Performance of Channel Estimation Schemes in the presence of Gaussian Mixture Model

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Abstract: Channel estimation (CE) plays a crucial role in establishing a wireless link, specifically at the receiver node. Most of the receivers that estimate the channel is in the presence of AWGN. However, these schemes perform expressively worse when the impulsive noise is added in AWGN which is introduced by manmade sources (pressure cooker, motorbike, electric supply) as well as natural noises (earthquakes and thundering). The major contribution of this research is to analyze the channel estimation schemes in the Gaussian mixture model (GMM) environment. The performance of channel estimation schemes has been compared in terms of mean square error (MSE) and bit error rate (BER). Four channel estimation schemes e.g., MMSE, DFT, correlation- based methods like Gauss-Seidel (GS) and Successive Over-Relaxation (SOR), are studied and analyzed. The study reveals that the correlation scheme based on the method of SOR is more effective as compared to the methods of DFT, MMSE and GS because of faster convergence rate along with the minimum number of iteration. SOR shows sustainable results up to the probability of an impulsive element of 5 Percent.

Keywords: GMM, LS, MMSE, DFT, GS, SOR.

1. Introduction

In the wireless communication system, due to the multipath effects, several complexities are associated with the transmitted signals such as reflection, scattering, and diffraction [1]. In most of the research, AWGN channel models are utilized for many wireless applications but whenever impulse noise occurs in the AWGN channel model, it adversely affects the wireless system. Thus, the synchronization and the estimation of the channel in the GMM (Gaussian mixture model) environment are among the highly complicated, yet vital issues in the advanced wireless communication system.

The four different approaches that are used in channel estimation which are as follows. First is the preamble-based approach which is stated as the simplest way is to sound the channel with known wideband noise like signal and listen to it at all frequencies. Equivalently, one can transmit an impulse signal and obtain its impulse response. This is how a preamble-based approach is performed. Preamble based approach is useful where channel variation is slow, in other words, slow fading channel [2]. The second approach is the pilot-based. In this approach, pilots are transmitted together with data, and channel variation can be tracked by the symbol [3, 4]. Hence, it is useful for the fast fading channel as well. In the pilot-based approach, one can transmit known pilots at selective frequencies and obtain responses at those frequencies. Then these responses are interpolated by different methods. Yet the third approach can be called the totally blind approach, where known measurements of the signals are used for channel estimation. The totally blind approach is suitable for applications where bandwidth is minimal and saves the training overhead [5, 6]. On the contrary side, it has a negative factor of being exceedingly computational. Semi blind approaches fill in between, is known as the fourth one.

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Frequency domain (FD) and Time domain (TD) are the main two domains are used for the characterization of Channel estimation. In the channel estimation scheme based on frequency domain (FD), channel frequency response (CFR) is assessed at each pilot. Subsequently, interpolation takes place by different techniques. Least Squares (LS) and Minimum Mean Squares Errors (MMSE) are utilized by the popular frequency domain (FD). In the Least Squares based, CFR can be simply stated as the ratio between output and input signal at pilot frequencies. Therefore, it is known as the facile estimation technique while inviting the issue of distortion. This flaw is addressed by MMSE, at the cost of complexity enhancement. In MMSE, MSE (average of the squares of the difference between the estimator and what is estimated) is minimized by the prior knowledge of distortion variance.

However, the TD channel estimation schemes are divided into discrete Fourier transforms (DFT) and correlation schemes. In the TD channel estimation strategy, the channel impulse response (CIR) is estimated first. Then, the estimated response is moved through a fast Fourier transform (FFT) operation for equalization of the channel at each subcarrier in the FD.

In the TD scheme, the correlation method is further classified into three types. Correction Error Cancellation (CEC), GS method and, Successive SOR. In [7], FD pilot and TD processing (FPTP) method is presented, in this method correlation error cancellations (CEC) technique is applied. In spite of being popular and efficient, the performance of mean square error is adversely affected when any of its neighboring routes are near to the strength of the strongest route. Consequently, additional computation power is required by FPTP, in the form of iteration in CEC. In [8], the author utilizes the GS method is suitable for less number of guard bands. When the number of guard bands are increased, the number of iterations will also increase as the consequences the complexity also goes up. In addition, if channel conditions are unknown then the number of iterations are also increased in Gauss-Seidel method. However, the SOR based model is more efficient as compared to the GS based model with less number of iterations. Thus, this paper presents SOR method. In the SOR, a few numbers of iterations are required to converge to a precise solution with unknown initial values [9-12].

