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Research Article

Pilot-Based Time Domain SNR Estimation for Broadcasting OFDM Systems

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The estimation of signal-to-noise ratio (SNR) is a major issue in wireless orthogonal frequency-division multiplexing (OFDM) system. In OFDM system, each frame starts with a preamble symbol that facilitates the SNR estimation. However, the performance of preamble-based SNR estimation schemes worsens in the fast-changing environment where channel changes symbol to symbol. Accordingly, in this paper, we propose a novel pilot-based SNR estimation scheme that optimally exploits the pilot subcarriers that are inserted in each data symbol of the OFDM frame. The proposed scheme computes the circular correlation between the received signal and the comb-type pilot sequence to obtain the SNR. The simulation results are compared with the conventional preamble-based Zadoff-Chu sequence SNR estimator. The results indicate that the proposed scheme generates near-ideal accuracy; especially in low SNR regimes, in terms of the normalized mean square error (NMSE). Moreover, this scheme offers a significant saving of computation over a conventional time domain SNR estimator.

1. Introduction

Noise variance and signal-to-noise ratio are the two important measures of channel quality in a wireless OFDM system, and their estimation helps in adaptive power control and adaptive modulation, thus optimizing the performance of the wireless communication system. Similarly, turbo coding, as well as hands-off algorithms, depends on the variation of the SNR in the time-varying channel. Therefore, the performance and capacity of OFDM systems are directly influenced by the precision and complexity of noise and SNR estimation.

In general, SNR estimation algorithms can be divided into two classes. In the first one, data-aided (DA) class, a known training sequence or pilot is transmitted to estimate the SNR at the receiver [1], and in the second, nondata-aided (NDA) class, the SNR is estimated blindly (without knowing anything a priori about the transmitted information). Both classes have their advantages and disadvantages with respect to their estimation accuracy and computational complexity.

In DA estimators, a considerable amount of literature has been published on the utilization of preamble-based estimation for equalization, carrier offset synchronization, and channel estimation [2–4]. Similarly, there is also abundant literature on SNR estimation based on the preamble [5]. For a packed OFDM system, preamble-based strategies are useful owing to the slow nature of the time-varying channel. In broadcasting OFDM systems, one uses the pilot-based strategies where channel variations are tracked symbol-by-symbol. However, for noise power estimation, the existing OFDM system utilizes the improved preamble-based noise estimation schemes rather than pilot-based schemes for frequency-selective fading channels [6, 7].

In OFDM receivers, two distinct domains are used for SNR estimation, namely post-FFT (frequency domain) and pre-FFT (time domain). Literature reveals that several studies have been conducted on the use of pilot-based channel estimation in the frequency domain. These studies show the performance of the channel estimation is directly affected by the placement of the pilot tones in each OFDM symbol. Therefore, previous studies [8–13] utilized the optimized pilot placement by using the artificial techniques, such as Particle Swarm Optimization, Artificial Bee Colony, Firefly Algorithm, Grey Wolf Optimizer, and Differential Evolution.

On the other hand, the estimation in the time domain is not affected by the loss of orthogonality that can occur due to carrier offset [14]. Moreover, the number of channel taps required for estimation in the time domain is significantly fewer than the number of FFT points where the channel frequency response needs to be estimated [15]. These features provide a robust basis for focusing on the time domain estimation schemes. Thus, a considerable amount of literature has been published on time domain estimation schemes that include the work of [16–19]. In [16, 17], Manzoor and Kim presented a correlation-based time domain SNR estimation scheme using preamble for AWGN channel. Similarly, Gafer et al. [18] introduced an SNR estimation scheme for flat fading channel in the time domain. Another SNR estimation algorithm for slow flat fading channel is proposed in [19], where maximum likelihood (ML) and data statistics approaches are utilized. In the frequency selective scenario, aforementioned schemes [17–19] are prone to performance degradation caused by variation of noise on each subcarrier. Thus, an SNR estimation per subcarrier is needed [20, 21]. These techniques can be extended to average SNR estimation schemes. Another way to overcome the limitation, due to frequency-selective channel, is to improve the structure and design of the preamble symbol, as shown in [22–25]. In [22], the whole band (total number of subcarriers) is divided into subbands (set of subcarriers). Then, time and frequency domain averaging is applied to estimate the variation of noise within the transmission bandwidth. In [23], it has been shown that by exploiting comb-type preamble, a low-complexity frequency domain SNR estimation method is achieved for the frequency-selective fading channels. In this method, the loaded preambles are arranged with a certain number of null subcarriers, which are used to estimate the noise power. However, the loaded preambles are utilized to obtain the total signal plus noise power. Similarly, Ijaz et al. [24] presented the time domain SNR estimation for the frequency-selective fading channel. It uses the correlation of the received preambles to estimate signal power while noise power is estimated by subtracting the estimated signal power from the total received symbol power. Yet another time domain preamble-based approach is presented in [25], where the comb-type pilot structure is designed by using the Zadoff-Chu (ZC) sequence, which outperforms the conventional time domain SNR estimators in terms of computational complexity due to perfect autocorrelation of the ZC sequence.

