Performance Enhancement in OFDM System Using Preamble-Based Time Domain SNR Estimation

Original Scientific Paper

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Abstract *– This work proposes a time domain signal-to-noise ratio (SNR) estimator for a single input-single output (SISO) orthogonal frequency division multiplexing (OFDM) system using a pre-fast Fourier transform (pre-FFT) SNR estimator. The pre-FFT SNR estimator requires no additional overhead since it reuses the preamble for synchronization in the OFDM system. In this work, a preamble structure proposed by Morelli and Mengali to overcome carrier frequency offset (CFO) due to Doppler effects is utilized. The proposed pre-FFT SNR estimator has been employed to estimate SNR for the SISO-OFDM system, and its performance has been evaluated against the corresponding frequency domain SNR estimator, also known as a post-FFT SNR estimator. The normalized mean square error (NMSE) of the pre-FFT SNR estimator has also been evaluated against the normalized Cramer-Rao bound (NCRB). The simulation results show that for the additive white Gaussian noise (AWGN) and Stanford University Interim-5 (SUI-5) channels, the pre-FFT SNR estimator exhibits 0.41 dB and 0.66 dB difference between the estimated SNR and the actual SNR, respectively. The NMSE of the pre-FFT SNR estimator outperforms the benchmarker post-FFT SNR estimator, which is close to the NCRB. The proposed pre-FFT SNR estimator achieved bit error rate (BER) improvements of about 1 dB and 2 dB for AWGN and SUI-5 channels, respectively, over the post-FFT SNR estimator at BER= 10^{-4}. Moreover, there is an approximately 50% reduction in complexity between the proposed pre-FFT SNR estimator and the benchmarker post-FFT SNR estimator.*

Keywords: *Adaptive modulation, Efficiency, OFDM, Preamble-based SNR estimator, Constant Amplitude Zero Autocorrelation preamble, Channel capacity*

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1. INTRODUCTION

The most widely used multicarrier modulation technology underpinning the fifth-generation (5G) mobile communications networks is orthogonal frequency division multiplexing (OFDM). It offers strong performance in frequency-selective channels and facilitates the effective use of the available channel capacity [1]. Adaptive transmission can significantly enhance an OFDM system's performance in the presence of a frequency-selective channel. Due to this, the signal-to-noise ratio (SNR) is a critical component of adaptive transmission. The SNR value denotes the channel quality, and an adaptive modulation and coding (AMC) scheme adapts parameters like modulation and coding schemes by the channel condition [2]. In the AMC scheme, SNR is computed at the receiver to assess channel quality, and its value is sent back to the transmitter for parameter adjustment [3, 4]. This process imposes feedback overhead.

Unmanned aerial vehicle (UAV) communication is an application in which where the AMC technique is utilized to alleviate problems in dynamically changing communication environments. Recent studies on AMC for UAV communication have utilized machine learning methods to assess channel quality for the modulation and coding scheme parameters selection [5-7]. The authors in [7] studied the AMC scheme in a UAV-to-ground free space optical communication system, which employed a machine learning-based channel estimator considering turbulence effects. In [8], deep reinforcement learning combined with a neural network was used to predict channel conditions for underwater acoustic OFDM communication systems, resulting in an improved bit-error rate (BER) and spectral efficiency. However, the proposed machine learning-based AMC schemes depend on the quality of the training data, such as the estimated SNR and other relevant channel atmospheric parameters. Improving SNR estimation accuracy would therefore prove advantageous.

SNR estimation is beneficial in a high-mobility environment, in which the channel condition is rapidly changing, and the Doppler effect is generated. Such fluctuations in the time domain require a well-estimated SNR for an adaptive transmission to achieve a significant throughput gain, resulting in an improved spectrum efficiency [3]. Therefore, a highly accurate SNR estimation method should ensure the intended level of communication performance by invoking the adaptive adjusted communication rate, modulation, and coding schemes [9]. However, a complicated SNR estimate method could result in feedback delays and worsen throughput performance.

There are two categories of SNR estimation, namely data-assisted (DA) and non-data-assisted (NDA) SNR estimation. The NDA-SNR estimator overcomes feedback overhead issues at the expense of lower accuracy because the transmitted signal's past information is not used to estimate SNR. This accuracy shortfall can be eliminated by employing a DA-SNR estimator, albeit at the expense of a throughput penalty, which increases the system's overhead. Nonetheless, research on DA-SNR that does not result in a throughput penalty has been done, such as the preamble-based SNR estimator of [10,11]. Thus, a preamble-based SNR estimator is considered in this study.

A preamble-based SNR estimator uses the OFDM system's synchronization preamble to estimate SNR. The OFDM system is sensitive to timing errors and frequency offsets, and various preamble structures have been proposed to address these limitations [12-15]. The SNR estimators proposed in [16-18] consider the carrier interference generated by the frequency offset, while most of the proposed SNR estimators assume perfect frequency synchronization.

Two main issues to be considered in developing SNR estimator are: (i) complexity and (ii) throughput penalty. There are two factors that can contribute to the computational complexity of a preamble-based SNR estimator, namely the type of SNR estimation domain and algorithm. In OFDM systems, SNR estimation is performed either in the frequency domain, also known as post-fast Fourier transform (FFT) estimation, or in the time domain, known as pre-FFT estimation. In the post-FFT estimation, the SNR is estimated after the FFT block of the OFDM system. In the pre-FFT estimation, SNR is estimated at the front-end of the receiver before demodulation of the received data. Thus, a pre-FFT estimation has lower complexity than a post-FFT estimation. In addition, pre-FFT estimation is less prone to carrier offset errors, hence avoiding losses in subcarrier orthogonality [19, 20]. On the other hand, some estimation algorithms use probabilistic approaches, which have higher computational complexity, in contrast to autocorrelation-based SNR estimation algorithms [11, 21].

Motivated by the advantages of the preamble-based SNR estimation algorithm in [11, 21], this study aims to develop an SNR estimator that has low computational complexity and low training symbol overhead. More specifically, this study developed a pre-FFT SNR estimation algorithm based on autocorrelation of the received signal at the receiver front-end and utilizing one preamble. However, the SNR estimation algorithm developed in [11, 21] used synchronization preamble structure in [14], which does not consider carrier frequency offset (CFO) in the algorithm. Therefore, this paper investigates an SNR estimation algorithm with a frequency offset. The proposed pre-FFT SNR estimator exploits the preamble structure of [12], where SNR is estimated using the autocorrelation function, and its algorithm utilizes one synchronization preamble. The performance of the proposed pre-FFT SNR estimator is contrasted with the benchmarker post-FFT SNR estimator of [16], which utilizes the second-order moment criterion for SNR estimation. The benchmark SNR estimator is referred to as the Millan post-FFT SNR estimator. The SNR estimator performance has also been evaluated against the normalized Cramer-Rao bound (NCRB) to assess how well the developed pre-FFT SNR estimator could approach the theoretically best achievable performance, thus ensuring system efficiency is not compromised.