Moreover, the literature states that several studies have paid attention to the assumption of AWGN noise models [13, 14] commonly these suppositions are beneficial for some applications nevertheless some distortions in the background exist practically which are improperly modeled due to the AWGN noise. At the point when the noise goes diverge from Gaussian, it affects the existing channel estimation techniques abruptly because the Gaussian-based estimation techniques are susceptible to noise. In this context the renowned noise model such as GMM presents impulsive noise known as non-Gaussian noise. The comprehensive domain of non-Gaussian noise distribution, is also identified by this model along this it also incorporates most of the noise types which is available in a variety of wireless communication systems [15-22].

In the OFDM system, the frequency-domain (FD) channel estimation schemes have gained much more popularity than time-domain schemes. In the frequency-domain approaches pilots are inserted in the FD and it easy to estimate channel using interpolation. However, the presented time-domain correlation-based channel estimation technique differs from frequency-domain estimators in such way that it does not depend on interpolation [23, 24]. In the correlation method by increasing or decreasing the number of pilot or pilot spacing, results would not be affected while in the interpolation method errors would occur due to the variation of the number of pilots and pilot spacing.

In this paper DFT, MMSE GS, and SOR methods are presented in the GMM environment where the SOR method is adopted expressively rather than the GS method. Because in the GS method when the number of guard bands increase the convergence rate or the number of iteration also increases. In addition, the MSE and BER are improved in the SOR method as compared to the GS method. This article is structured in the following sections. The overview of the GMM based OFDM system model is explained in Section 2. In Section 3 the conventional channel and proposed channel estimation techniques are discussed. Section 4 defines the simulation parameters that are used in this work. Section 5 includes the Results and analysis. Lastly, the conclusion of this research work is presented in Section 6 whereas last section contains the references.

2. System Model

The system block diagram of the frequency and time-domain channel estimation model is shown in Figure 1 [25]. The model begins with the generation of pilots, data subcarriers $P[K]$ and $D[K]$ respectively. Subsequently in mux block theses subcarriers are added and give the frequency-domain samples $X[K]$. Then Inverse Fast Fourier is applied on $X[K]$ samples that transforms FD samples $X[K]$ into TD $x(n)$, which is given as:

$$x(n) = IFFT\{X[K]\} = \sum_{k=0}^{N-1} X[K] e^{\frac{j2\pi kn}{N_{FFT}}} \quad (1)$$

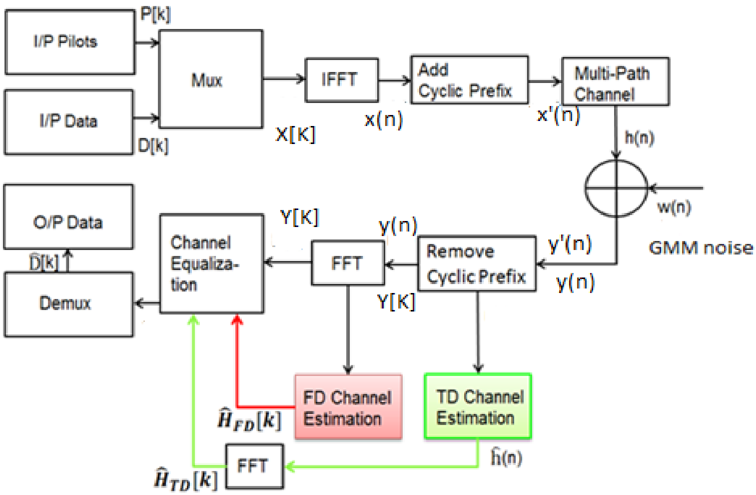

Figure 1. System block diagram of FD CE and TD CE

Where N_{FFT} signifies the number of Fast Fourier Transform. To eliminate inter-symbol interference, cyclic prefix N_g are inserted in each OFDM symbol and samples become $x'(n)$, that can be stated as:

$$x'(n) = \begin{cases} x(N_{FFT} + n), & n = -N_G + 1 \ldots, -1 \\ x(n), & n = 0,1, \ldots\ldots, N_{FFT} - 1 \end{cases} \quad (2)$$