By reviewing these studies, it is found that the majority of the schemes utilize the preamble-based structure for the frequency-selective fading channel [22–25]. In the fast-changing environment, the variation of noise is not same in all OFDM symbols of the frame. Thus, the performance of these schemes degrades, and the noise at each symbol needs to be tracked. Furthermore, if man-made noise is considered, these schemes can not work. Consequently, it is more desirable to develop a SNR estimation scheme in which the noise variation is tracked symbol-by-symbol instead of at the beginning of frame using a preamble symbol. According to the best knowledge of the author, none of the time domain SNR estimators utilize the pilot subcarriers inserted in data symbol for SNR estimation. Moreover, the peak-to-average power ratio (PAPR) of OFDM symbol remains same as no extra preamble is utilized for estimation.

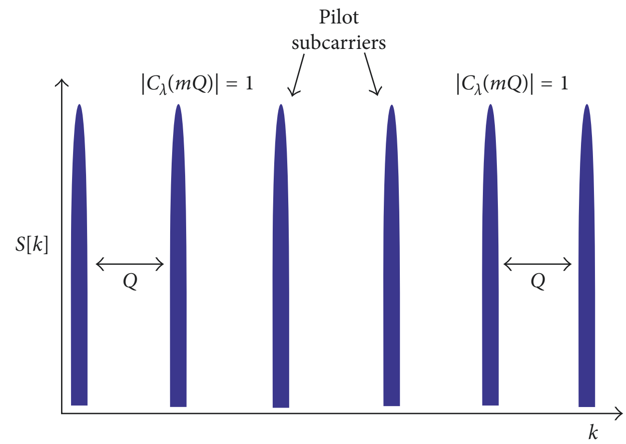

Figure 1: Conventional preamble symbol with comb-type arrangement for SNR estimation.

The remainder of this paper is organized as follows: In the next section, the conventional preamble-based estimator utilizing Zadoff-Chu sequence is presented. In Section 3, the system model used for pilot-based SNR estimation is described. In Section 4, a detailed description of the proposed pilot-based time domain SNR estimator is presented. Section 5 explains the complexity analysis. Simulation parameters are explained in Section 6. Results and analysis are given in Section 7. Section 8 concludes the paper.

2. Conventional Preamble-Based Time Domain Zadoff-Chu Sequence SNR Estimator

In a conventional preamble-based ZC sequence SNR estimator, comb-type pilot subcarriers are loaded with a ZC sequence. It utilizes Q identical parts in each preamble symbol, which contains $N_{\mathrm{P}} = N_{\mathrm{FFT}}/Q$ number of loaded pilot subcarriers, as depicted in Figure 1. Starting from the 0th, each Qth, subcarrier is modulated with a ZC sequence symbol $C_\lambda(mQ)$ with $|C_\lambda(mQ)| = 1$, for $m = 0, \ldots, N_{\mathrm{P}} - 1$. The remainder of $N_{\mathrm{Z}} = N_{\mathrm{FFT}} - N_{\mathrm{P}} = (Q-1)N_{\mathrm{FFT}}/Q$ subcarriers are not used (nulled). According to [25], the nth received time sample can be written as

$$r(n) = r(mQ+q) = \begin{cases} r_{\mathrm{P}}(m) & q = 0 \\ r_{\mathrm{Z}}(mQ+q) & q = 1, \ldots, Q-1, \end{cases} \tag{1}$$

