A Novel LS/LMMSE Based PSO Approach for 3D-Channel Estimation in Rayleigh Fading

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Abstract

A high transmission rate can be obtained using Multi Input Multi Output (MIMO) Orthogonal Frequency Division Multiplexing (OFDM) model. The most commonly used 3D-pilot aided channel estimation (PACE) techniques are Least Square (LS) and Least Minimum Mean Square (LMMSE) error. Both of the methods suffer from high mean square error and computational complexity. The LS is quite simple and LMMSE being superior in performance to LS providing low Bit Error Rate (BER) at high Signal to Noise ratio (SNR). Artificial Intelligence when combined with these two methods produces remarkable results by reducing the error between transmission and reception of data signal. The essence of LS and LMMSE is used priory to estimate the channel parameters. The bit error so obtained is compared and the least bit error value is fine-tuned using particle swarm optimization (PSO) to obtained better channel parameters and improved BER. The channel parameter corresponding to the low value of bit error rate obtained from LS/LMMSE is also used for particle initialization. Thus, the particles advance from the obtained channel parameters and are processed to find a better solution against the lowest bit error value obtained by LS/LMMSE. If the particles fail to do so, then the bit error value obtained by LS/LMMSE is finally considered. It has emerged from the simulated results that the performance of the proposed system is better than the LS/LMMSE estimations. The performance of OFDM systems using proposed technique can be observed from the imitation and relative results.

1. Introduction

The current research over some years have been successfully implemented communication standards for 3G and 4G systems in wireless communications and now research is concentrated and extended towards processing 5G systems. Such systems had effectively and efficiently used Multi input multi output (MIMO) orthogonal frequency division multiplexing (OFDM) technology [1]. MIMO–OFDM promises higher energy and spectral efficiencies, while mitigating inter symbol interference (ISI) [2]. Starting with 3G, the wireless communications standards have incorporated OFDM technology, to reduce the inter symbol interference; obtain higher data rates and better system spectral efficiency.

The heart of any OFDM receiver is the channel estimation block. Efficiency of the channel estimation has a direct impact on the bit error rate (BER) performance of the OFDM system. Frequency domain channel estimation techniques employ known symbols called pilots at known positions in the OFDM symbol grid. Various arrangements of pilots are employed for improving MIMO-OFDM system performance. These pilots are arranged in a regular manner as comb type, block-type [3] or 2D-grid type [4]. In a comb-type arrangement, the pilots are present in few subcarriers of all OFDM symbols, while in block-type arrangement, the pilots are present in few OFDM symbols on all subcarriers. In 2D-grid type arrangement, the pilots are present in few subcarriers of few OFDM symbols. Thus, the number of pilots in 2D-grid type is less than that in Comb type or block-type arrangements. However, reliability in terms of system BER is better for comb-type arrangement in fast fading channel environments. At the receiver, the channel is estimated using known and the received pilot symbols. Frequency domain channel estimation techniques are either LS based, MMSE based or maximum likelihood (ML) based ones. In this paper, LS and MMSE techniques have been primarily considered. OFDM has been adopted by several wireless systems and standards such as WLAN IEEE802.11a/n,4G LTE, WiMAX IEEE 802.16d/e, Digital Audio Broadcasting (DAB), Terrestrial Digital Video Broadcasting DVB-T and DVB-T2 [5].

Wireless channels have many difficulties to deal with, especially in multipath fading. A satisfactory candidate that eliminates a need for the complex equalizers is the Orthogonal Frequency Division Multiplexing. OFDM is a popular modulation technique for high spectral efficiency, robustness against multipath fading, frequency selective fading and low computational complexity. Besides of these advantages, it also faces two major disadvantages, those are, high peak-to-average power ratio (PAPR) and Carrier frequency offset CFO and phase noise which cause the subcarriers to deviate from the spacing required for orthogonality, causing Inter carrier interference (ICI). They also cause high BER in the system. On the other hand, Multiple-input multiple-output systems are occupied to complete one of the following two objectives: separating a number of distinct signals properly from noise and fading effects; and combining the signals to attain the desired property such as assembling a narrow transmission or reception beam. However, MIMO systems have some drawbacks too such as, decoding complexity, complex digital signal processing algorithms. But the combination of MIMO and OFDM has the stringent potential of optimizing these problems since MIMO can boost the capacity and the diversity [6-8] and OFDM can mitigate the detrimental effects due to multipath fading [9].