When the received signal travels through the frequency selective multipath channel, it becomes $x'(n)$

$$y(n) = x'(n) \otimes h(n) + w(n) \quad (3)$$

Here the additive Gaussian mixture noise is signifies by the term $w(n)$. The impulse response of multi-path channel $h(n)$ can be stated as:

$$h(n,\tau) = \sum_{i=0}^{L-1} h_i e^{j\left(\frac{2\pi}{N_{FFT}}\right) f_{D_i} T n} \delta(\tau - \tau_i) \quad (4)$$

where h_i represents the i^{th}complex part of path gain, f_{D_i} is the i^{th}path Doppler frequency shift, τ_i is the route delay of matching normalized and the term L shows the entire number of channel taps. Without losing the simplification, there is a possibility to use a model having low-pass system and therefore the received signal is $y'(n)$ with cyclic prefix that would be $y(n)$ after removal of the cyclic prefix, can be represented as:

$$y(n) = \sum_{m=0}^{N_{FFT}-1} h(m) \left[d((n-m))_{N_{FFT}} + \ p((n-m))_{N_{FFT}} \right] + w(n) \quad (5)$$

where m is the indexing used in TD , $(.)_{N_{FFT}}$represents the modulo of N_{FFT} and, $w(n)$ is GMM noise. When FFT is applied to Equation (5) it would be rewritten as:

$$Y[k] = FFT\{y(n)\} = \frac{1}{N_{FFT}} \sum_{n=0}^{N_{FFT}-1} y(n)\, e^{\frac{j2\pi kn}{N_{FFT}}} \quad (6)$$

$n = 1,2, \ldots . N_{FFT} - 1$

When considering the much smaller length of CIR than the guard band interval as consequences there is no ISI.

The response of $Y[k]$ can be represented as:

$$Y[k] \ = X[k]H[k] + W[k] \quad (7)$$

$W[k]$ and $H[k]$ are the Fourier transform of $w(n)$ and $h(n)$ respectively. Where $w(n)$ can be defined by GMM [26], distribution as:

$$p(w(n)) = (1 - \emptyset).\mathcal{CN}(0, \sigma_n^2) + \emptyset.\mathcal{CN}(0, T\sigma_n^2) \quad (8)$$

where $T \gg 1$ represent magnitude of the impulsive-noise and $\mathcal{CN}(0, T\sigma_n^2)$ represents the distribution of Gaussian signal having zero mean and variance σ_n^2, and to get control over the noise level in GMM model $\emptyset$ is the mixture parameter. As per Equation (8), it can be inferred that stronger GMM noise by higher noise variance $T\sigma_n^2$as well as higher mixture parameter $\emptyset$. Thus, the variance of GMM is obtained as:

$$\sigma_z^2 = (1 - \emptyset)\sigma_n^2 + \emptyset\, T\sigma_n^2 \quad (9)$$

3. Conventional Channel Estimation Techniques

Three different types of conventional CE techniques are presented in this paper. These are as follow DFT, MMSE, and Correlation methods. Consider a system model in FD systems by using Equation (7), such as:

$$Y[k] = X[k]H[k] + W[k] \qquad 0 \le k \le N_{FFT} - 1 \quad (10)$$

where X and Y represent transmitted and received FD signals at each subcarrier respectively. However, H and W represent the channel transfer function and GMM noise for OFDM symbol, respectively.

A. MMSE Evaluation

In MMSE, CE requires the prior familiarity of auto covariance matrix R_{HH} and noise variance σ_N^2 . Let the error in channel estimation *e* as:

$$e = H - \widehat{H} \quad (11)$$

Now, MSE can be defined as the average of the squares of the difference between the estimators and what is estimated:

$$E\{|e|^2\} = E\left\{\left|H - \widehat{H}\right|^2\right\} \quad (12)$$

The MMSE-based channel estimation can be simplified as [27-30]:

$$\widehat{H}_{MMSE} = R_{HH}(R_{HH} + \sigma_N^2(X^H X)^{-1})^{-1}\widehat{H}_{P,LS} \quad (13)$$

where auto covariance matrixes of H is denoted by R_{HH}. The performance of MMSE estimator is better as compared to LS [31]. However, because of the inversion of the matrix in Equation (13), it has high computational complexity as compared to LS.