where

$$r_{\mathrm{P}}(m) = s(mQ)e^{2\pi\varepsilon mQ/N_{\mathrm{FFT}}} + w(mQ) \tag{2}$$

represents the received time domain signal containing the phase shifted signal and additional noise component and

$$r_{\mathrm{Z}}(mQ+q) = w(mQ+q) \tag{3}$$

shows the time domain noise signal. Thus, the time domain received signal that contains the signal plus noise is given by

$$\widehat{P}_{\mathrm{S+N}} = \frac{1}{N_{\mathrm{P}}} \sum_{m=0}^{N_{\mathrm{p}}-1} \left| r_{\mathrm{P}}(m) \right|^2. \tag{4}$$

Similarly, the received samples containing only the noise component can be obtained as

$$\widehat{P}_{\mathrm{N}} = \frac{1}{N_{\mathrm{P}}(Q-1)} \sum_{m=0}^{N_{\mathrm{p}}-1} \sum_{q=0}^{Q-1} \left| r_{Z}(mQ+q) \right|^2. \tag{5}$$

Finally, the estimated $\widehat{\mathrm{SNR}}$ can be expressed as

$$\widehat{\mathrm{SNR}} = \frac{1}{Q}\left(\frac{\widehat{P}_{\mathrm{S+N}} - \widehat{P}_{\mathrm{N}}}{\widehat{P}_{\mathrm{N}}}\right). \tag{6}$$

3. System Model for Pilot-Based Time Domain SNR Estimator

In this section, the system model used for pilot-based time domain SNR is discussed. Consider a baseband model for a typical OFDM transceiver where binary data is first mapped by utilizing the 16-quadrature amplitude modulation (16-QAM). The frequency domain data signal can be expressed as [26]

$$D[k] = \sum_{n=0}^{N_{\mathrm{FFT}}-1} d(n) e^{-j2\pi kn/N_{\mathrm{FFT}}}, \quad k = n = 0, 1, \ldots, N_{\mathrm{FFT}} - 1, \tag{7}$$

where n is the time domain indexed and $d(n)$ denotes the data sequence. Then, the modulated data symbols are inserted with pilot subcarriers in such a way that they are zeros except at their corresponding subcarriers. Thus, the frequency domain discrete transmitted signal $S[k]$ is given as

$$S[k] = D[k] + P[k]. \tag{8}$$

Figure 2 depicts the conventional OFDM data symbol, where pilot subcarriers are periodic and comb-type in nature.

Each OFDM symbol is passed through an inverse Fourier transform (IFFT) block and converted to the time domain, given as

$$s(n) = \frac{1}{\sqrt{N_{\mathrm{FFT}}}} \sum_{k=0}^{N_{\mathrm{FFT}}-1} S[k] e^{j2\pi kn/N_{\mathrm{FFT}}}. \tag{9}$$

Similarly, the corresponding time domain pilot sequence can be expressed as

$$p(n) = p\left(m + qN_{\mathrm{p}}\right) = \begin{cases} K = \dfrac{1}{Q} & m = 0 \\ 0 & m = 1, \ldots, N_{\mathrm{p}} - 1, \end{cases} \tag{10}$$

where K is the amplitude and N_{p} represents is periodicity of the pilot sequence $p(n)$. In order to avoid intersymbol interference (ISI) in the channel, a cyclic prefix (CP) is attached at the start of each OFDM symbol. CP is the replica of the last part of any given OFDM symbol in the time domain.

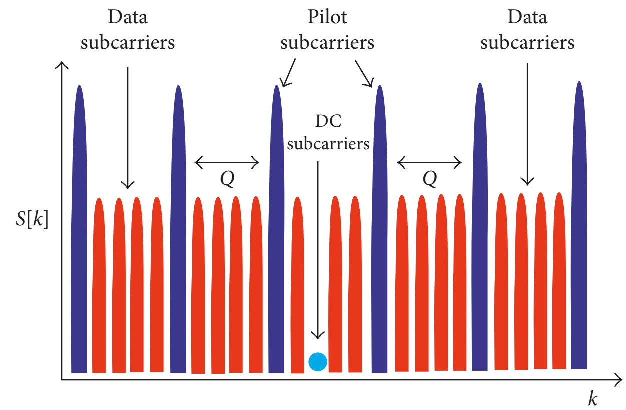

FIGURE 2: Conventional OFDM data symbol that contains pilot subcarriers.