The contributions of this paper are as follows:

1. A pre-FFT SNR estimator that utilizes the preamble structure for synchronization in the OFDM system of [12] is contrived. Hence, there is no throughput penalty associated with the proposed SNR estimate. Moreover, this SNR estimator utilizes one preamble that reduces the training symbol overhead.
2. The proposed SNR estimation algorithm has low computational complexity for two reasons: (i) the SNR estimation is done at the front end of the receiver, prior to the demodulation; and (ii) it is derived from the autocorrelation function.

The remainder of the paper is structured as follows: The review of the related work is presented in Section 2. Section 3 discusses the description of the single-input single-output (SISO)-OFDM system that incorporates the proposed pre-FFT SNR estimator. Section 4 elaborates on both the proposed pre-FFT SNR estimator and Milan's post-FFT SNR estimator benchmark. Section 5 compares the performance of the proposed pre-FFT SNR estimator with that of Milan post-FFT SNR estimator and the NCRB to assess how well the proposed SNR estimator can come close to the theoretical best performance. This section also presents the computational complexity analysis of various preamble-based SNR estimators. Finally, Section 6 offers conclusions.

2. RELATED WORK

Many preamble-based SNR estimation methods have been developed over the years. The application of machine learning to the SNR estimate algorithm has garnered more attention lately [22, 23]. In [22], a deep-learning-based SNR estimator was reported that provided accurate estimation and improved the system performance at the expense of computational complexity both during training and inference. Supervised learning requires a sufficient set of training data, including SNR values [23], for a reliable model.

Table 1 provides an overview of previous studies on preamble-based SNR estimators in OFDM systems. These SNR estimators took advantage of various synchronization preamble structures.

SNR is an important parameter that reflects channel quality. Accurate SNR estimation plays a crucial role in ensuring a desired communication performance in a rapidly changing environment, such as in UAV communication systems. As discussed in Section 1, the benefits of a preamble-based SNR estimator are two-fold: (i) It is a DA-SNR estimator that has higher estimation accuracy, and (ii) it utilizes synchronization preamble, which eliminates throughput penalty. However, it is also favorable to ensure that the SNR estimation algorithm has low computational complexity. Therefore, per Table 1, the pre-FFT SNR estimation algorithms in [11, 19, 21, 24, 25, 28] are less complex since SNR is estimated at the receiver's front-end prior to demodulation of received data.

Table 1 also shows that the computational complexity of a preamble-based SNR estimator is highly dependent on the estimation algorithm, which uses maximum likelihood, second-order moment criteria, correlation, circular correlation, and autocorrelation function. For example, compared to the SNR estimator based on autocorrelation, second-order moment, which uses probabilistic approaches, has higher computational costs since it includes more multiplication and addition operations.

Table 1. Summary of preamble-based SNR estimations in the literature

Year	Author(s)	SNR Estimation Domain	SNR estimation algorithm	Contribution	Challenges
2009	Zivkovic, M. & Mathar, R. [16]	Post-FFT	Second-order moment	• Proposed SNR estimator that exploited preamble structure in [12]. • It used only one preamble to minimize the transmission overhead	• Showed poor normalized mean square error (NMSE) performance in the low region of channel SNR
2010	Zivkovic, M. & Mathar, R. [17]	Post-FFT	Second-order moment	• Extension of SNR estimator in [16]. • Improved SNR estimation for all SNRs • Utilized the method for adaptive selection of significant channel impulse response	• Post-FFT estimator performance degraded in the presence of inter-carrier interference • High complexity
2014	Ijaz, A. et all. [24]	Pre-FFT	Correlation	• Low complexity time domain SNR estimation is proposed for the OFDM system • It used one synchronization preamble proposed by Schmidl and Cox [13]	• Poor performance at low SNR
2014	Zivkovic, M. & Mathar, M. [25]	Pre-FFT	Second-order moment	• Improved Zadoff-Chu Preamble-based SNR estimation in the time domain is proposed for the OFDM system. Improved SNR estimation compared to [16, 17] using one preamble with $Q > 2$ equal parts • Results are robust if $Q > 8$	• High complexity
2016	Ishtiaq, N. et al [26]	Post-FFT	Maximum likelihood	• Data-aided SNR estimation is done in the frequency domain using maximum likelihood • Use one preamble of [13] with known pilot value insertion • The accuracy of the estimates shows improvement in the lower region	• Higher bandwidth utilization and higher complexity
2018	Aloui, A. et al. [27]	Post-FFT	Expectation statistical method	• SNR estimation is proposed for IEEE 802.15.4g OFDM • Use two preambles, one for synchronization and one for SNR estimation, as proposed by Schmidl and Cox [13]	• In lower SNR values, the estimates show a higher bias than the actual SNR • High complexity.
2018	Abid, M.K. et al. [28]	Pre-FFT	Circular correlation	• Pilot data-aided time domain SNR estimation is proposed for the OFDM system • Known pilot values inserted in the preamble signal	• Complexity is higher to achieve accurate SNR estimates
2018	Manzoor, S. & Othman, N, [21]	Pre-FFT	Autocorrelation	• The time synchronization preamble of [14] is used for time domain SNR estimation in cooperative systems. • Enhanced performance at low SNR region	• Did not consider CFO
2020	Rao, B.N. et al. [19]	Pre-FFT	Second order moment	• Preamble-based noise power estimation for the OFDM system is proposed • Time domain SNR estimation is less prone to frequency offset • Use one preamble having a preamble structure of [12]	• Did not consider CFO • Poor NMSE performance at low SNR region
2022	Manzoor, S. & Othman, N, [11]	Pre-FFT	Autocorrelation	• Utilized a modified synchronization preamble from [14] • Enhanced perfromance at low region as compared with the SNR estimator in [21] • Improved system performance with SNR estimation-based adaptive modulation scheme	• Did not consider CFO

In [12], Morelli and Mengali proposed a preamble structure for an algorithm to estimate frequency offset in an OFDM system with a reduction of training symbol overhead by employing a single preamble. Thus, the authors in [16] exploited the beneficial feature of this preamble structure in the proposed post-FFT SNR estimator. The post-FFT SNR estimator exploited the periodic nature of the preamble structure and used only one preamble, therefore minimizing the transmission overhead. The SNR estimation algorithm was derived using the second-order moment algorithm. However, the SNR estimator in [16] showed poor normalized mean squared error (NMSE) performance in the low region of channel SNR. The post-FFT SNR estimation algorithm was further improved by utilizing the method for adaptive selection of significant channel impulse response, which resulted in an improved SNR estimation for all SNRs, as presented in [17]. Similarly, a low complexity pre-FFT SNR estimator proposed in [24] also struggled with accuracy in the low region of channel SNR.