Literature shows Particle swarm optimization being used by researcher in improving various parameters innovatively for MIMO-OFDM based systems. Generally, channel estimation can be seen as an optimization problem, that is, to minimize the Euclidean distance between the estimated and the true channel coefficients. The straightforward solution to this problem incorporates matrix inversion and leads to the well-known least-squares (LS) and/or MMSE estimator Heuristic, nature-inspired algorithms, such as particle swarm optimization (PSO) [10,11] or genetic algorithms (GA) [12,13] are attractive low-complexity solutions to facilitate MIMO channel estimation. PSO is a population-based heuristic global optimization algorithm, which originated in modeling the social behavior of bird flocks and fish schools. It has been applied to a variety of technical optimization problems, including channel and parameter estimation as well as data detection and multiuser detection. Unfortunately, a fair evaluation of PSO is rather difficult due to the wide range of available modifications and the fact that the algorithm is often tuned to optimum performance for a specific optimization problem by empirical measures.

In [14] PSO was used to reduce number of iteration while estimating channel for MMO-OFDM. In the iteration of the estimator, the proposed PSO algorithm finds desired MIMO weights matrix through the interaction of individuals in a population of weights matrices. It was shown that the Bit error performance was better than conventional adaptive equalizer. In [15], the main idea is to directly minimize the BER by employing a particle swarm optimization (PSO) algorithm on the estimated BER function in order to adaptively adjust the weights of the MBER detectors. Simulation results demonstrate that this adaptive minimum-BER detection using PSO algorithm (MBER-PSO) can achieve significantly superior performance, which is very close to that of the optimal maximum-likelihood sequence estimation (MLSE) detector.

In this paper the system performance in terms of signal to noise rate (SNR) of a Multiple-input Multi-output (MIMO) 2x2 Orthogonal Frequency-Division Multiplexing system and the channel is suffering a Rayleigh fading. This channel impulse response is estimated by inserting various pilots at some pre-determined locations of the OFDM resource block by utilizing Least Square (LS) and Least Mean MSE algorithms. 3D-Channel estimation can be described by the Pilot based Channel Estimation Techniques. In 3D-Pilot based estimation, the Channel Impulse Response (CIR) is estimated with a help of a known training sequence of bits sent in every transmission burst. At the receiver end with the assist of these training bits, the receiver is able to generate its own response. Channel is estimated based on the training sequence which is known to both transmitter and receiver. The receiver can utilize the known training bits and the corresponding received samples for estimating the Channel [16]. The MIMO system considered is as shown in Fig. 1. below.

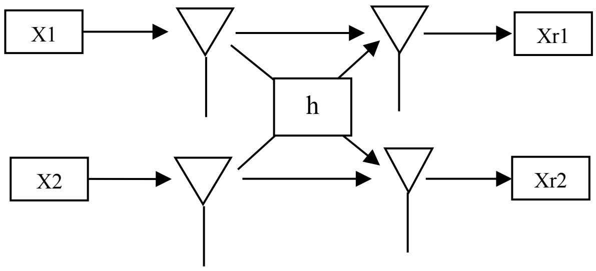

Figure 1: 2x2 MIMO Channel

2. Channel Estimation

2.1 The LS Estimate

The following equations were used for channel estimation for complex pilots and channel coefficients. Equations (1) & (2) are final equations for estimating channel coefficients and data vectors respectively [17].

$\mathrm{v1} = \mathrm{X}' * \mathrm{X};$

$\mathrm{v2} = \mathrm{inv(v1)};$

$\mathrm{v3} = \mathrm{Y}' * \mathrm{X};$

$$\mathrm{Hls} = \mathrm{v2} * \mathrm{v3}; \tag{1}$$

% Estimate data vector for LS

% X = Y/H

$$\mathrm{Xrls} = \left(\mathrm{inv(Hls)} * \mathrm{Yr}'\right); \tag{2}$$

Where,

'X' is transmitted pilot vector

'Y' is received pilot vector

'Hls' is the channel estimate and

'Xrls' is the estimated data vector from estimated channel matrix Hls.