Then, OFDM symbols are transmitted through a frequency-selective channel in the presence of additive white Gaussian noise, which can be expressed as

$$h(n) = \sum_{i=0}^{L-1} h_i e^{j(2\pi/N_{\mathrm{FFT}}) f_{D_i} Tn} \delta(\lambda - \tau_i), \tag{11}$$

where h_i is the ith complex path gain, f_{D_i} is the ith path Doppler frequency shift, τ_i is the corresponding normalized path delay, λ is delay index, T is sample period, and L is the total number of channel taps. At the receiver, without loss of generality, it is possible to use the low-pass system model. Thus, after eliminating the CP from the symbol, the received sequence $r(n)$ can be written as

$$r(n) = s(n) \otimes h(n) + w(n), \tag{12}$$

where $\otimes$ represents the circular convolution and $w(n)$ is additive white Gaussian noise with zero mean and variance σ^2.

4. Proposed Pilot-Based Time Domain (PTD) SNR Estimation

In the proposed PTD SNR estimation scheme, a circular cross-correlation approach is utilized to obtain the noise power $\widehat{P}_{\mathrm{N}}$ in the time domain. However, signal power $\widehat{P}_{\mathrm{S}}$ is obtained from the difference of total received symbol and noise power, as depicted in Figure 3. For noise power estimation, the received sequence $r(n)$ is circular correlated Ⓝ with the pilot sequence $p(n)$ as shown in Figure 3, which yields

$$C_{\mathrm{rp}}(n) = h(n) \,Ⓝ\, \left[C_{\mathrm{dp}}(n) + C_{\mathrm{pp}}(n)\right] + C_{\mathrm{wp}}(n). \tag{13}$$

In general, $C_{xy}(n)$ is Ⓝ between the $x(n)$ and $y(n)$ sequences. In (13), $C_{\mathrm{dp}}(n) = 0$, as presented in Appendix A of [27]. Thus, (13) reduces to

$$C_{\mathrm{rp}}(n) = h(n) \,Ⓝ\, \left[C_{\mathrm{pp}}(n)\right] + C_{\mathrm{wp}}(n). \tag{14}$$

Due to the periodicity of pilot sequence $p(n)$ in (10), the correlation terms $C_{\mathrm{rp}}(n)$ and $C_{\mathrm{pp}}(n)$ are periodic with the period of N_{P}. Thus,

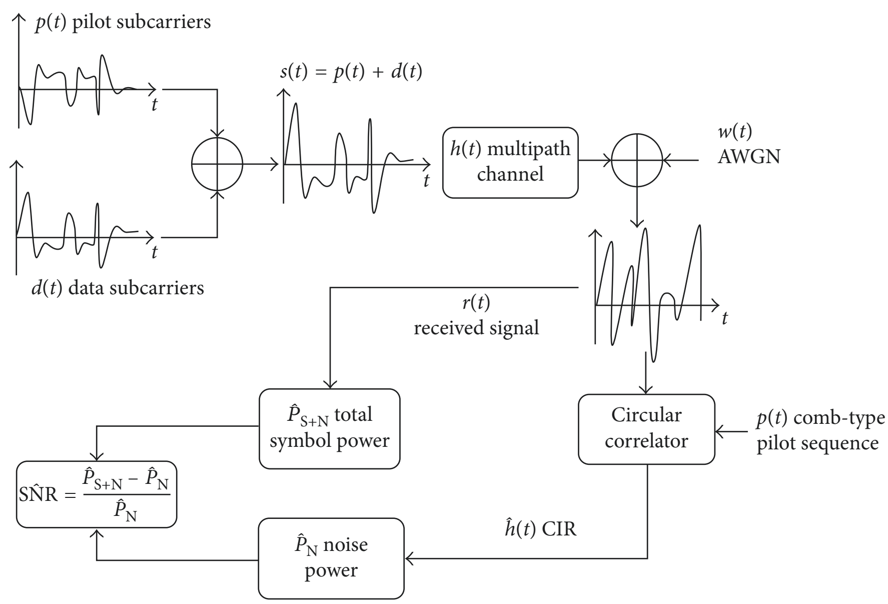

Figure 3: Block diagram for proposed PTD SNR estimation scheme.