As a further enhancement, the authors in [26] proposed a post-FFT SNR estimation using a maximum likelihood approach, which improved channel SNR in the low region. However, the performance of the post-FFT SNR estimator degraded in an imperfectly synchronized system due to inter-carrier interference (ICI) caused by carrier frequency offset [25].

The preamble structure from [14] was utilized by the authors in [21] to construct an SNR estimator invoked in a cooperative SISO-OFDM system. In [11], the proposed adaptive modulation with SNR estimator utilized the modified OFDM synchronization preamble structure developed in [14]. Both SNR estimators are categorized as pre-FFT SNR estimators, in which the SNR is estimated in the time domain, and the SNR estimation algorithm utilizes autocorrelation. Thus, the SNR estimators developed in [11, 21] are attractive due to these two criteria, which result in low computational complexity.

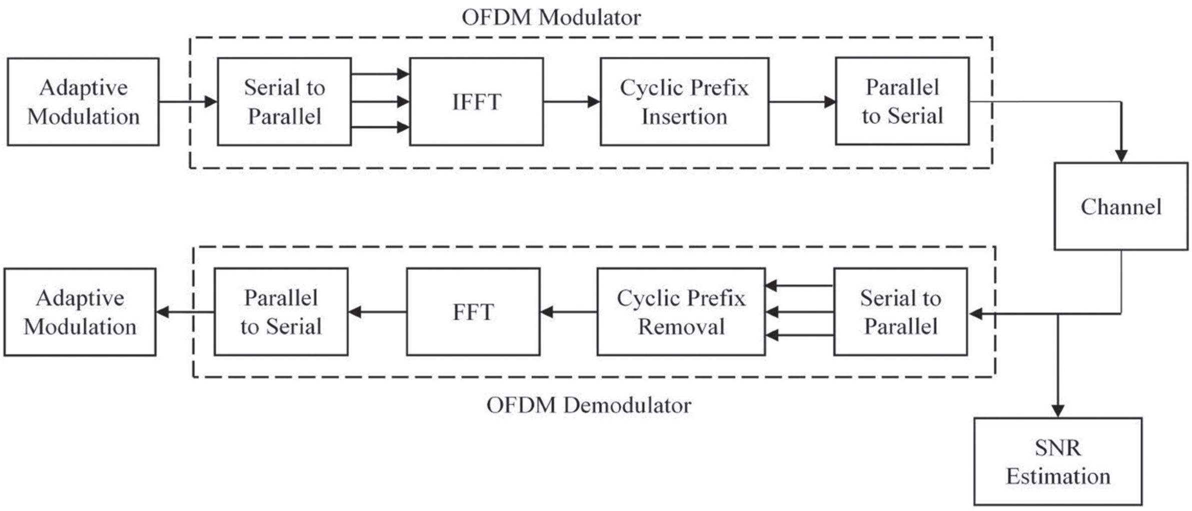


Fig. 1. SISO-OFDM system block diagram

3. SYSTEM DESCRIPTION

This paper considers a SISO-OFDM system that invokes the pre-FFT SNR estimator, as shown in Fig. 1. At the receiver, SNR estimation is performed before FFT processing.

The input data is mapped into symbols using quadrature phase shift keying (QPSK) which are then converted from serial-to-parallel stream. Next, the symbols are transformed into time domain symbols using the inverse fast Fourier transform (IFFT). More specifically, at the transmitter, the time domain OFDM signal after applying IFFT is given as:

$$x(n) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X(k) e^{j2\pi nk/N}, n = 0, \dots, (N-1) \quad (1)$$

where N is the size of IFFT, $X(k)$ represents the QPSK constellation point modulated data on the kth subcarrier, while in the time domain, $x(n)$ denotes the nth data sample.

A cyclic prefix, C_p is inserted into each QPSK symbol as the guard interval to avoid inter-symbol interference to form an OFDM symbol. Then, the OFDM signal is transmitted to the receiver via a wireless channel.

The OFDM signal at the input of the receiver in the presence of the CFO can be described as follows:

$$r(n) = x(n).\, e^{j2\pi\varepsilon n/N} + w(n) \quad (2)$$

where $w(n)$ is the noise signal at the receiver antenna, and ε is the CFO normalized to the subcarrier spacing. The SNR estimation is performed on the CFO compensated received signal before FFT processing.

4. PROPOSED PRE-FFT SNR ESTIMATION

As discussed in Section 1, the proposed pre-FFT SNR estimator performs SNR estimation in the time domain. It utilizes the preamble structure that was proposed in [12], which comprised of one OFDM symbol with Q equal sections that are all having N/Q length, where N is the IFFT size and Q>2. Fig. 2 shows the preamble, which has a repetitive structure is utilized, where P_N represents the pseudo-noise sequence, Q=4 and N=256 bits. The same preamble is also used for synchronization in the OFDM system. Thus, its use in SNR estimation does not penalize the system throughput. For benchmarking, the proposed pre-FFT SNR estimator's performance is evaluated against the Milan post-FFT SNR estimator [16]. Both estimators use the same preamble structure as shown in Fig. 3, with Q=4, N=256 bits and C_p=64 bits for the SNR estimation algorithm.