2.2 The LMMSE Estimate

The following equations were used for channel estimation using LMMSE for complex pilots and channel coefficients. Equations (3) & (4) are final equations for estimating channel coefficients and data vectors respectively [18].

$\mathrm{sigma} = 10\text{^}(\mathrm{snr}/10);$

$\mathrm{t1} = (\mathrm{X}' * \mathrm{X})./\,(\mathrm{Nr} * \mathrm{sigma});$

$\mathrm{t2} = \mathrm{eye\ (Nt)}./\,(\mathrm{Nr} * \mathrm{sigmah});$

$\mathrm{t3} = \mathrm{inv\ (t1 + t2)};$

$\mathrm{t4} = (\mathrm{X}' * \mathrm{Y})./\,(\mathrm{Nr} * \mathrm{sigma});$

$$\mathrm{Hlmmse} = \mathrm{t3} * 4; \tag{3}$$

% Estimate data vector

% X = Y/H

$$\mathrm{Xr} = \left(\mathrm{Yr} * \mathrm{inv\ (Hlmmse)}\right)'; \tag{4}$$

The range of values of signal to noise ratio are from 0 – 40 dB at an offset of 5dB. Therefore 9 values are plotted for bit error rate v/s signal to noise ratio. The value of sigmah is constant and equals to 0.25.

Each value of signal to noise ratio is run for 20 iterations for both the channel estimate techniques (LS and LMMSE) and the minimum value of the bit error rate is considered for PSO optimization. The minimum value to be considered for PSO optimization is the smaller value of bit error rate taken from the LS and the LMMSE estimate.

The parameters used for 2x2 MIMO are listed in Table 1

Table 1: Parameters for 2x2 MIMO systems

Sr. No.	Parameter	Value
1	Number of Transmit Antenna	2
2	Number of Receive Antenna	2
3	Data	64 (Random & Complex)
4	Pilots	64 (Random & Complex)
5	Modulation Scheme	4-ary
6	Pilot Position	1:2:128
7	Data Position	2:2:128
8	Sigmah	0.25
9	Signal to Noise Ratio	0:5:40
10	Iteration for SNR value	20
11	Guard Band	32

The length of the signal transmitted is 64+64+32=160 complex symbols. The following is the sequence of steps carried during transmission.

1. Generate 3-dimensional random data to allocate 3D MIMO-OFDM system for two transmitter –x1and x2(integer numbers with scheme)
2. Modulate the data symbols – xm1 and xm2
3. Insert 3D-scattered pilots – xp1and xp2
4. Find Inverse Fast Fourier transform – xifft1 & xifft2
5. Add cyclic prefix – xg1 & xg2
6. Perform Y=XH using equations (5) & (6),

$$y1 = xg1.* h(1,1) + xg2.* h(1,2); \quad (5)$$
$$y2 = xg1.* h(2,1) + xg2.* h(2,2); \quad (6)$$

7. Combine signals for transmission
   Y =[y1 y2];
8. Add Additive White Gaussian Noise
9. Transmit the signal over the Rayleigh fading environment

Following are the steps carried out at the receiver end.

1. Separate the signals corresponding to transmitters
2. Remove the guard band
3. Find Fast Fourier transform
4. Separate the data and pilots
5. Perform the LS estimate
6. Perform the LMMSE estimate
7. Demodulate the data vectors obtained from the estimation techniques
8. Compare with the transmitted data vectors and find bit error rate
9. Repeat the process for 20 iterations
10. Get the minimum bit error rate value for each of the estimate
11. The channel coefficients obtained here from LMMSE estimate are used for PSO optimization
12. Compare and store the minimum value of BER from both the estimate for PSO optimization
13. Continue the process of transmission and reception for all values of signal to noise ratio [0:5:40]

3. The PSO Equations and Parameters

The velocity and position update equations for PSO are listed in equation (7) & (8) respectively.