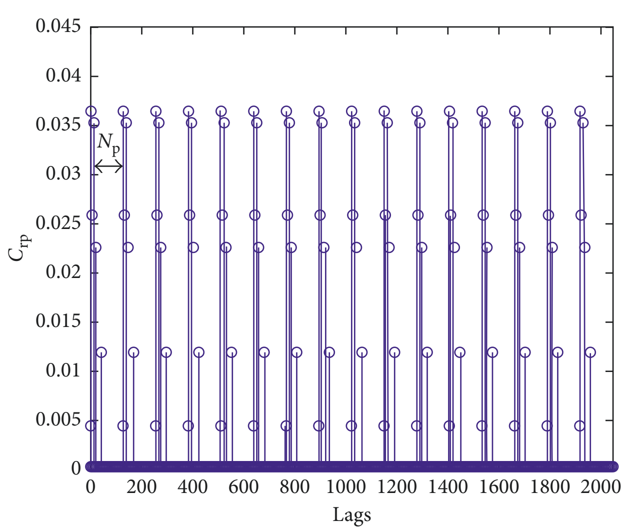

Figure 4: Circular correlation between received and comb-type pilot sequence.

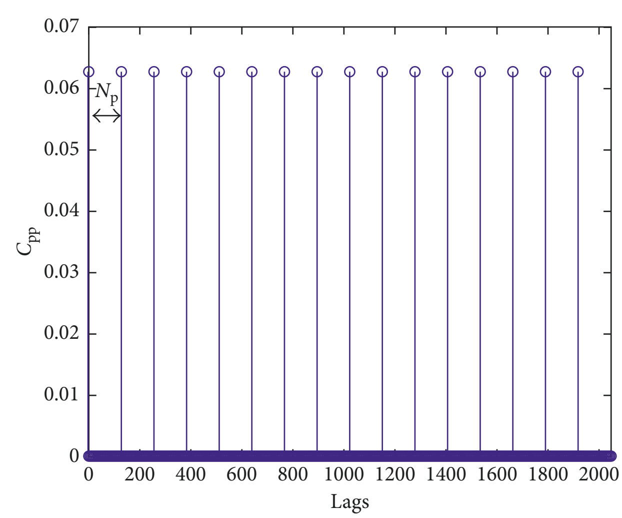

Figure 5: Circular autocorrelation of comb-type pilot sequence.

$$C_{rp}(n) = C_{rp}\left(m + qN_p\right), \tag{15}$$

$$C_{pp}(n) = C_{pp}\left(m + qN_p\right) = \begin{cases} K = \dfrac{1}{Q} & m = 0 \\ 0 & m = 1, \ldots, N_p - 1. \end{cases} \tag{16}$$

Figures 4 and 5 depict the periodicity as N_p. Therefore, the estimated CIR can be obtained from (14) as

$$\hat{h}\left(m_L\right) = \frac{C_{rp}\left(m_L\right)}{K} - \tilde{w}\left(m_L\right), \quad m_L = 0, 1, \ldots, L-1 \ \left(L < N_p\right), \tag{17}$$

where $\tilde{w}(m_L) = C_{wp}(m_L)/K$. Reference [28] is exploited to extract the most significant channel taps form (17), which is independent to the knowledge of channel statistics. By utilizing (10) and (16), (14) can be rewritten as

$$\widehat{w}(m) = r(m) - \widehat{h}(m) \circledN p(m), \tag{18}$$

where $\widehat{w}(m)$ is the estimated noise. Hence, the estimated noise power $\widehat{P}_N$ becomes

$$\widehat{P}_N = \frac{1}{N_p} \sum_{m=0}^{N_p - 1} \left|\widehat{w}(m)\right|^2. \tag{19}$$

Similarly, the total received symbol power is from (12) as

$$\widehat{P}_{S+N} = \frac{1}{N_p} \sum_{m=0}^{N_p - 1} \left|r(m)\right|^2. \tag{20}$$

Finally, the proposed $\widehat{SNR}$ estimator is defined as

Table 1: Complexity comparison of PTD and conventional time domain SNR estimators ($N_{\mathrm{FFT}} = 2048$, $L = 6$, $N_{\mathrm{P}} = 128$, and $Q = 16$).