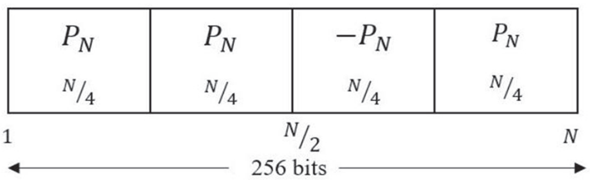


Fig. 2. Morrelli synchronization preamble structure [12]

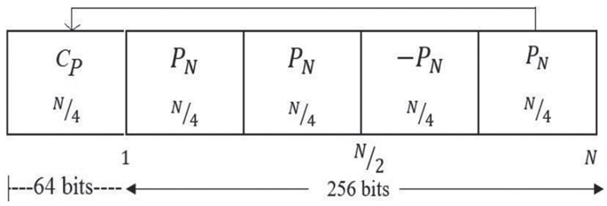


Fig. 3. Morrelli synchronization preamble structure with cyclic prefix

The Morelli and Mengali preamble structure in [12] has a periodic structure in the time domain, which corresponds to a comb-type structure in the frequency domain. Thus, for the SNR estimation algorithm in [16], the total number of N subcarriers are divided into Q parts. Each part consists of N_p=N/Q subcarriers. In each part, starting from the zeroth, every Q-th subcarrier was modulated with a QPSK signal, $X_p(n)$ for n=0,…,(N_p-1), while the remainder of the subcarriers are not used (null). The same Morelli preamble structure and the modulation technique are utilized in the proposed pre-FFT SNR estimator.

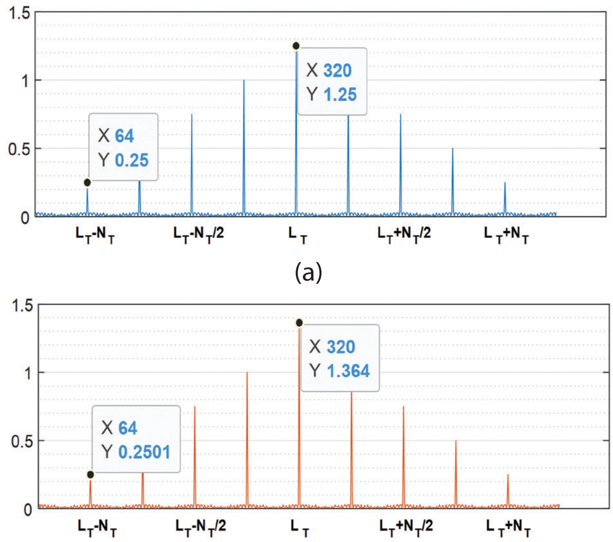
The SNR estimation algorithm of the proposed pre-FFT SNR estimator utilizes the autocorrelation function of the received signal of Eq. 2 to estimate the signal and noise power. The autocorrelation of the received signal with additional noise from the channel, $r_{rx}(t)$, can be written as:

$$r_{rx}(t) = r_{tx}(t) + r_{nw}(t) \tag{3}$$

where $r_{tx}(t)$ denotes the autocorrelation of the transmitted OFDM signal. For the noise signal's autocorrelation, $r_{nw}(t)$ for the AWGN channel with the noise variance of σ^2, can be expressed as follows:

$$r_{nw}(t) = \sigma^2\delta(t) \tag{4}$$

where $\delta(t)$ is Dirac delta function. Similarly, the transmitted OFDM signal's autocorrelation can be written as $r_{tx}(t)$=P_{tx} $\delta(t)$, where P_{tx} is the signal power. Hence, at zeroth lag, the received OFDM signal's autocorrelation consists of both the signal and noise power. On the other hand, the transmitted OFDM signal's autocorrelation consists of signal power only. Thus, the difference between the received OFDM signal's autocorrelation value at zeroth lag and the estimated signal power can be used to estimate noise power.



(b)

Fig. 4. Autocorrelation illustration at SNR=10 dB (**a**) The transmitted OFDM signal (Transmitted Signal Autocorrelation at SNR = 10 dB). (**b**) The corresponding received OFDM signal (Received Signal Autocorrelation at SNR = 10 dB).

Fig. 4 shows the autocorrelation plot of the transmitted and the received OFDM signals at 10 dB channel SNR. In Fig. 4, the X-axis represents the lag between the signal and its shifted version, while the Y-axis represents the autocorrelation values at each lag. There is one prominent peak at L_T, and there are four side peaks on its right and left sides. The four side peaks on the left side appeared at specific lags of (L_T-N_T), (L_T- (3/4) N_T), (L_T- (1/2) N_T) and (L_T- (1/4) N_T).

Fig. 5 illustrates the autocorrelation stages resulting in the plot in Fig. 4. As a result, the estimation of signal power can be written as:

$$P_{tx}^{*} = 3\, r_{rx}\left(L_T - \frac{3}{4}N_T\right) - r_{rx}(L_T - N_T) \tag{5}$$

where N_T is the OFDM signal length and L_T= N_T + C_p is the total length, which includes C_p = L_T-N_T.

Having the estimated signal power defined by Eq. 5, the noise power can be estimated as:

$$\sigma_{est}^2 = r_{rx}(L_T) - P_{tx}^{*} \tag{6}$$

where $r_{rx}(L_T)$ is the maximum peak indicating the received OFDM signal's autocorrelation value at zeroth-lag. Therefore, the estimated SNR can be calculated by utilizing Eq. 5 and Eq. 6, which can be written as:

$$SNR_{Est} = \frac{P_{tx}^{*}}{\sigma_{est}^2} \tag{7}$$

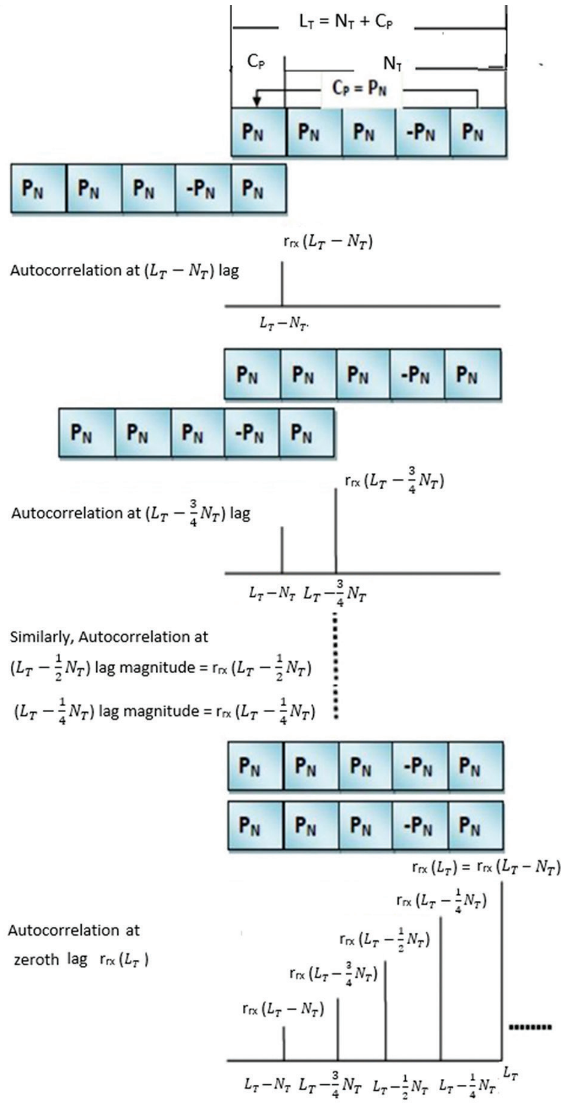


Fig. 5. The transmitted OFDM signal's autocorrelation function, which includes the cyclic prefix