B. DFT Evaluation

In the TD DFT method, the CE is first obtained in the FD as usual, and then it is transformed into time-domain in form of inverse-DFT where noise is removed from all the time locations where channel taps are not present. After cleaning, the estimations are transformed back to the FD using DFT. The DFT-based algorithm provides enhanced estimation precision when compared with orthodox LS and MMSE estimators since it permits decrease of noise outside the most extreme channel delay length D. DFT-based algorithm can be done in the additional advances:

- Use Calculate $\widehat{H}_{LS}[k]$, the LS-based channel transfer function as:

$$\widehat{H}\_LS\ [k] = Y[k]/X[k] \ = H[k] + W[k]/X[k] \quad (14)$$

- Convert $\widehat{H}_{LS}[k]$ into time-domain and use IDFT.

$$IDFT\{\hat{H}_{LS}[k]\} \triangleq \hat{h}(n) = h(n) + w(n) \tag{15}$$

Here actual and estimated CIR are represented by $h(n)$ and $\hat{h}(n)$ respectively and $w(n)$ represents the time-domain noise component.

- Minimize the effect of noise in TD by defining coefficients for maximum channel delay length D as:
$$\hat{h}_{DFT}(n) = \begin{cases} h(n) + w(n) & n = 0,1 \dots D-1 \\ 0 & otherwise \end{cases} \tag{16}$$
- Use Convert $\hat{h}_{DFT}(n)$into FD by using DFT.
$$\hat{H}_{DFT}[k] = DFT\{\hat{h}_{DFT}(n)\} \tag{17}$$

However, DFT suffers leakage of energy in non-significant channel taps when $(n \geq D)$, which can be minimized in the proposed TD CE [25], as shown in Figure 2.

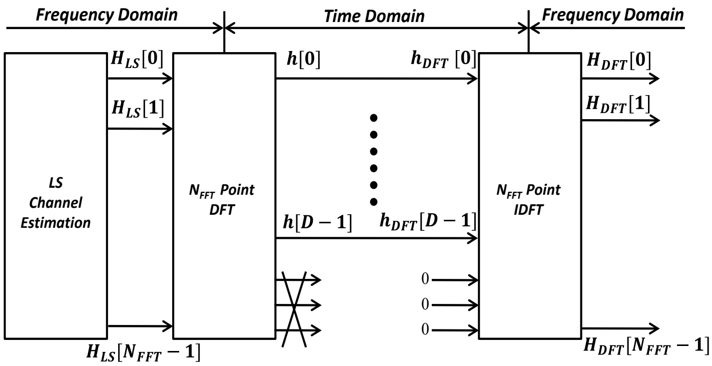

Figure 2. Channel estimation based on DFT

C. Proposed Correlation Method (SOR)

In this section, first the brief review of Gauss-Seidel iterative method is explained then its extension i.e. SOR method with the relaxation factor is discussed.

C.1. Gauss-Seidel method

To estimate channel impulse response, Gauss-Seidel iterative method can be used. However, the convergence rate of Gauss-Seidel is high due to having a large number of iteration. Therefore, to improve the convergence rate of Gauss-Seidel, a proper initial guess such as component without windowing aspect can be utilized. Consequently, the cyclic correlation is taken with the locally generated $p_1(n)$ for the received signal $y(n)$,

$$C_{yp_1}(n) = h(n) \otimes \left[C_{dp_1}(n) + C_{p_1p_1}(n) + C_{p_2p_1}(n)\right] + C_{wp_1}(n) \tag{18}$$

In general $C_{xy}(n)$ is the cyclic correlation between x and y. From it is know that $C_{dp_1}(n) = 0$. Therefore, the response of cyclic correlation becomes,

$$C_{yp1}(n) = h(n) \otimes \left[C_{p_1p_1}(n) + C_{p_2p_1}(n)\right] + C_{wp_1}(n) \tag{19}$$

It can be shown that both the real and imaginary components of the cross-correlation of noise $w(n)$ with $p_1(n)$, $C_{wp_1}(l)$, can be estimated as zero mean based Gaussian mixture noise and variance σ_z^2. Also, $C_{wp_1}(l) = \widetilde{w}(l)$. Therefore, Equation (19) may be formed as:

$$C_{yp_1}(l) = h(l) \otimes \left[C_{p_1p_1}(l) + C_{p_2p_1}(l)\right] + \widetilde{w}(l) \tag{20}$$
$$0 \leq l \leq N_P - 1$$