$$v[] = w * v[] + c1 * rand() * (pbest[] - present[]) + c2 * rand() * (gbest[] - present[]) \quad (7)$$

$$New\_present\,[] = present\,[] + v[] \quad (8)$$

where, v[] is the particle velocity.
present [] is the current particle (solution).
New_present [] is the updated particle (solution).
pbest[] and gbest[] are defined as stated before.
rand() is a random number between (0, 1).
c1, c2 are learning factors.
w – Inertia factor

The PSO optimization for BER takes on the following initial parameters. Number of PSO particles taken is equal to the size of H estimate of LMMSE = 20. Particles are initialized with the channel coefficients (HH) of LMMSE. Initial velocities of the particles are considered to be random complex numbers. Initial particle best values are again set to channel coefficients (HH) values of LMMSE. The Initial global best value is set to the best value from channel coefficients estimate of LMMSE and LS. The following Fig.2. shows how PSO is tuned with the channel parameters of LS and LMMSE for finding low bit error rate.

The following constant parameters are considered

```
% Number of iterations for particle update
iter = 100;  % Maximum numbers of iterations or epoch

% PSO constants
c1 = 2;   % Constant
c2 = 2;   % Constant

t = 0: 0.5/iter: 0.9;  % Parameter

% Maximum and minimum values for velocities
Vmax = 25 * sqrt(2);  % Limit to max velocity

% Maximum and minimum values for particles
Xmax = 3 * sqrt(2);  % Limit position - max
Xmin = 0;   % Limit position - min

% Error tolerance
tol = 0;% Tolerance between actual and target
```

The main loop with LS and LMMSE channel estimation for 2x2 MIMO-OFDM system is used iterates for 20 iterations for every value of SNR from 0:5:40. The minimum value of BER from these 20 iterations for LS and LMMSE are stored. Both these minimum BER values (each for LS and LMMSE) are then compared and the final minimum BER value is chosen as a target value for PSO. The channel parameter H corresponding to this minimum value obtained above is used as the initial Gbest value for the particle swarm. It is proved in the literature that LMMSE performs better than LS estimation. The channel parameter H of LMMSE obtained for 20 iterations are considered as initial particle positions for 20 particles and their initial Pbest values. The PSO iterates for 100 iterations and evaluate the fitness function (LS/LMMSE estimate) and checks whether any particle is able to find a better H estimate than a normal LS/LMMSE estimate function. This is achieved by comparing the minimum bit error rate value to that obtained from the PSO estimate. The target value set corresponds to the fittest value as obtained from the LS/LMMSE estimate. Here we are interested to find Hpso (PSO obtained channel parameter matrix) so that the estimated data vector nearly or completely matches to that of the transmitted data vector.