4.1. POST-FFT SNR ESTIMATION BENCHMARKER

Milan's post-FFT SNR estimator benchmarker of [16] is used for comparison with the proposed pre-FFT SNR estimator. More specifically, the SNR estimation in the benchmarker SNR estimator is performed in the frequency domain after FFT processing. For a fair comparison, both the proposed pre-FFT SNR estimator and the benchmarker SNR estimator utilize the Morelli and Mengali preamble structure of [12], as shown in Fig. 2, which consists of Q parts, each containing $N_p=N/Q$ samples.

Similarly, the same OFDM modulation method is used for both the proposed pre-FFT SNR estimator and the benchmarker SNR estimator, where the QPSK signal, $X_p(m)$ for $m=0,\dots,(N_p-1)$ is loaded in every Q-th subcarrier. The remainder (N-N_p) of the subcarriers are not used (nulled). Therefore, the transmitted signal on the kth subcarrier can be expressed as [16]:

$$X(k) = X(mQ+q) = \begin{cases} X_P(m), & q=0 \\ 0, & q=1,\cdots,Q-1 \end{cases} \quad (8)$$

where $k=mQ+q$, with $m=0,\dots,(N_p-1)$ and $q=0,\cdots,(Q-1)$. Hence, the index of the loaded subcarriers is $k=mQ$, with $m=0,\dots,(N_p-1)$ and $q=0$.

Milan's post-FFT SNR estimation algorithm was developed based on the second-order moment of the demodulated OFDM signal to estimate the SNR at the receiver. After the CFO compensation, the received signal on the loaded subcarrier can be expressed as [16]:

$$Y(k) = Y(mQ) = \sqrt{SQ}X_P(m)H_P(m) + \sqrt{W}\sigma(m) \quad (9)$$

where SQ is the total transmit power and H_p (m) is the channel response on the loaded subcarriers. W is the noise power on each subcarrier, and $\sigma(m)$ is the corresponding sampled zero-mean AWGN with unit variance.

The received signal on the nulled subcarriers consists of only noise signal and is given as [16]:

$$Y(k) = Y(mQ+q) = \sqrt{W}\sigma(mQ+q) \quad (10)$$

where $q=1,\dots,(Q-1)$.

The second-order moment is applied to the received signal, $Y(mQ)$ on the loaded subcarriers as shown in Eq. 10, using expressions of [16]:

$$P_{RS} = \frac{1}{N_p}\sum_{m=0}^{N_p-1} |Y(mQ)|^2 \quad (11)$$

Similarly, the received noise power from the nulled subcarrier is given as [16]:

$$P_{RN} = \frac{1}{N_p(Q-1)}\sum_{m=0}^{N_p-1}\sum_{q=1}^{Q-1} |Y(mQ+q)|^2 \quad (12)$$

Thus, the SNR estimation can be determined using the following equation:

$$SNR_{Est} = \frac{1}{Q}\left(\frac{P_{RS}-P_{RN}}{P_{RN}}\right) \quad (13)$$

5. RESULTS AND DISCUSSION

In this section, the performance of the proposed pre-FFT SNR estimator is characterized when it is invoked in the SISO-OFDM system, as described in Section 3. The comparison performance of the proposed pre-FFT SNR estimator is also investigated against the post-FFT SNR estimator benchmarker using estimated SNR, BER, NMSE, and computational complexity. Table 2 displays the simulation settings for the SISO-OFDM system, which were selected from the IEEE802.16d standard [29].

Table. 2. IEEE802.16d Standard Parameters for OFDM [29]

Parameters	Value
$IFFT_{Length}$, N_{ifft}	256
$Sampling_{Frequency}$, F_s	20 MHz
$SubCar_{Spacing}$, $\Delta f = F_s/_N$	1×10^{5}
$Symbol_{Time}$, $T_{sy}=1/\Delta f$	1×10^{-5}
$Guard_{Interval}$, $T_{gi}=G_i \times T_{sy}$	2.5×10^{-6}
$OFDM_{Symb\text{-}time}$, $T_s=T_{sy}+T_{gi}$	1.25×10^{-5}
$Channel_{Used}$	AWGN, SUI-5

As discussed in Section 4, the preamble structure with Q=4, N=256 bits and C_P length of $N/4$=64 bits are utilized in this work. Thus, the total frame length is L_T=N+C_P=320 bits. The simulation results consider the advocated scheme when communicating over the AWGN and SUI-5 channels. The SUI-5 channel parameters used in this study are shown in Table 3, indicating the multipath delay and power profile. The SUI channels are designed to model three outdoor-terrain categories, as shown in Table 3, and have been adopted by IEEE802.16d standard [30]. Table 4 also shows that the SUI-5 channel models type A terrain, which deals with huge path loss and it is most suited for hilly terrain with high densities of foliage. The estimated SNR is obtained for both the SNR estimators, and estimates of SNR are obtained by averaging over M_t=2000 iterations.

Table. 3. Channel Description of SUI-5 Wireless Channel [30]

SUI5 channel	Path 1	Path 2	Path 3	Unit
$Path_{Delay}$	0	4	10	μsec
$Path_{Power}$	0	-11	-22	dB
K_{Factor}	2	0	0	–

Table. 4. Types of Terrain Corresponding to SUI Channels [30]

TerrainTypes	SUIChannels
C	SUI-1, SUI-2
B	SUI-3, SUI-4
A	SUI-5, SUI-6

Fig. 6 shows the estimated SNR performance of the proposed pre-FFT SNR estimator and the corresponding benchmarker post-FFT SNR estimator for transmission over the AWGN channel. The proposed pre-FFT estimator is further compared against the preamble-based pre-FFT estimators proposed in [11]. More specifically, in [11], the preamble pre-FFT estimators exploit the synchronization preamble structure proposed in [14], referred to as the CAZAC pre-FFT SNR estimator.