Here it is noticed that over the extent of N_P, $C_{p_1p_1}(0)$ and $C_{p_2p_1}(0)$ behave like delta functions. Thus, In the context of convolution sum the Equation (20) can be restricted as:

$$C_{yp_1}(l) = h(l).\left[C_{p_1p_1}(0) + C_{p_2p_1}(0)\right] +$$

$$\left[\sum_{\substack{n_1=0,\\ n_1\neq l}}^{L-1} h(n_1).\, C_{p_2p_1}(N_P + l - n_1)\right] + \widetilde{w}(l) \tag{21}$$

To estimate the CIR $\hat{h}(l)$, one can write Equation (21), as:

$$\hat{h}(l) = \frac{C_{yp_1}(l) - \sum_{\substack{n_1=0,\\ n_1\neq l}}^{L-1} h_{n_1}.C_{p_2p_1}(N_P + l - n_1) - \widetilde{w}(l)}{C_{p_1p_1}(0) + C_{p_2p_1}(0)} \tag{22}$$

The estimated initial guess can be written as $\hat{h}_l^{(k)}$:

$$\hat{h}_l^{(0)} = \left[\hat{h}_0^{(0)}, \hat{h}_1^{(0)}, \ldots\ldots \hat{h}_{n-1}^{(0)}\right] = [0,0, \ldots 0], \tag{23}$$

Substitute the values of $\hat{h}_l^k$ in Equation (23) to find the new estimates as $\hat{h}_l^{k+1}$.

$$\hat{h}_l^{(K+1)} = \hat{h}_l^k - \frac{\sum_{\substack{n_1=0,\\ n_1\neq l}}^{L-1} \hat{h}_{n_1}^k.C_{p_2p_1}(N_p - l - n_1)}{C_{p_1p_1}(0) + C_{p_2p_1}(0)} \tag{24}$$

C.2. Successive Over-Relaxation method

The SOR method starts with the extension of Equation (24) of GS method that contain the relaxation factor ω.

$$\hat{h}_l^{(k+1)} = \hat{h}_l^{(k)} + \omega\left(\hat{h}_l^{(k+1)} - \hat{h}_l^{(k)}\right) \tag{25}$$

The relaxation factor affects the performance of SOR in a large extent. For instance, if $\omega = 1$ the SOR method becomes Gauss-Seidel method. For over-relaxation $1 < \omega < 2$ for under relaxation $0 < \omega < 1$. In proposed method, $\omega = 1.25$.

After each iteration check if the difference in error is smaller than the threshold value.

$$\in_r = \left|\frac{\hat{h}_l^{(k+1)} - \hat{h}_l^{(k)}}{\hat{h}_l^{(k+1)}}\right| \tag{26}$$

Until achieving the smaller difference in errors as compared to tolerance $\in_r$, the iteration process is continued. In the presented work $\in_r$=0.001.

1. Simulation Parameters

In this paper, orthodox CE techniques (MMSE and DFT) are compared with the correlation methods (GS and SOR) in the GMM environment for typical urban reception (TU6), the OFDM simulation parameters has been shown in Table 1. In the presented work the cross correlation between data and pilots subcarriers are zero, therefore is no performance degradation is observed

2. Table 1. Simulation Parameters of OFDM

Parameters	**OFDM**
FFT Size	1,024
No. of used Data Subcarriers	960
No. of Pilot Subcarriers	64
Pilot Spacing	16
Cyclic Prefix or Guard Time (N_G)	1/16
Signal Constellation D[k]	BPSK
FFT Sampling Frequency (F_s)	9.142x1E^6
Bandwidth (MH_z)	8
Pilot Pattern	16
Speed of Receiver	50km/h
Doppler Shift	29Hz
Location of non-zero Channel taps	[0 1 4 14 21 45]

when higher data constellation is used in simulation. Therefore, BPSK signal constellation is used [32, 33]. Furthermore, the BER and MSE are used as figures of merit with various probability values of GMM channel i.e. ∅ = 0, ∅ = 0.005, and ∅ = 0.05.

4. Results and Analysis

In this paper, four- channel estimation schemes are tested in AWGN and GMM environments. In [8], different time domain channel estimation methods are performed based on the cyclic correlation method that required less complexity of computation and AWGN channel model was used. The AWGN channel model is used in various applications however the performance of channel estimation schemes deteriorates abruptly when it comes across impulsive noise. In the presented work four different channel estimation schemes are tested in GMM environment. Which can perform very well in both AWGN and GMM environment. An optimized method (Gauss-Seidel) is presented that has the less complexity with improved efficiency. In the proposed work four channel estimation schemes are tested (MMSE, DFT, GS and SOR) in terms of BER and MSE and shown that SOR method is more accurate than GS method.

