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CHANNEL ESTIMATION OF MIMO-OFDM USING CUCKOO SEARCH ALGORITHM

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ABSTRACT

In wireless communication, Multiple Input Multiple Output-Orthogonal Frequency Division Multiplexing (MIMO-OFDM) plays a major role because of its high transmission rate. Channel estimation and tracking have many different techniques available in OFDM systems. Among them, the most important techniques are least square (LS) and minimum mean square error (MMSE). In least square channel estimation method, the process is simple but the major drawback is it has very high mean square error. Whereas, the performance of MMSE is superior to LS in low SNR, but its main problem is it has high computational complexity. While comparing with LS and MMSE method individually, the combined LS and MMSE method using evolutionary programming can greatly reduce the error. If the error is reduced to a very low value, then an exact signal will be received. Thus, we propose a hybrid technique that includes cuckoo search algorithm performs the conventional LS and MMSE channel estimation followed by enabling a fine tuning on the obtained channel model. The result shows the performance of the proposed method is better than LS and MMSE method in all the mutation & crossover values and also in all the iterations computed. We illustrate the performance of OFDM systems using propose technique can be observed from the imitation and relative results.

Key words: *OFDM, Channel estimation, cuckoo search algorithm, LS, MMSE*

1. INTRODUCTION

OFDM is a most prominent technique that transmits the signal over wireless channels [14]. In OFDM, the entire channel is spitted into many narrow parallel sub channels, so the duration of symbol is increased and the inter symbol interference (ISI) produced by the multi-path environment is reduced or eliminated [1] [2]. OFDM supports high data rate traffic because the incoming serial data stream is divided into parallel low-rate streams that are transmitted on orthogonal sub-carriers simultaneously [3]. OFDM system has the ability of extenuating a frequency selective fading channel to a set of parallel flat fading channels, which require simple processes for channel equalization [4]. The available spectrum in an OFDM system is divided into manifold sub-carriers and all these sub-carriers are orthogonal to each other [5]. OFDM has been standardized for several applications, such as digital audio broadcasting (DAB), digital television broadcasting, wireless local area networks (WLANs), and asymmetric digital subscriber lines (ADSLs) [6] [15].

The capability of OFDM system is improved by using MIMO technique, which spatially multiplexes data streams via multiple antennas [13]. MIMO - OFDM, the combination of both OFDM and MIMO technologies, is currently under study and is one of the most propitious candidates for future communication systems, ranging from wireless LAN to broadband access [7]. The MIMO communication systems use multiple transmit and receive antennas, increase the data rate without increasing the bandwidth, increase the diversity, and improve the performance against fading channels using space-time codes [8]. It has been found that the capability of MIMO-OFDM systems grow linearly with the number of antennas, when optimal knowledge of the wireless channel is available at the receiver. The channel condition is not known in practical application. Thus, the channel estimation i.e., channel identification plays a major role in MIMO-OFDM system [18].

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Channel estimation is one of the most salient processes in communication system [12]. A perfect channel estimation algorithm should comprise both the time and frequency domain characteristics for the OFDM systems [11]. The performance of OFDM system can be improved by allowing for coherent demodulation using an exact channel estimation algorithm [10]. In OFDM transmission system, numerous channel estimation methods have been developed under the assumption of a slow fading channel, wherein the channel transfer function remain stable within one OFDM data block [9]. Several channel estimation techniques have already been developed for MIMO–OFDM systems. These techniques are broadly classified into three categories, namely, (i) training based technique, (ii) blind technique, and (iii) semi-blind technique, which is a combination of the first two techniques [17] [16].

Here, PSO and CS are used to estimate the channel by combining least square and minimum mean square error. The rest of the paper is structured as follows: The related works are briefly reviewed in Section 2, and the proposed technique with adequate mathematical models and illustrations are detailed in section 3. The implementation results are discussed in Section 4 and the section 5 concludes the paper.

2. RELATED WORKS

Some of the recent research works regarding the topic of OFDM channel estimation are discussed in this section.

Sarmadi *et al*. [19] have presented a blind channel estimation method for orthogonally coded MIMO-OFDM systems. Here, the finite impulse response (FIR) channel parameters in the time domain have been computed using the specific properties of the orthogonal space–time block codes (OSTBCs), rather than doing this process in the frequency domain separately for each subcarrier. The experimental outcomes have proved that the parsimony of the channel parametric model has been enhanced significantly than the direct per sub carrier channel estimation techniques, as well as the proposed technique has allowed for a coherent processing across the sub carriers. Furthermore, the channel estimation problem was approximated as a convex semi definite programming (SDP) problem by the semi definite relaxation (SDR) approach, and then the SDP problem has been solved successfully via convex optimization techniques.

Based on pilot aided arrangement, Bagadi *et al*. [20] have evaluated the channel state information for both SISO and MIMO systems. Here, the estimation of channel at pilot frequencies by traditional LS and MMSE estimation algorithms has been done through MATLAB simulation. The capability of MIMO-OFDM and SISO-OFDM system has been examined in terms of Bit Error Rate (BER) and Mean Square Error (MSE) level. The performance of both systems has been further improved via maximum diversity Space Time Block Coding (STBC) and Maximum Likelihood (ML) Detection at transmitting and receiving ends respectively.