Estimator	FLOPs
PTD	$2N_{\mathrm{P}}(Q) + 3N_{\mathrm{P}} + L$
Conventional ZC [25]	$4N_{\mathrm{FFT}} + 2$

$$\widehat{\mathrm{SNR}} = \sum_{m=0}^{N_{\mathrm{P}}-1} \frac{|r(m)|^2 - |\widehat{w}(m)|^2}{|\widehat{w}(m)|^2}. \tag{21}$$

In (18), it is assumed that the average transmitted signal is equal to one. Therefore,

$$\widehat{\mathrm{SNR}} = \sum_{m=0}^{N_{\mathrm{P}}-1} \frac{|\widehat{h}(m)|^2}{|\widehat{w}(m)|^2}. \tag{22}$$

5. Complexity Analysis

In this section, the computational complexity of the PTD scheme is evaluated and compared with the conventional Zadoff-Chu preamble-based time domain method [25], considering the floating point operations per second (FLOPs) as a complexity metric. In general, FLOPs means the number of complex additions and multiplications required to perform one SNR estimate.

It can be observed from (21) that the computational complexity of the SNR estimator is generated from two parts: noise power $\widehat{P}_{\mathrm{N}}$ and total received symbol power $\widehat{P}_{\mathrm{S+N}}$. For noise power estimation, the PTD stipulates the (13), (17), and (19). The circular correlation in (13) can be computed more efficiently by using periodicity of comb-type sequence $p(n)$. Thus, it requires $N_{\mathrm{p}}(Q-1)$ number of complex additions and $N_{\mathrm{p}}(Q)$ multiplications. Similarly, (17) involves L number of multiplications. Then, (19) requires $N_{\mathrm{P}} - 1$ and $N_{\mathrm{P}} + 1$ number of additions and multiplications, respectively. However, the computational load due to total received symbol power is same as (19). Consequently, the overall number of FLOPs required for the PTD SNR technique is $2N_{\mathrm{P}}(Q) + 3N_{\mathrm{P}} + L$.

On the other hand, the Zadoff-Chu sequence SNR estimator involves $4N_{\mathrm{FFT}} + 2$ number of FLOPs, as given in Table 1 of [25]. Hence, the PTD SNR estimator provides the computational saving of approximately 45% (for $Q = 16$) compared to the conventional Zadoff-Chu sequence estimator. Furthermore, complexity depends on the number of pilot subcarriers N_{p} and channel taps L. A complexity comparison of two different SNR estimators is given in Table 1.

6. Performance Evaluation over Typical Urban (TU6) Channel Model

The performance of the PTD scheme is analyzed over TU6 channel model in terms of normalized mean squared error (NMSE), given as

$$\mathrm{NMSE} = \frac{1}{10000} \sum_{i=1}^{10000} \frac{\left(\widehat{\mathrm{SNR}}_i - \mathrm{SNR}_i\right)^2}{\mathrm{SNR}_i^2}. \tag{23}$$

Table 2: OFDM simulation parameters [29].

Parameter	Value
FFT points (N_{FFT})	2048 (2K-Mode)
Carrier spacing	4.46 kHz
Cyclic prefix	1/16
Pilots spacing (Q)	16
Number of pilots (N_{P})	128
Pilot constellation $P[k]$	Unipolar BPSK
Sampling frequency (F_{S})	9.14 MHz
Bandwidth	8 MHz
Pilot pattern ($D_x \times D_y$)	(16×4)
Velocity	50 km/h
Doppler shift	28.98 Hz

The TU6 channel profile has been adopted because it reproduces the terrestrial propagation for mobile reception. It consists of 6 paths having wide dispersion in delay and relatively strong power, reproducing an urban environment with NLOS, and consequently, following a Rayleigh model. In the simulation, a perfect synchronization between transmitter and receiver is assumed because the estimates in the time domain are robust to carrier frequency offset [25]. The OFDM simulation parameters for DVB-Mobile transmission are shown in Table 2.