Figure 3 shows the number of iterations for the SOR based TD CE method has been tested at 20 dB SNR, where the MSE of the estimated CIR is designed in contrast to the number of iterations. The legend AWGN ∅ = 0 represents in the AWGN channel. However, the GMM ∅ = 0.005, ∅ = 0.01 and ∅ = 0.05 represent the probability values of GMM channel. It is verified that the CE schemes perform expressively worse when the impulsive noise is added in AWGN in Figure 3. Moreover, it shows that the GMM scheme is converged in the second iteration for different values of ∅ = 0, ∅ = 0.005, ∅ = 0.01 and ∅ = 0.05.

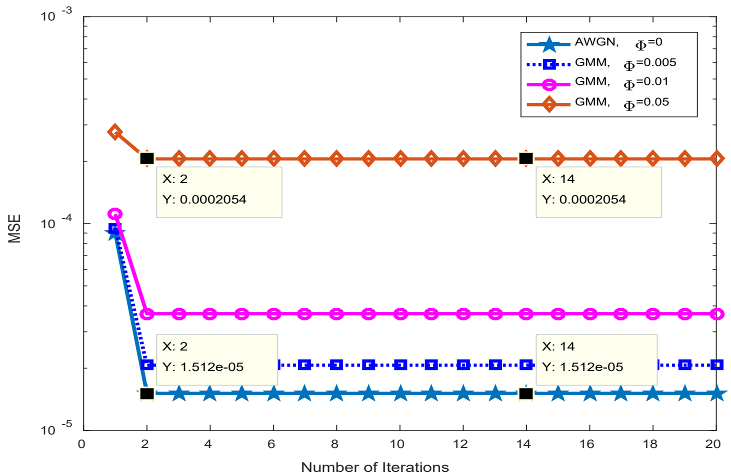

Figure 3. Number of Iterations at different values of ∅

In Figure 4, the MSE performance of conventional channel estimators (DFT, MMSE, GS) is compared with the SOR, $\omega = 1.25$ in the AWGN channel where ∅ = 0. It is obvious that the SOR method performs much better than other estimators. It also shows that the difference of MSE between GS and SOR is dominant as compared to the high SNR regime. Because in a low SNR regime up to 5 dB, the AWGN noise component is dominant as compared to correlation error. However, at higher SNR it is vice versa. Furthermore, the significant MSE difference can also be seen in Figure 4 at a high SNR regime between conventional and SOR. In Figures 5 and 6, the overall MSE of four estimators increases whenever these estimators expose in the GMM environment. However, the SOR shows the lowest MSE among all other estimators. It is also investigated that the difference of MSE between GS and SOR is decreased because the GMM noise component is dominant as compared to AWGN and correlation error.

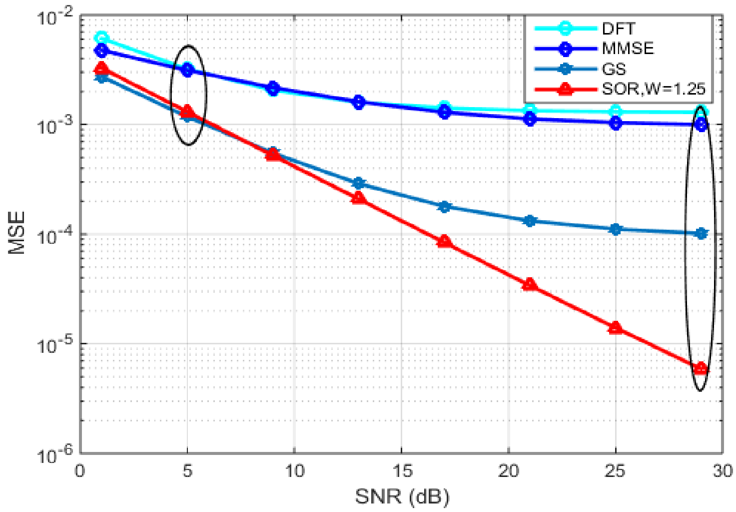

Figure 4. SNR's performance in AWGN channel using $\emptyset = \mathbf{0}, \mathbf{T} = \mathbf{0}$