Huang *et al*. [21] have introduced a block-by-block iterative receiver for underwater MIMO-OFDM, which includes channel estimation, MIMO detection, and low-density parity-check (LDPC) channel decoding. Here, the channel estimator was based on a compressive sensing method for utilizing the channel sparsity, the MIMO detector comprise a hybrid use of successive interference cancellation (SIC) and soft minimum mean-square error (MMSE) equalization, and the channel codes used were non-binary LDPC codes. They have considered two groups of threshold mechanism based feedback strategies namely, hard decision feedback and soft decision feedback for channel estimation.

Rana *et al.* [22] have proposed an adaptive channel estimation techniques such as normalized least mean square (NLMS) and recursive least squares (RLS) for the MIMO-OFDM systems. An adaptive estimator has been used, which has the potential to update the parameters of the estimator constantly and thus, the facts of channel and noise statistics are not needed. The proposed NLMS/RLS CE algorithm has required only the knowledge of the received signal. Simulation results have confirmed that the RLS CE technique has better performance than the NLMS CE technique for MIMO OFDM systems. Also, a higher performance has been achieved by the exploitation of more multiple antennas at the transmitter and/or receiver than with fewer antennas.

A transmission approach for MIMO-OFDM systems has been presented by Omri *et al*. [23]. The proposed approach was competent and mainly apposite for symmetric channels i.e., link between two base stations or between two antennas on radio beam transmission. Here, the channel parameters of a pilot data, which was send by the receiver to the transmitter, have been estimated. Subsequently, the estimated channel parameters have been utilized by

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the transmitter for coding the transmitted signal in order to modify the signal to the channel variations.

Saleem *et al*. [24] have discussed two linear channel estimation approaches such as LSE and Linear Minimum Mean Square Error (LMMSE) with their modified versions, for reduced intricacy, in LTE-Advanced MIMO-OFDM technology. As compared to LSE, the LMMSE has provided superior performance but its intricacy is high than LSE, because it necessitates the knowledge of channel and noise statistics. Hence, the LSE and LMMSE approaches have been adapted for optimizing the performance and complexity. Moreover, CIR samples and multi-path channel taps have been utilized for evaluating these algorithms.

In order to optimize both placement and power of the comb-type pilot tones, which are employed in LS channel estimation algorithm in MIMO-OFDM systems, a particle swarm optimization (PSO) has been utilized by Seyman *et al.* [25]. Experimental results have confirmed that the optimized pilot tones derived by PSO in terms of MSE and BER have performed better than the orthogonal and random pilot tones. Also, the simulations have been done over the channels with diverse Doppler shifts values in order to reveal the effect of Doppler shifts on several pilot tones performance.

3. CHANNEL ESTIMATION IN OFDM USING PSO AND CS

In the proposed method LS and MMSE methods are combined using Cuckoo search Algorithm. For OFDM channel model, initially the best channel is estimated by means of LS and MMSE independently using PSO and then, the LS and MMSE are combined via CS algorithm for computing the best channel with reduce in error. Here, the process is performed in three stages: PSO is used two stages and CS algorithm is used in one stage. The process takes place in each stage is explained briefly in below sections. Figure.1 shows the overall process takes place in our method.

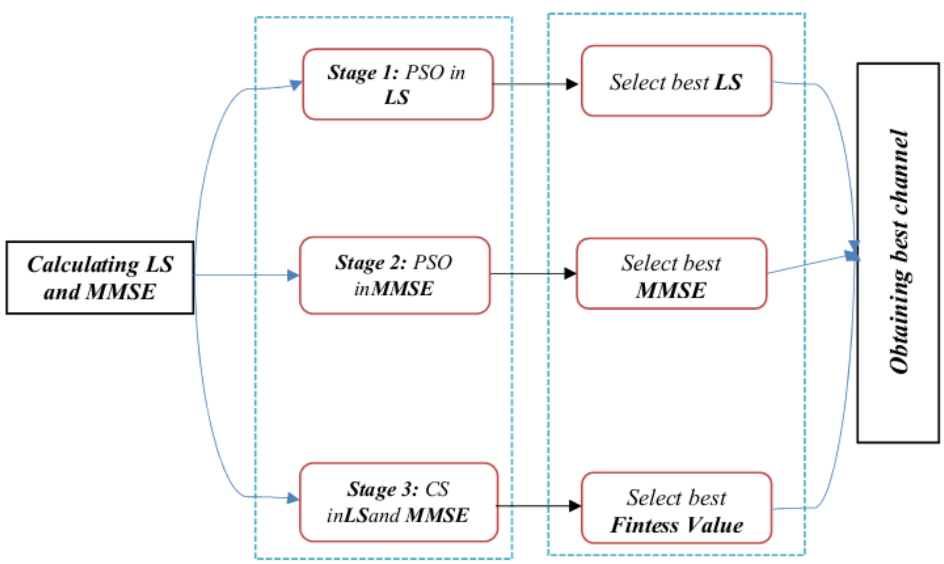

Figure 1. *Proposed Method For Channel Estimation Using PSO And CS*

3.1.OFDM System Model

Consider a MIMO-OFDM system with L OFDM subcarriers and K OFDM symbols per frame. The equivalent discrete-time model of a MIMO channel with NT transmit (Tx) and NR receive (Rx) antennas can be written in complex baseband notation as OFDM system model. Let, x_t be the transmitted signals and y_k be the received signals in the system. The transmitted signals x_t are taken from multi amplitude signal constellation. The channel impulse response of the system is calculated by using the following equation.

