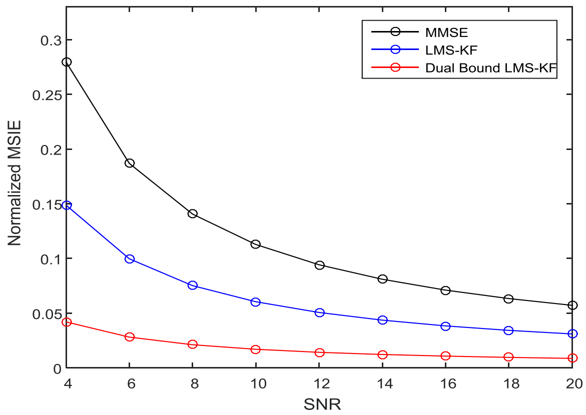

Figure 4. MSIE performance of the developed approach compared with conventional estimation approaches

The normalized MSIE results are obtained by varying the SNR with optimal step-size value over a frequency selective channel with L_c=4 tap as shown in Figure 4. The MSIE results for the Dual bound LMS algorithm are again observed to exhibit a good MSIE performance for various SNR values. In this case, the large step-size value contributes to the self-noise part and the small step-size value amplifies the lag part of the associated MSIE. The optimal step-size appears to obtain the best performance and has greater chances to track much faster channels. As the SNR increases, the MSIE value decreases in Dual bound LMS algorithm compared to LMS-KF algorithm and the MMSE approaches.

Table 3 Normalized MSIE at Lc=2 for MMSE, LMS-KF, and proposed Dual bound LMS-KF.

SNR	MMSE	LMS-KF	Dual bound LMS-KF
4	0.2794	0.2594	0.1487
6	0.1869	0.1669	0.0997
8	0.1406	0.1206	0.0752
10	0.1128	0.0927	0.0604
12	0.0942	0.0742	0.0506
14	0.0810	0.0610	0.0436
16	0.0711	0.0511	0.0384
18	0.0634	0.0434	0.0357
20	0.0572	0.0372	0.0318

Table 4 Normalized MSIE at L_c=4 for MMSE, LMS-KF, Dual bound LMS-KF

SNR	MMSE	LMS-KF	Dual bound LMS-KF
4	0.4321	0.3815	0.2724
6	0.3396	0.2890	0.2234
8	0.2933	0.2427	0.1989
10	0.2655	0.2149	0.1842
12	0.2470	0.1964	0.1744
14	0.2337	0.1732	0.1674
16	0.2238	0.1655	0.1621
18	0.2161	0.1593	0.1580
20	0.2049	0.1543	0.1521

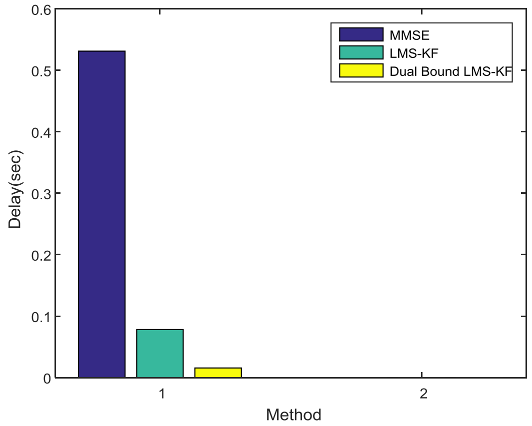

Figure 5. Delay performance of the developed approach compared with the conventional estimation approach

Figure 5 illustrates the performance of Dual bound LMS-KF for the convergence time. The convergence time of the proposed approach is observed to be less compared with conventional MMSE, LMS-KF approaches. With the increment in the step size, the delay is decreased. Compared with conventional approaches, the proposed approach converges faster due to block processing and observing the gradient factor of measured error.

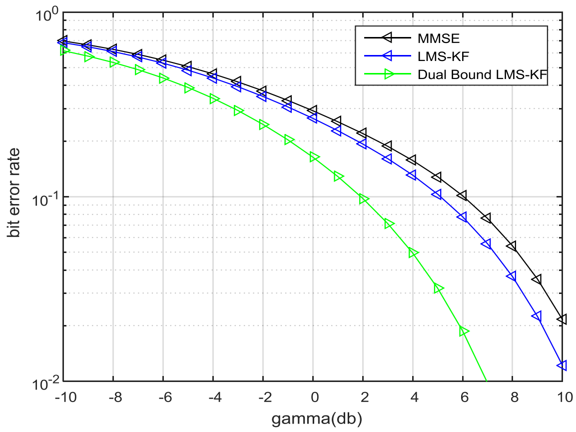

Figure 6 BER performance of the developed approach compared with conventional estimation approaches

Figure 6 illustrates the BER performance for different step-size values optimally derived for a number of channel estimation to be 5 for M=21 resulting satisfactory convergence. It is observed that the BER values are significantly improved through iterative estimation of perfectly initialized Dual bound LMS-KF algorithm in comparison to that of conventional approaches.

VI. CONCLUSION

The developed approach presents a new estimation approach under channel diverse condition, where the convergence time is observed to be high. The limitation of convergence is observed due to symbol–by-symbol operation. The performance is observed to be improved by the proposed Dual bound LMS-KF logic, by computing an optimal step size for weight updating, which is derived from a block-by-block processing of received data. The convergence is improved by introducing a gradient factor

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over the measured error, which defines the deviations in the measured forward and backward error. From the observations obtained simulating for the proposed and the conventional model, illustrates the enhancement in the MSIE by 0.2976 compared to MMSE, with 0.2153 compared to LMS-KF and with 0.1118compared to Dual bound LMS-KF operation. The BER observed is improved by a factor of 0.0972 compared to MMSE, 0.0570 compared to LMS-KF and 0.0120 compared to Dual bound LMS-KF.

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