4. The Novel Approach of Estimating Channel Parameters with PSO

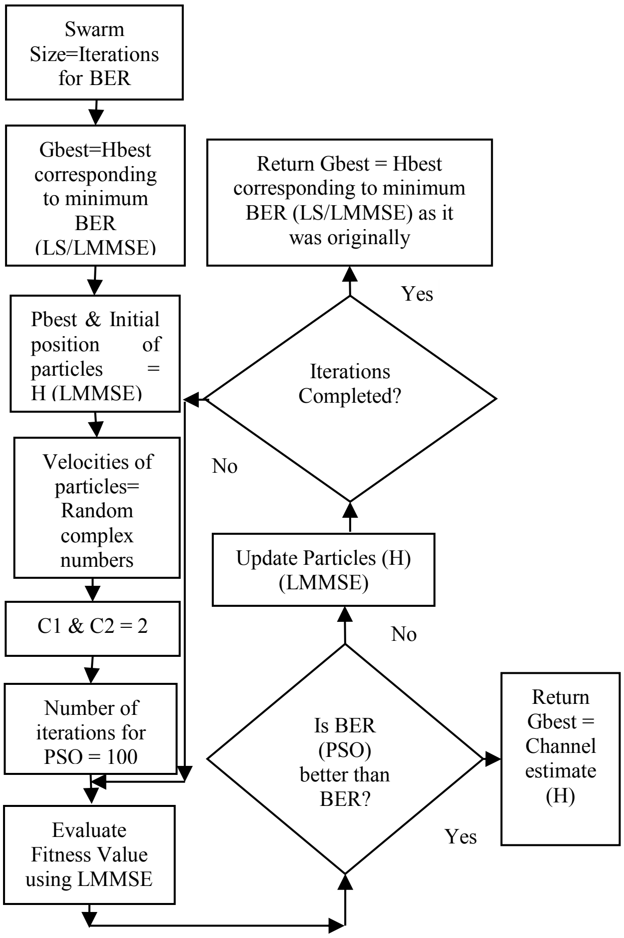

Figure 2: Flowchart of the novel approach to optimize BER using PSO

The Fig.2. indicates the process of BER optimization in 2x2 MIMO-OFDM systems. It shows that the PSO continues to find better H parameter than obtained by LS and LMMSE which results in improved BER value as compared to LS/LMMSE techniques. Since the LMMSE is better than LS, the fitness value calculated in PSO using equations as discusses in the section of LMMSE estimate. Further all the nature inspired algorithm performance depends on their parameter selection for their performance, PSO may fail to find a better solution in some cases. Therefore, the complete system is executed for numbers of run and the best results are shown in this paper. The initial particle values and the number of iterations for the PSO are crucial parameters for convergence at the goal. For reducing complexity, the number of iteration is kept to 100. Experimental results showed that iterating PSO over 100 iterations do not provide significant results. The initial positions of the particles are assumed to be the channel parameters obtained from LMMSE estimate assuming its performance over LS. Another choice is to select random data for initial positions of the particles.

The Fig.3 below shows how the fitness value and best BER in PSO is estimated using parameters obtained from LS/LMMSE techniques for Rayleigh fading channel. The loop is iterated for 100 iterations to find minimum BER value as compared to the minimum BER value obtained by LS/LMMSE technique.

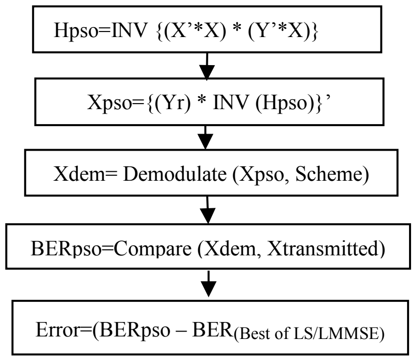

Figure 3: Calculation of PSO fitness value and Error in BER

5. Results and Conclusions

Results shown in Fig. 4-11 below with respect to signal to noise ratio and bit error rate indicates that PSO optimized channel coefficients for Rayleigh fading channel have low BER values as compared to LS/LMMSE estimated coefficients. We have used random pilots and channel parameters which are initialized priory. Depending upon the channel coefficients and the pilots, the system performance varies. The range of values considered for Doppler frequency (f_d) is [30 500], with t_s = 0.07µsec for the Rayleigh fading channel. The BER goes on increasing as the Doppler frequency is increased from 30 to 500 Hz for 2x2 MIMO-OFDM systems. The proposed estimation has improved performance at all Doppler frequencies. The blue colored line in the graph represents the performance of the proposed channel estimation technique. At higher Doppler frequencies the performance of LS degrades while LMMSE performs better. The LS/LMMSE based PSO performance depends upon the channel estimated matrix produced by the LMMSE at the end of the 20th iteration since the channel estimated matrix is used as the initial position of the PSO particles. The performance of the proposed channel estimation techniques also depends on the PSO parameters. Results show that the range of SNR values over which the proposed system has improved BER is not bounded for specific values of SNR. The performance of the proposed channel estimation technique is distributed over all range of SNR values. An advance version of PSO and fine tuning of PSO parameters would produce better result than the PSO used in this work. Also, the system can be tested over other antenna configurations higher than 2x2 systems.