$$S(t) = \sum_{i=-\infty}^{+\infty} \sum_{K=1}^{N_{SC}} C_{Ki} S_k (t - iT_S) \quad (1)$$

$$S(t) = \prod(t) e^{j2xf_k{}^t} \quad (2)$$

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Where, C_{Ki} is the i[th] information symbol at the channel estimation, k[th] is the amplitude and X is a matrix with the elements of x on its diagonal and $x=[x_0, x_1....x_{N-1}]^{\tau}$.

$$H=\begin{bmatrix} h_{11} & ..\ ....h_{1N} \\ . & \\ . & \\ h_{M1} & ..\ ....h_{MN} \end{bmatrix} \quad (3)$$

$$\mathrm{H_N}^{nk}=\frac{1}{\sqrt{N}}.e^{-j2\pi\frac{nk}{N}} \quad (4)$$

$$H(k)=[HH^T+((M)I_N)^{-1}]H \quad (5)$$

After generating the OFDM system model, the next process is channel estimation using MMSE and LS techniques, which are explained briefly in the below sections.

3.2. MMSE Channel Estimation Model

If the channel vector g is Gaussian and uncorrelated with the channel noise n, the MMSE estimate of g becomes MMSE channel estimation is calculated by using the equation,

$$H_{MMSE}=R_{gy}\,R^{-1}{}_{yy}\,y$$

$$H_{MMSE}=F.Q_{MMSE}=.F^H{}_{MMSE}\;F^H X^H.y \quad (6)$$

$$Q_{MMSE}=R_{gg}[(F^H.X^H.X.F)^{-1}.\sigma_n{}^2+R_{gg}]^{-1}.(F^H.X^H.X.F)^{-1} \quad (7)$$

Where, R_{gg} is the auto covariance matrix of g with upper left $A\times A$ corner and $\sigma_n{}^2$ is the noise variance.

$$A=\frac{T_G}{T_s} \quad (8)$$

Where, T_G is the time length to eradicate inter block interference and to preserve the orthogonally of the tones, T is the first A columns of the DFT matrix F. This MMSE channel estimator (9). If g is not Gaussian, h MMSE is not necessarily a minimum mean-square error estimator. It is however the best linear estimator in the mean-square error sense. According to using the above equation, the channel is estimated using MMSE method and in second steps we use the channel estimation process using LS method.

3.3. LS Channel Estimation Model

The LS channel estimator does not use the statistics of the channel. Intuitively, excluding low energy taps of g will to some extent compensate for this shortcoming since the energy of g decreases rapidly outside the first L taps, while the noise energy is assumed to be constant over the entire range. The first L taps of g into account, thus implicitly using channel statistics, the modified LS estimator becomes

$$H_{LS}=F.Q_{LS}.F^H.X^H.y \quad (9)$$

Where, $Q_{LS}=(F^H.X^H.X.F)^{-1}$ (10)

Here, H_{LS} and H_{MMSE} are estimated using the equations (6) and (9) respectively. From this H_{LS} and H_{MMSE} values, the channel with reduce in error values is estimated by combining LS and MMSE channel using PSO and CS algorithm. Initially, we see about the best channel obtained for LS and MMSE together using PSO.

3.4. MMSE Channel using PSO and CS

PSO is a population based, heuristic, iterative optimization algorithm. Due to the heuristic approach, no gradient information is required to converge to the global optimum. Hence, it can easily be adopted to a wide range of technical optimization problems. Here, PSO is used to identify the best channel for MMSE channel estimation method. The proposed PSO method consists of four stages: initializing the particle, evaluation function, updating the initial particle, and termination. The process takes place in each stage is explained briefly in the below sections.

Stage 1: Initializing the particle in MMSE Channel Model

Initially, the MMSE channels are Initialize. The initial particles are $\{H_{MMSE}{}^1, H_{MMSE}{}^2.......H_{MMSE}{}^r\}$. Where, r is the number of iterations used for generating new channels models by varying the bits. Then analyze the fitness value for each new channel models generated i.e. $\{H_{LS}{}^1, H_{LS}{}^2.......H_{LS}{}^r\}$. According to different MMSE channel, the best channel is identified using the evaluation function.

Stage 2:Evaluation function in MMSE Channel Model

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In this stage, the mutation process is evaluate the MMSE channel model. The best channel estimation is selected based on the evaluation function. The evaluation formula used for selecting the best channel estimation. The evaluation function is used to evaluate the best initial particle.

$$Evaluationfunction = \left(\frac{H - H_{MMSE}}{H} \right)^2 \quad (11)$$

Where, H is the reference channel model.

The next step after Evaluation function of initial particle is updating the initial particle.