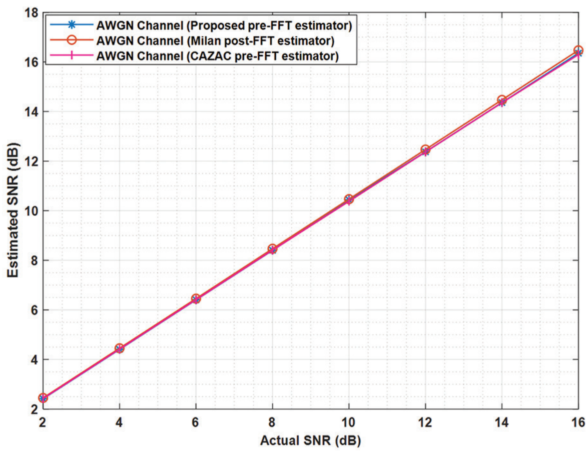


Fig. 6. Performance of the pre-FFT SNR estimator invoked in QPSK-SISO-OFDM system for transmission over AWGN channel in terms of estimated SNR

The close-up of Fig. 6 is shown in Fig. 7, where it can be observed that the proposed pre-FFT SNR estimator exhibited 0.41 dB difference from the actual SNR, which is referred to as bias. The benchmarker Milan post-FFT SNR estimator exhibited bias of 0.454 dB. On the other hand, the CAZAC pre-FFT SNR estimator exhibited bias of approximately 0.419 dB. The SNR estimation performance was estimated with the presence of CFO.

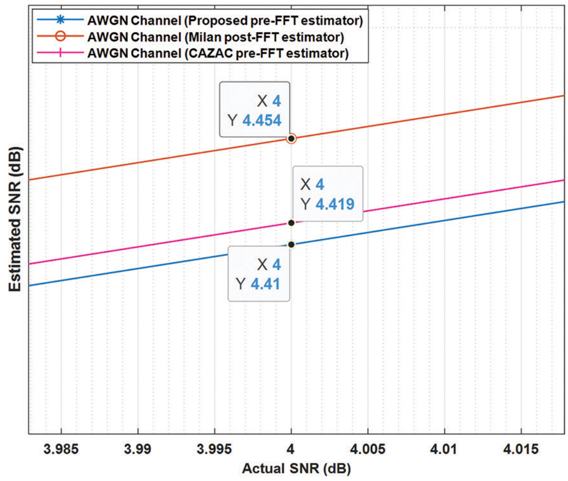


Fig. 7. Close-up of Fig. 6

Fig. 8 shows the estimated SNR performance of the proposed pre-FFT SNR estimator when communicating over the SUI-5 channel. The close-up of Fig. 8 is shown in Fig. 9, and it can be observed that the proposed pre-FFT SNR estimator exhibited a 0.66 dB difference between the estimated SNR and the actual SNR. The benchmarker Milan post-FFT SNR estimator exhibited 0.72 dB bias. Hence, the proposed pre-FFT SNR estimator outperformed its corresponding benchmarker. The CAZAC pre-FFT SNR estimator of [11] was outperformed by exhibiting a 0.663 dB difference between the estimated and actual SNR values.

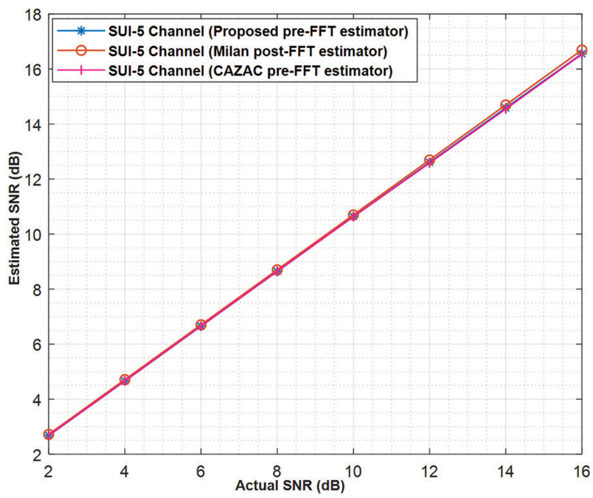


Fig. 8. Performance of the proposed pre-FFT SNR estimator invoked in the QPSK-SISO-OFDM system for transmission over the SUI-5 channel in terms of estimated SNR

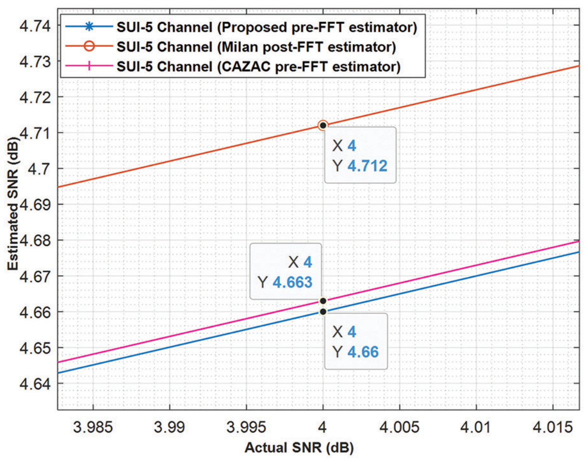


Fig. 9. Close-up of Fig. 8

In both cases, the preamble-based pre-FFT SNR estimators demonstrated better SNR estimation than the Milan post-FFT SNR estimator. Thus, the pre-FFT SNR estimators exhibit beneficial performance for dynamic environments in the presence of the CFO due to Doppler effects, such as in UAV or vehicular communication systems [18]. Thus, employing such an SNR estimator is beneficial for applying AMC to maximize throughput performance in the dynamic fading of wireless channels. Moreover, the proposed pre-FFT SNR estimator performed better in terms of SNR estimation under the CFO scenario.

Fig. 10 shows the average difference between the estimated SNR and the actual SNR, which is referred to as bias. It is observed that the average bias of the pre-FFT SNR estimator exhibits better performance in the region of low values of the actual SNR for transmission over the SUI-5 channel than that of its corresponding benchmarker post-FFT SNR estimator.