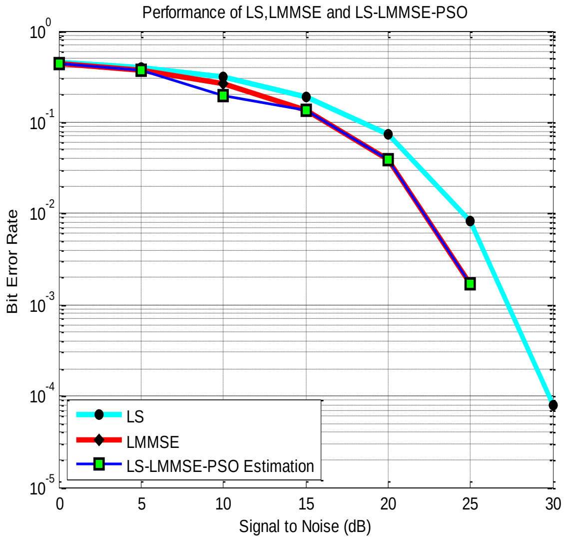

Figure 4: BER v/s SNR at Doppler frequency – 500 Hz

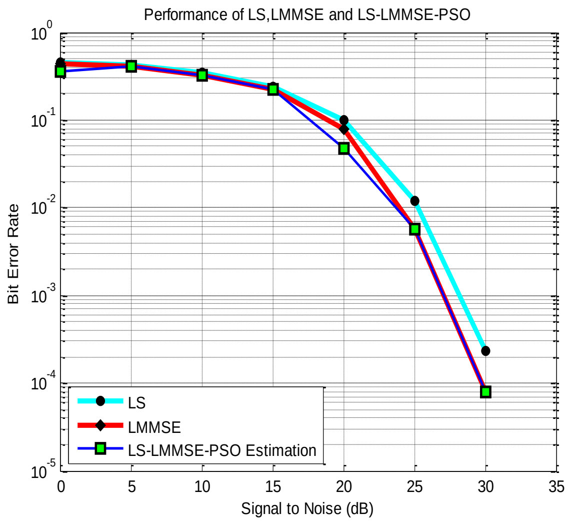

Figure 5: BER v/s SNR at Doppler frequency – 400 Hz

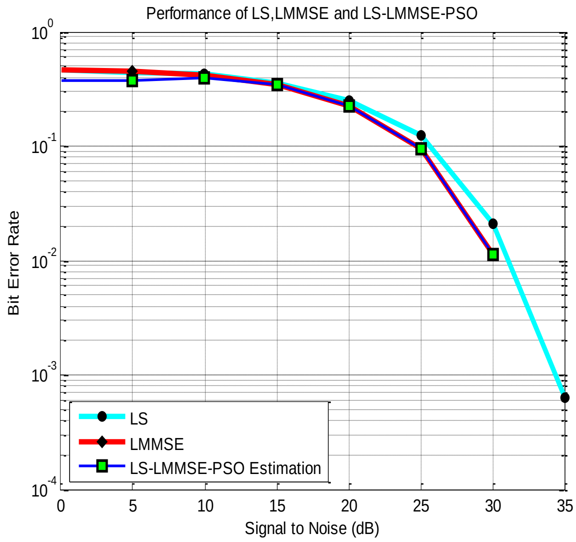

Figure 6: BER v/s SNR at Doppler frequency – 300 Hz

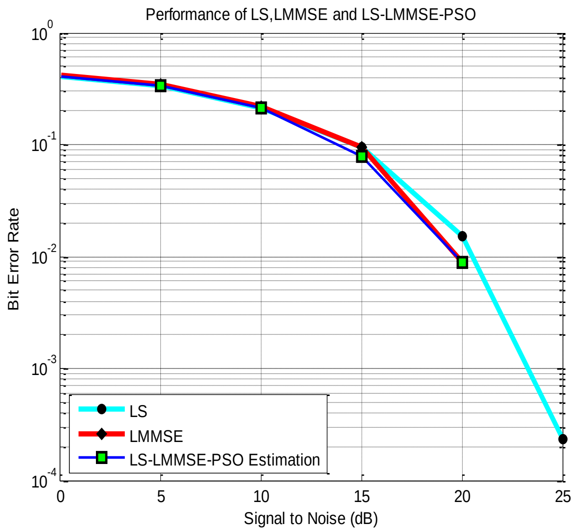

Figure 7: BER v/s SNR at Doppler frequency – 200 Hz

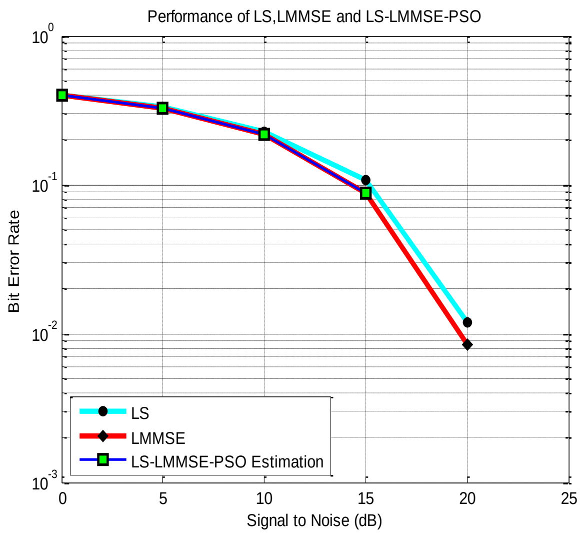