Stage 3:Updating the initial particle in MMSE Channel Model

In this stage, The MMSE channels model particles are updated with cuckoo lays timing and dumping randomly the best estimation by using the equation given below. Second principle: The best nests with high quality of eggs will carry over to the next generation and third principle:

$$H_{MMSE} = \sum_{i=1}^{d} H_i^2 , x_i \in [-1,1] \quad (12)$$

$$H_{MMSE} = H_i^t + \alpha \oplus Le'vy(\lambda) \quad (13)$$

Where, $\alpha > 0$ is the number of iterations used for generating new channels models by changing the bits, which should be related to the scale of the problem of MMSE channel. The MMSE $\oplus$ means entry-wise multiplications. In this paper, we consider a Levy flight in which the step-lengths are distributed according to the following probability distribution. Then calculate the fitness value for each new channel models generated i.e. $\left\{ H_{MMSE}{}^1, H_{MMSE}{}^2 ....H_{MMSE}{}^r \right\}$.

Stage 4:Termination in MMSE Channel Model

In this stage, the iteration process is applied in the MMSE channel model obtained in equation (13). Here bits in the channel models are randomly changed with an iteration rate λ the best channel is estimated based on the evaluation function. The best channel obtained at the end of termination process is as follows.

$$H_{MMSE}\,\lambda = Best[H_{MMSE}{}^{-\lambda}], (1 < \lambda \le 3) \quad (14)$$

The one best channel estimation is obtained from this stage and the best channel estimation is calculated using the fitness function.

3.5. Identifying Best LS Channel using PSO and CS

Here, the best LS channel is identified using PSO with CS. The process that takes place in PSO with CS is explained briefly in Identifying best LS channel model.

Stage 1: Initializing the particle in LS Channel Model

Initially, the LS channels are computed based on LS Channel estimation Model. The initial particles are $\left\{ H_{LS}{}^1, H_{LS}{}^2 ....H_{LS}{}^r \right\}$. The initial particles are $\left\{ H_{MMSE}{}^1, H_{MMSE}{}^2 ....H_{MMSE}{}^r \right\}$. Where, r is the number of iterations used for generating new channels models by varying the bits. From the above different LS channel, the best channel is identified using the evaluation function.

Stage 2:Evaluation function in LS Channel Model

In this stage, the mutation process is evaluate the MMSE channel model. The best channel estimation is selected based on the evaluation function. The evaluation formula used for selecting the best channel estimation. The evaluation function is used to evaluate the best initial particle. The evaluation function is used to evaluate the best initial particle.

$$Evaluationfunction = \left(\frac{H - H_{LS}}{H} \right)^2 \quad (15)$$

Where, H is the reference channel model.

The next step after evaluating the initial particle is updating initial particle.

Stage 3:Updating the initial particle in LS Channel Model

In this stage, The LS channels model particles are updated using the equation given below.

$$H_{LS} = \sum_{i=1}^{d} H_i^2 , x_i \in [-1,1] \quad (16)$$

$$H_{MMSE} = H_i^t + \alpha \oplus Le'vy(\lambda) \quad (17)$$

Where, $\alpha > 0$ is the number of iterations used for obtaining the best channel estimation, compare the channel estimation obtained from stage 1&2 and selects the best among that channel estimation which should be related to the scale of the problem of LS channel. In LS $\oplus$ means entry-wise multiplications. In this paper, we consider a Levy

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flight the fitness should be related to the difference in solutions. Therefore, it is a good idea to do a random walk in a biased way with some random step sizes. Then calculate the fitness value for each new channel models generated i.e. $\left\{ H_{LS}{}^{1}, H_{LS}{}^{2} ....H_{LS}{}^{r} \right\}$.The next step after updating the initial particle is termination.

Stage 4:Termination in LS Channel Model

In the termination process, the best channel is estimated based on the evaluation function. The best channel obtained at the end of termination process is as follows.

$$H_{LS}\ \lambda = Best\,[H_{LS}{}^{-\lambda}],\ (1 < \lambda \le 3) \qquad (18)$$

Here, H_{LS} channel estimation and then, iteration operation is done in the result of best operation is $[H_{LS1}, H_{LS2}]$.

3.6. Identifying Best Channel using Proposed Method

For obtaining the best channel estimation, the channel estimation obtained from stage 1, 2 & 3 are compared and among that channel estimation, the best channel is selected based on the minimum error value. In this case, when generating new channels $x(t+1)$ for a cuckoo *i*, a Levy flight integrating with controls the search ability is performed. Then, the optimization rate is changed and generated more number of new channel estimation. New channel estimation generated after search operation is $\{[H_{11}, H_{12}], [H_{21}, H_{22}] ....[H_{n1}, H_{n2}]\}$.Then CS optimization is obtained a new channel model to determine optimal best value

$$[H_{cs}] = Best\{H_1, H_2 ....H_r\} \qquad (19)$$

The minimum error value channel estimation is selected as the best channel estimation.

$$H_{best} = error \min\left\{\breve{H}_{LS}, \breve{H}_{MMSE}, H_{CS}\right\} \qquad (20)$$

Here, H_{best} gives the best channel estimation obtained from our proposed method. For that, the error value is calculated for $\breve{H}_{MMSE}$, $\breve{H}_{LS}$ & H_{CS} individually. Then, the error values obtained from all the channel estimation are compared and finally, the channel estimation with minimum error is chosen as the best channel estimation.