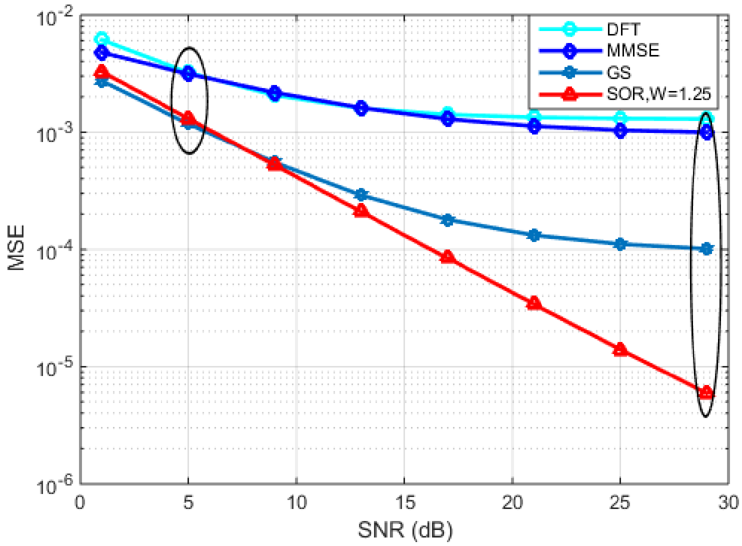

Figure 4. Performance of SNR in GMM channel using
$\emptyset = \mathbf{0.005}, \mathbf{T} = \mathbf{100}$

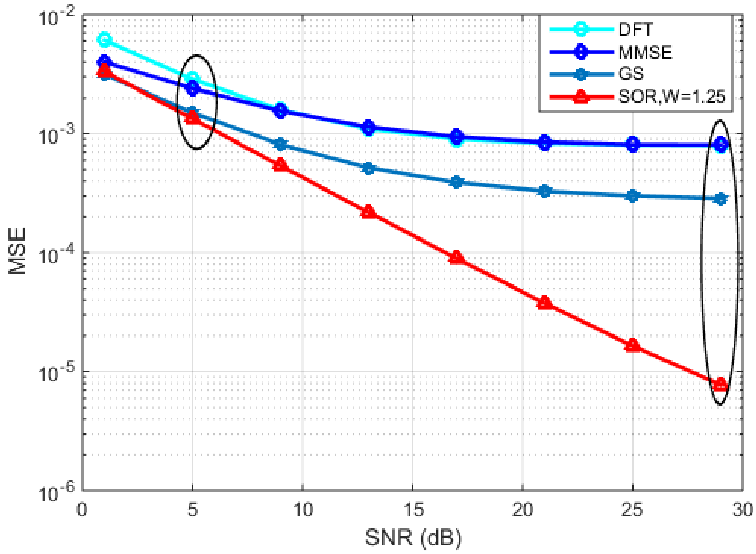

Figure 6. Performance of SNR in GMM channel using
$\emptyset = \mathbf{0.05}, \mathbf{T} = \mathbf{100}$

Figures 7 and 8 show the BER curves under GMM environments in which SOR shows the lowest BER as compared to the other schemes. The convolution code that are utilized in BER performance, in such way that with the code rate of $^{1}/_{2}$ and the generator polynomials of mother code G_1=171_{OCT} and G_2=131_{OCT}. It is also observed in Figures 8 and 9 that when $\emptyset = \mathbf{0.005}$ and $\emptyset = \mathbf{0.05}$ the BER of all the estimators is increased; however, the SOR sustains at the lowest value among all. P

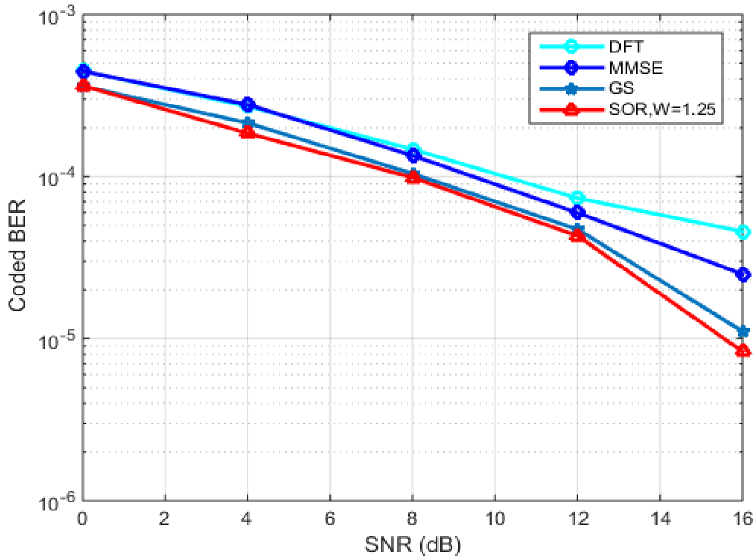

Figure 7. Performance of the CE in AWGN channel using $\emptyset = \mathbf{0}, \mathbf{T} = \mathbf{0}$