Figure 8: BER v/s SNR at Doppler frequency – 100 Hz

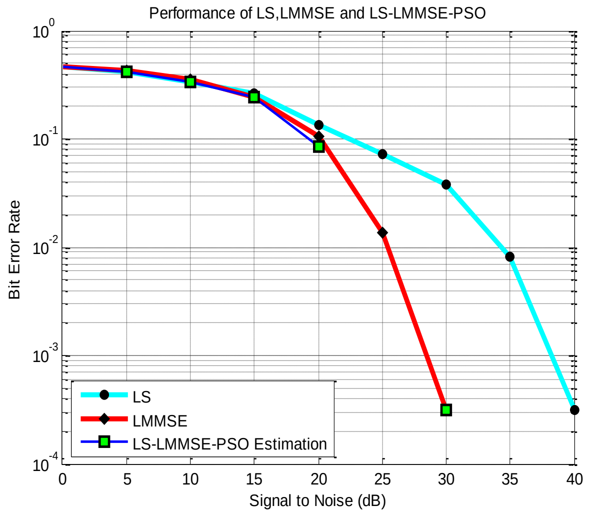

Figure 9: BER v/s SNR at Doppler frequency – 50 Hz

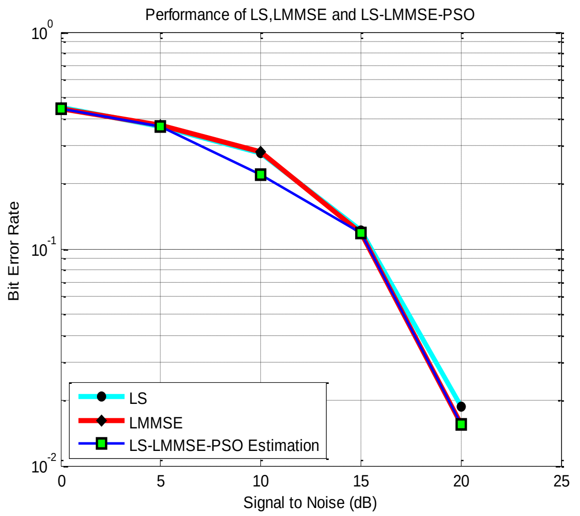

Figure 10: BER v/s SNR at Doppler frequency – 40 Hz

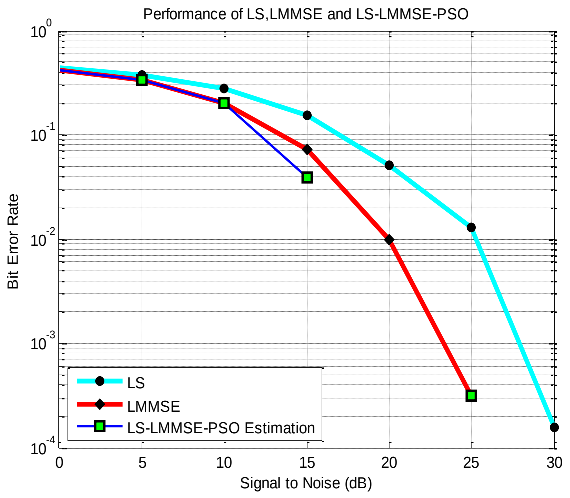

Figure 11: BER v/s SNR at Doppler frequency – 30 Hz

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