4. RESULT AND DISCUSSIONS

The proposed channel estimation in OFDM is implemented in MATLAB 2011 B and its performance is evaluated from the SNR vs Mean Squared Error graph. In evaluate the results are changing the number of iterations. The performances of our proposed channel estimator are compared to MMSE and LS with PSO and CS algorithms. The results obtained are shown in the below figures.

Initially, we see about the best result obtained at each stage for number of iterations: 50, Mutation Rate: 0.01, Crossover value: 0.5. Now, we can see about the result obtained at each stage using the proposed method.

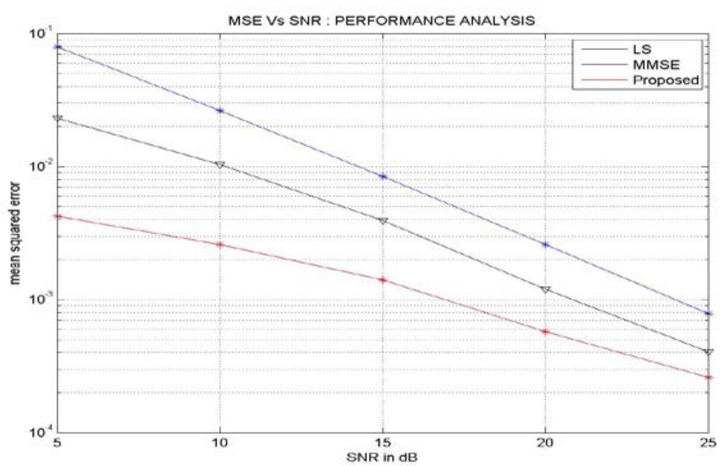

Figure 2.*MSE Vs SNR Graph For Best Channel Using Proposed Method For Iterations 50, Mutation Rate: 0.01 & Crossover Value: 0.5.*

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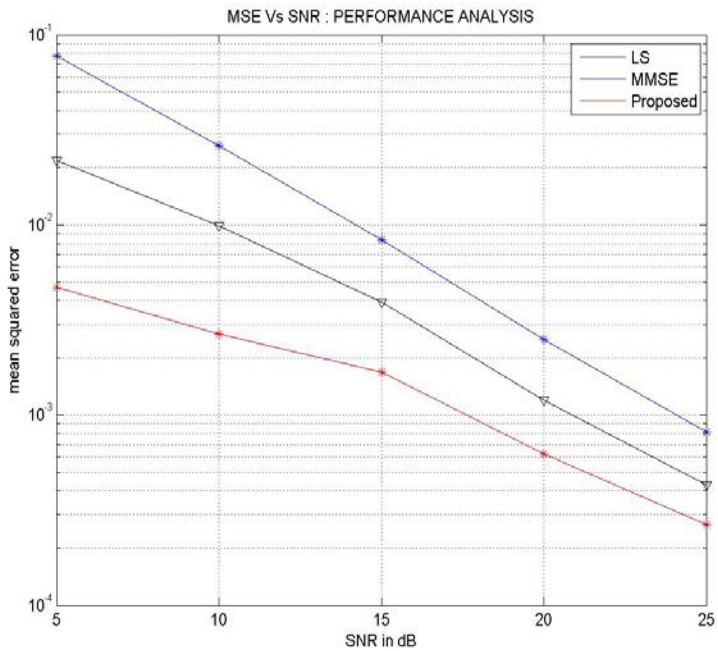

Figure 3*.MSE Vs SNR Graph For Best Channel Using Proposed Method For Iterations 50, Mutation Rate: 0.01 & Crossover Value: 0.7*

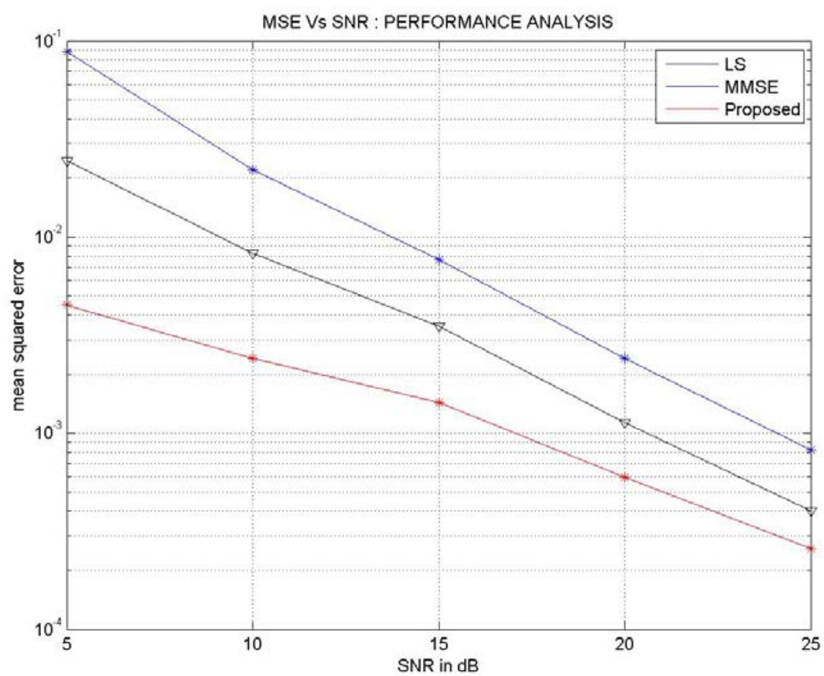

Figure 4*.MSE Vs SNR Graph For Best Channel Using Proposed Method For Iterations 50, Mutation Rate: 0.01 & Crossover Value: 0.9*