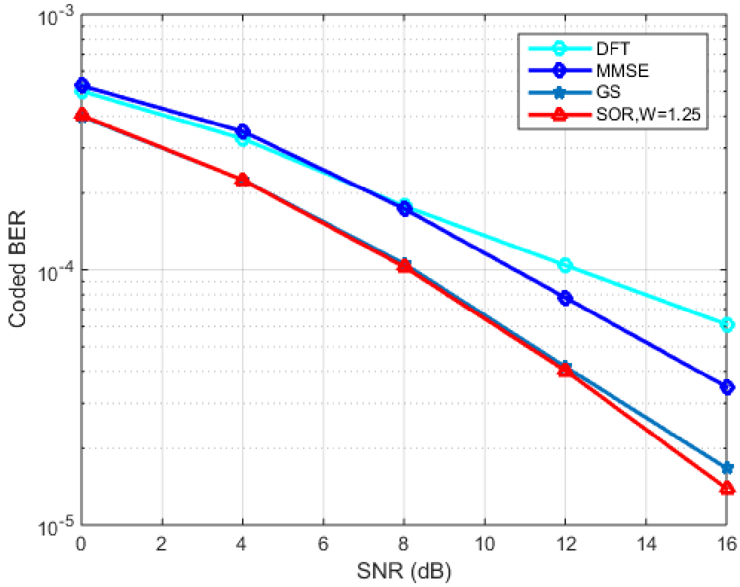

Figure 8. Performance of the CE in GMM channel using $\emptyset = \mathbf{0.005}, \mathbf{T} = \mathbf{100}$

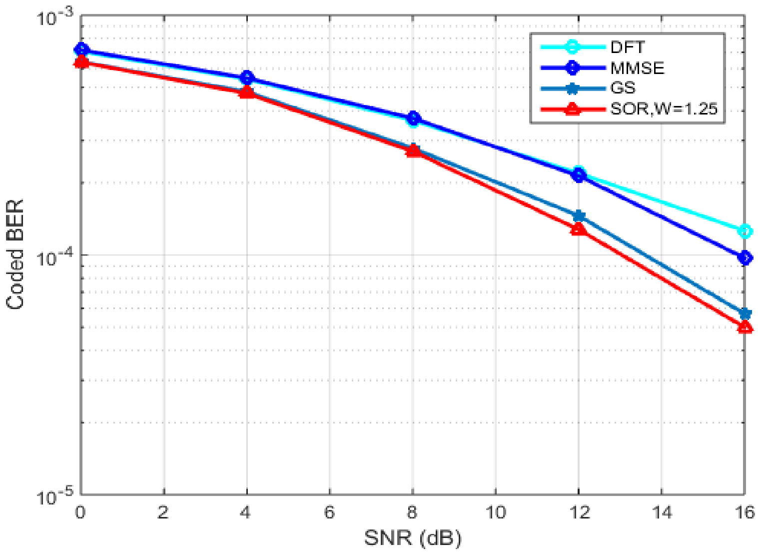

Figure 9. Performance of the CE in AWGN channel with $\emptyset = \mathbf{0.05}, \mathbf{T} = \mathbf{0}$

5. Conclusion

In this work, four diverse wireless channel estimation schemes are tested for AWGN and GMM environments. Furthermore, the performance of channel estimators is calculated with regard to MSE and BER. The analysis shows that the performance of all channel estimation schemes is deteriorated due to the presence of an impulsive component in the GMM environment. However, the SOR scheme has much better performance as compared to conventional DFT, MMSE and GS schemes. The SOR scheme has achieved improved performance by utilizing the high convergence rate due to the selection of an appropriate relaxation factor. The possible extension of this study is to analyze the hardware realization of

GS and SOR schemes on FPGA implementation. FPGA implementation can provide re-configurability, resources allocation, symmetric, and the timing diagram. Moreover, in the presented work channel estimation schemes are tested in AWGN and GMM environment it can be tested in the colored noise as a part of extension to this study in future.

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