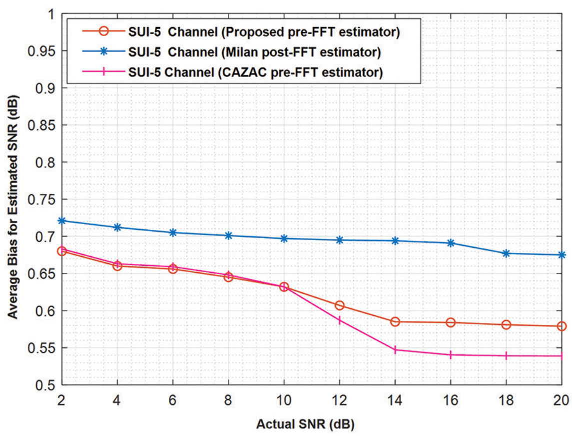


Fig. 10. Estimated SNR bias versus actual SNR performance

The pre-FFT SNR estimator performance has also been evaluated in terms of NMSE. Hence, the NMSE performance is quantified using Eq. 14, where SNR_{act} denotes the average value of the actual SNR, while SNR_{Est} for the proposed pre-FFT SNR and the benchmarker post-FFT SNR estimators can be calculated using Eq. 7 and Eq. 13, respectively:

$$NMSE = \frac{1}{M_t}\sum_{n=1}^{M_t}\left[\frac{SNR_{Est} - SNR_{act}}{SNR_{act}}\right]^2 \tag{14}$$

The performance of the proposed SNR estimator is evaluated against the NCRB for frequency selective channel to assess how effectively the proposed SNR estimator performance approaches the theoretical optimum. The CRB was derived in [31] as follows:

$$CRB_{(SNR_{Est})} = \left[\frac{1 + Q(SNR_{act})}{\sqrt{N(Q-1)}}\right]^2 \tag{15}$$

where N=256 bits is the preamble length, Q=4 is the number of preamble parts, as discussed in Section 4.

The variance of CRB can be found by taking the inverse of the Fisher information matrix (FIM) [31]. Hence, the NCRB can be obtained by dividing Eq. 15 by $(SNR_{act})^2$ and written as follows:

$$NCRB(SNR_{Est}) = \frac{CRB_{(SNR_{Est})}}{(SNR_{act})^2} \tag{16}$$

where SNR_{Est} for the proposed pre-FFT SNR and the benchmarker post-FFT SNR estimators can be calculated using Eq. 7 and Eq. 13, respectively.

Figs. 11 and 12 illustrate the NMSE comparison performance of the proposed pre-FFT SNR estimator and the benchmark post-FFT SNR estimator for AWGN and SUI-5 channels, respectively. The pre-FFT SNR estimator outperforms its benchmarker post-FFT SNR estimator, as seen in Fig. 11. In the region of high values of an actual SNR of more than 6 dB, the NMSE performance of the pre-FFT SNR estimator improves with an increase in actual SNR for the AWGN channel. On the other hand, the NMSE performance of the benchmarker post-FFT SNR estimator shows no further improvement in the region of actual SNR of more than 12 dB. It can also be seen that the NMSE performance of the proposed pre-FFT SNR approaches the NCRB and outperforms the considered post-FFT SNR estimator.

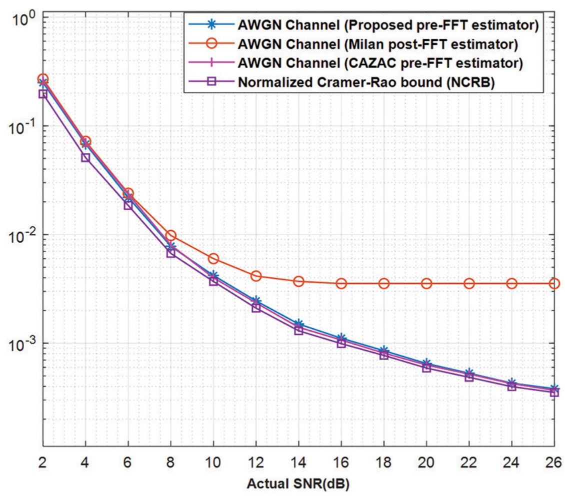


Fig. 11. Comparison of NMSE performance of the pre-FFT SNR estimator and that of its corresponding benchmarker for transmission over AWGN channel

Similarly, for transmission over SUI-5 channel, there is no more NMSE improvement in the region of high values of actual SNR of more than 16 dB for post-FFT SNR estimator, as shown in Fig. 12. The NMSE performance of the proposed pre-FFT SNR outperforms the post-FFT SNR estimator at all regions of SNR. It is observed that the pre-FFT SNR NMSE performance approaches the NCRB. In both cases, the preamble-based pre-FFT SNR estimators demonstrated similar NMSE performance with the CAZAC pre-FFT SNR estimator. This observation aligns with the SNR estimated performances shown in Fig. 7 and Fig. 9.

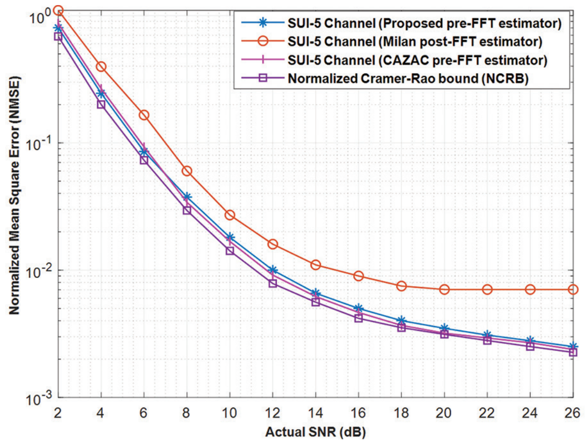


Fig. 12. Comparison of NMSE performance of the pre-FFT SNR estimator and that of its corresponding benchmarker for transmission over the SUI-5 channel

Fig. 13 and Fig. 14 compare the BER performance of the proposed pre-FFT SNR estimator and that of its corresponding post-FFT SNR estimator benchmark for the AWGN and SUI-5 channels, respectively. From Fig. 13, the QPSK-SISO-OFDM scheme that invokes the pre-FFT SNR estimator outperforms the benchmark scheme with post-FFT SNR estimator by about 1.0 dB at BER=10^{-4}. Similarly, it can be seen in Fig. 14 that the pre-FFT SNR estimator outperforms the post-FFT SNR estimator benchmark scheme by about 2.0 dB at BER=10^{-4}.