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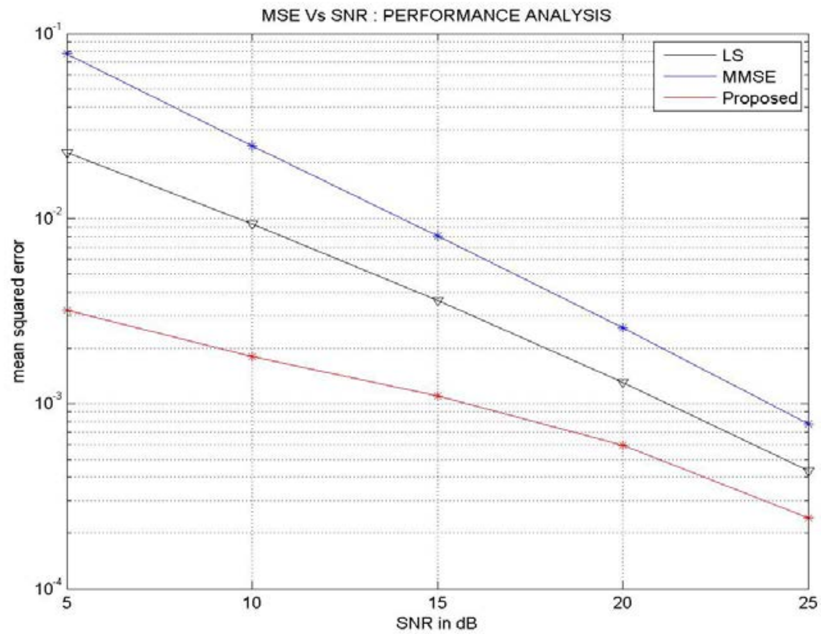

Figure 5*.MSE Vs SNR Graph For Best Channel Using Proposed Method For Iterations 70, Mutation Rate: 0.01 & Crossover Value: 0.5*

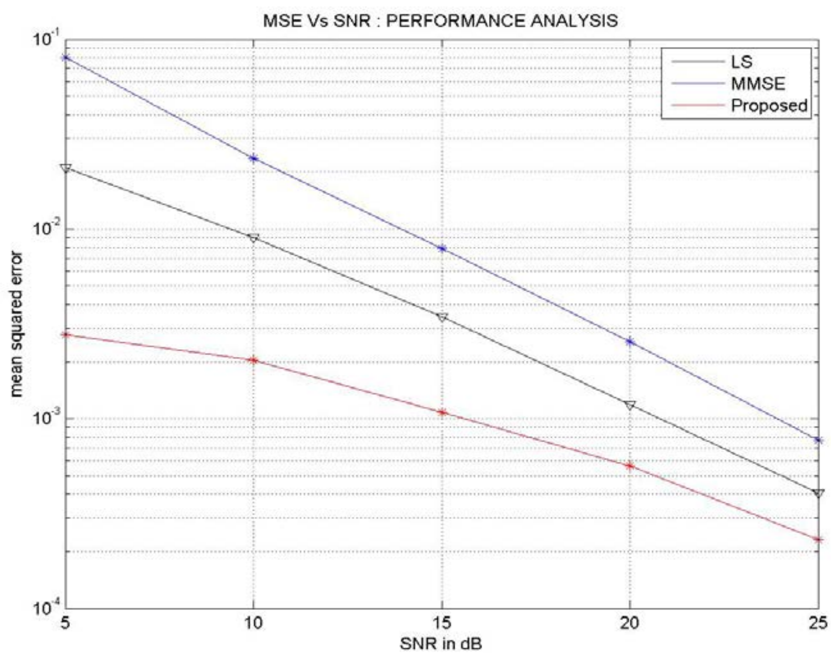

Figure 6*.MSE Vs SNR Graph For Best Channel Using Proposed Method For Iterations 70, Mutation Rate: 0.01 & Crossover Value: 0.7*

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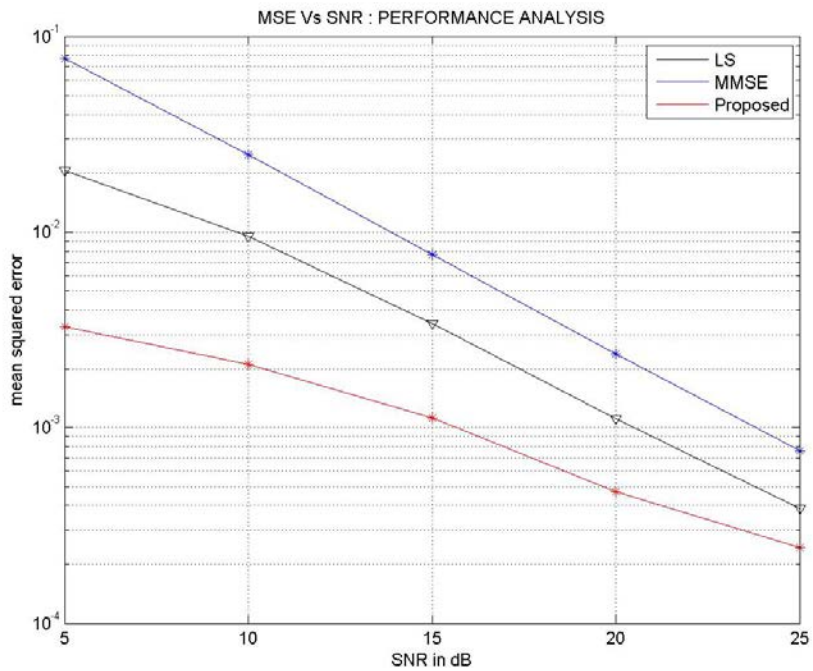

Figure 7*.MSE Vs SNR Graph For Best Channel Using Proposed Method For Iterations 70, Mutation Rate: 0.01 & Crossover Value: 0.9*

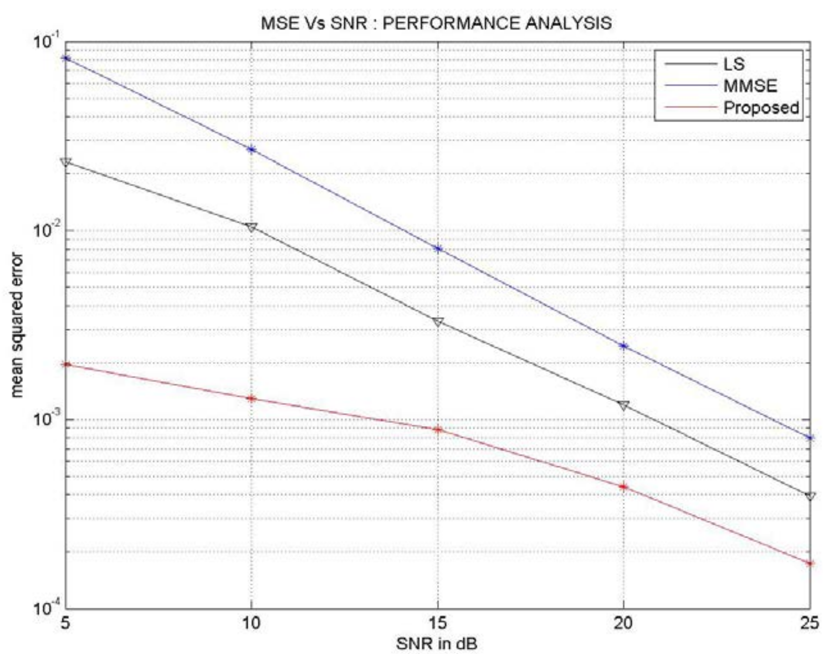

Figure 8*.MSE Vs SNR Graph For Best Channel Using Proposed Method For Iterations 100, Mutation Rate: 0.01 & Crossover Value: 0.5*

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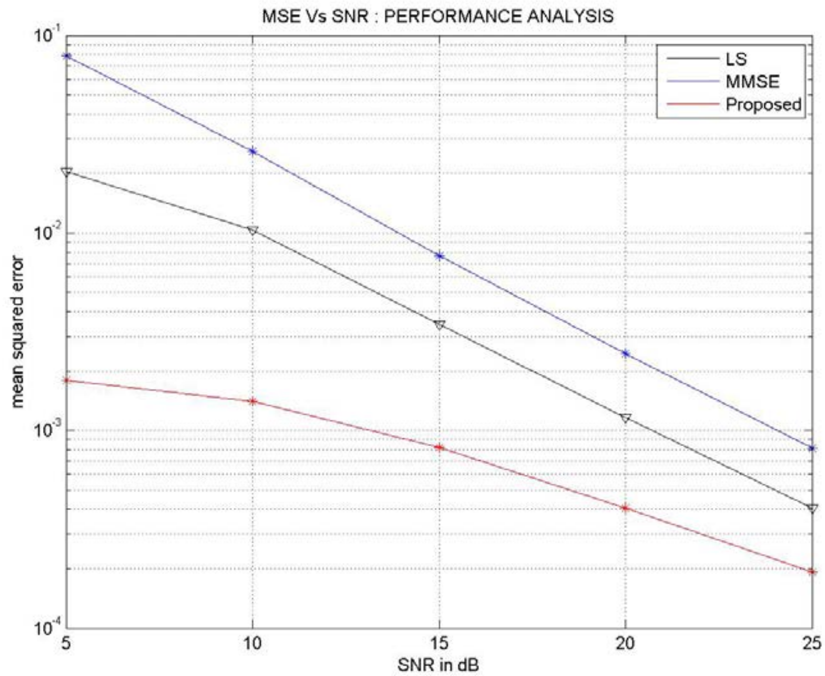

Figure 9*.MSE Vs SNR Graph For Best Channel Using Proposed Method For Iterations 100, Mutation Rate: 0.01 &Crossover Value: 0.7*