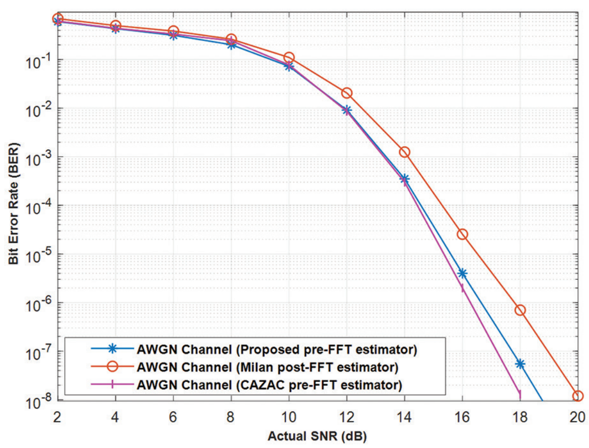


Fig. 13. Performance of the QPSK-SISO-OFDM system for transmission over AWGN channel in terms of BER

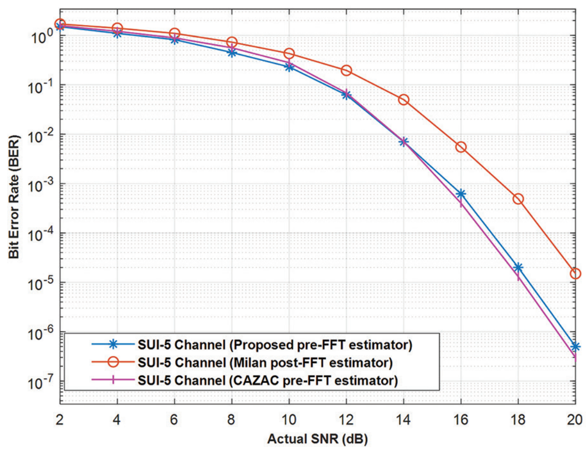


Fig. 14. Performance of the QPSK-SISO-OFDM system for transmission over the SUI-5 channel in terms of BER

The simulation results show that the SNR estimation in time domain is less prone to CFO error than the SNR estimation in frequency domain.

5.1. COMPLEXITY ANALYSIS

The floating point operations per second (FLOP) complexity metric is used to assess the complexity of the pre-FFT SNR estimate. Table 5 depicts the complexity comparison. Generally, FLOPs refer to the number of computations needed for a single SNR estimate.

Table. 5. Complexity Analysis

SNR Estimator	SNR estimation algorithm	SNR Estimation Domain	FLOPs
PTD [28]	Circular correlation	Pre-FFT	$2N_p(Q_p)+3N_p+L$
TLSE [24]	Second order moment	Pre-FFT	$5N$
TPSE [20]	Second order moment	Pre-FFT	$7.5N+4$
TDZCE [25]	Second order moment	Pre-FFT	$4N+2$
Milan [16]	Second order moment	Post-FFT	$4N+2$
Proposed	Autocorrelation	Pre-FFT	$2N$-1

The pre-FFT SNR estimator proposed in this study is based on the autocorrelation of the received signal in the time domain. As explained in Section 4, the signal power and noise power are estimated using Eq. 5 and Eq. 6, respectively. Generally, the autocorrelation function calculates the product of the received signal and its lagged version at each time step and then sums these products for all time steps within the overlapping range. Moreover, the autocorrelation function is computed at zeroth lag; the computational complexity is only based on the multiplications of N bits and (N –1) additions. Hence, the pre-FFT SNR estimator required (N+N-1= 2N–1) FLOPs for one SNR estimation.

The complexity of the proposed pre-FFT SNR estimator is compared with SNR estimators developed in previous studies as [16], [20] [24, 25], [28]. According to [28], the pilot-based time domain SNR estimator (PTD) requires ($2N_p(Q)$+$3N_p$+L_p) FLOPs, and the complexity relies on the number of pilot subcarriers $N_p = N/Q$., and L_p channel taps, in which Q represents the number of preamble parts, as discussed in Section 4.

The time domain low complexity SNR estimator (TLSE) was investigated in [24]. This requires $5N$ FLOPs and depends on the number of periodic parts Q. The authors in [20] introduced the time domain preamble-based SNR estimator (TPSE), which requires ($7.5N + 4$) FLOPs to perform estimation of one SNR estimate. Time domain Zadoff-Chu preamble-based SNR estimator (TDZCE) presented in [25], needs ($4N + 2$) FLOPs. The Milan SNR estimator [16], presented in Section 4.1, involves ($4N + 2$) FLOPs to compute one SNR estimate.

Therefore, Table 5 shows that the proposed SNR estimator has the lowest complexity for estimating SNR. It can also be observed that the benchmarker post-FFT Milan SNR estimator requires ($4N + 2$) FLOPs, in comparison with the proposed pre-FFT SNR estimator, which allows a 50% reduction in FLOPs.

6. CONCLUSION

This work presents a pre-FFT SNR estimator that utilizes preamble structure for synchronization in OFDM system in [12]. The performance comparison between the proposed pre-FFT SNR estimator and Milan post-FFT SNR estimator is presented, in which both SNR estimators utilize the same preamble structure. On the other hand, the auto-correlation function is the basis for the pre-FFT SNR estimation algorithm. The second-order moment is utilized in the post-FFT SNR estimator algorithm, which incurs higher computational complexity. The estimated SNR using the pre-FFT SNR estimator exhibited 0.41 dB and 0.66 dB bias when communicating over AWGN and SUI-5 channels, respectively. The benchmark post-FFT Milan SNR estimator exhibited 0.454 dB bias and 0.72 bias over AWGN and SUI-5 channels, respectively. Similarly, the pre-FFT SNR estimator outperformed the benchmarker Milan post-FFT SNR estimator in terms of NMSE. More specifically, the NMSE performance of Milan SNR estimator showed no further improvements in the region of actual SNR of more than 12 dB and 16 dB for AWGN and SUI-5 channels, respectively. It was also demonstrated that the NMSE performance of the proposed pre-FFT SNR estimator approached the theoretical limit set by the NCRB. Moreover, the NMSE performance of the benchmarker post-FFT in comparison to the post-FFT Milan SNR estimator, the proposed pre-FFT SNR estimator achieved BER improvements of about 1 dB and 2 dB, respectively, at BER=10^{-4} for transmission over AWGN and SUI-5 channels. There is about a 50% reduction in complexity between the proposed pre-FFT SNR estimator and the benchmarker post-FFT SNR estimator. Further studies should consider the development of a preamble-based SNR estimator for UAV communication, which considers the Doppler effect due to the flight speed. OFDM technology can successfully be leveraged into UAV communication. However, knowledge of exact UAV communication channels is required.

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