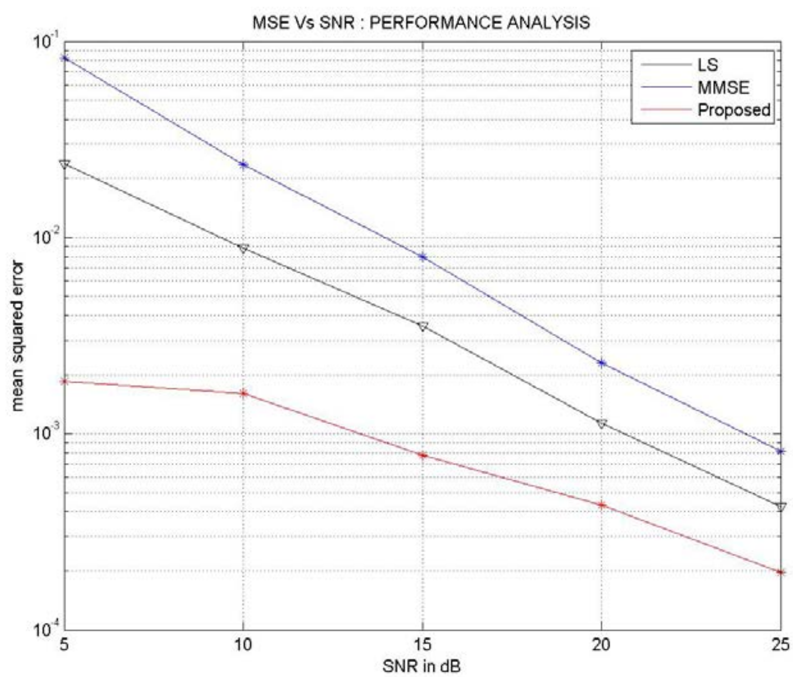

Figure 10*.MSE Vs SNR Graph For Best Channel Using Proposed Method Foriterations100, Mutation Rate: 0.01 & Crossover Value: 0.9*

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All figures shows the best channel obtained using the proposed method. The best channel obtained for proposed method is compared to LS and MMSE channel individually. From the above graph, it is clear that the proposed method is better than the LS and MMSE channel.

Figure 2 shows the best channel obtained using the proposed method for iterations: 50, mutation rate: 0.01 & crossover rate: 0.5. The best channel obtained for proposed method is compared with LS and MMSE channel individually. From the above graph, it is clear that the proposed method is better than the LS and MMSE channel.

Figure 3 shows the best channel obtained using the proposed method for iterations: 50, mutation rate: 0.01 & crossover rate: 0.7. The best channel obtained for proposed method is compared with LS and MMSE channel individually. From the above graph, it is clear that the proposed method is better than the LS and MMSE channel.

Figure 4 shows the best channel obtained using the proposed method for iterations 50, mutation rate: 0.01 & crossover rate: 0.9. The best channel obtained for proposed method is compared to LS and MMSE channel individually. From the above graph, it is clear that the proposed method is better than the LS and MMSE channel

Figure 5 shows the best channel obtained using the proposed method for iterations: 70, mutation rate: 0.01 & crossover rate: 0.5. The best channel obtained for proposed method is compared with LS and MMSE channel individually. From the above graph, it is clear that the proposed method is better than the LS and MMSE channel.

Figure 6 shows the best channel obtained using the proposed method for iterations: 70, mutation rate: 0.01 & crossover rate: 0.7. The best channel obtained for proposed method is compared with LS and MMSE channel individually. From the above graph, it is clear that the proposed method is better than the LS and MMSE channel.

Figure 7 shows the best channel obtained using the proposed method for iterations 70, mutation rate: 0.01 & crossover rate: 0.9. The best channel obtained for proposed method is compared to LS and MMSE channel individually. From the above graph, it is clear that the proposed method is better than the LS and MMSE channel

Figure 8 shows the best channel obtained using the proposed method for iterations: 100, mutation rate: 0.01 & crossover rate: 0.5. The best channel obtained for proposed method is compared with LS and MMSE channel individually. From the above graph, it is clear that the proposed method is better than the LS and MMSE channel.

Figure 9 shows the best channel obtained using the proposed method for iterations: 100, mutation rate: 0.01 & crossover rate: 0.7. The best channel obtained for proposed method is compared with LS and MMSE channel individually. From the above graph, it is clear that the proposed method is better than the LS and MMSE channel.

Figure 10 shows the best channel obtained using the proposed method for iterations 100, mutation rate: 0.01 & crossover rate: 0.9. The best channel obtained for proposed method is compared to LS and MMSE channel individually. From the above graph, it is clear that the proposed method is better than the LS and MMSE channel.

5. CONCLUSION

In this paper, new channel estimation method with PSO and CS to estimate the best channel using LS and MMSE method. Initially, the best channel for LS and MMSE individually using PSO was computed and then the LS and MMSE best channel were combined using CS algorithms. In our proposal, we find Evolutionary Programming by using PSO and CS with best channel with minimum error is selected from the three best channels. From the performance results, our proposed estimator performs better than other LS and MMSE channel estimator method. For this reason this approach has less computational complexity.

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