7. Results and Analysis

This section presents the results and analysis for the proposed PTD estimator. It is observed from the description of the PTD that it solely depends upon the estimated CIR. Thus, an important feature of the PTD is shown in Figure 6 where CIR is obtained from (16) for TU6 channel model at 10 dB SNR. In the simulation, after utilization of the time resolution $1/F_{\mathrm{S}}$, the number of significant channel taps that can be resolved are $L = 6$. The amplitude of $C_{\mathrm{rp}}(n)$ at the $n = 45$ can be seen in Figure 6. It is further seen that the amplitudes of nonsignificant channel taps are much lower than the significant ones; this is due to the zero correlation of data to pilot sequence, as discussed for (13). It shows that the estimation of channel impulse response is independent of the transmitted data constellation. Figure 7 depicts the MSE comparison of the estimated CIR with the existing time domain channel estimator [30]. In the comparison of MSE, the legend Chu.Seq. represents the conventional time domain channel estimator, where pilot subcarriers are generated by utilizing the Chu. Sequence (magnitude = 1). However, CRB represents the Cramer-Rao Bound as shown in Equation (24) of [30]. It can be clearly seen that in the fast fading scenario ($v = 50$ m/h), the performance of the PTD channel estimator is similar to the existing Chu. Seq. estimator. This is due to the utilization of similar magnitudes of pilot subcarriers. The investigation suggests that the error component exists in the PTD channel estimation is only AWGN. Consequently, it reduces the MSE and presents near-ideal estimation CRB, as shown in Figure 7. It is also investigated that the PTD scheme is independent of time/frequency interpolation; hence, it offers accuracy even in the low density of pilot subcarriers.

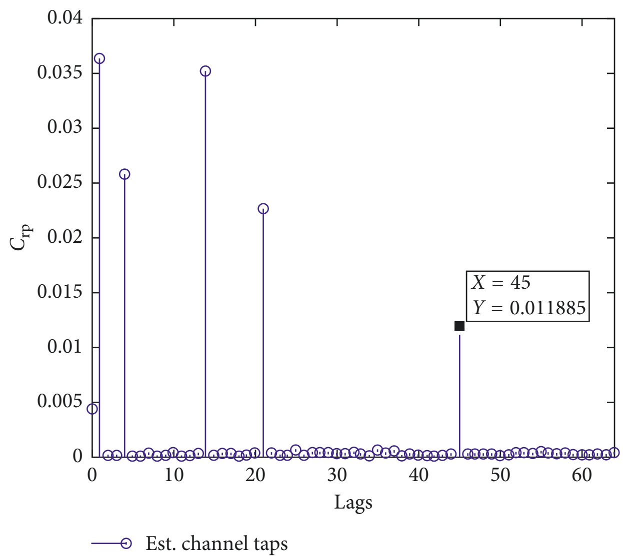

FIGURE 6: Estimated channel taps at (0, 1, 4, 14, 21, and 45).

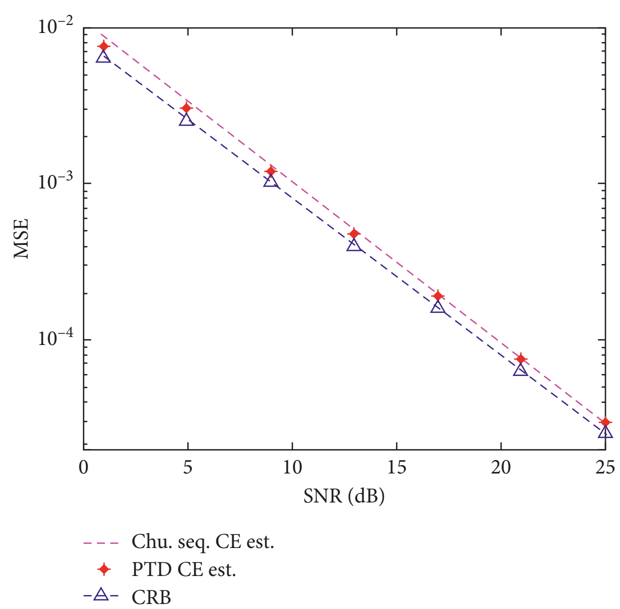

FIGURE 7: Comparison of the estimated channel impulse response in terms of MSE.

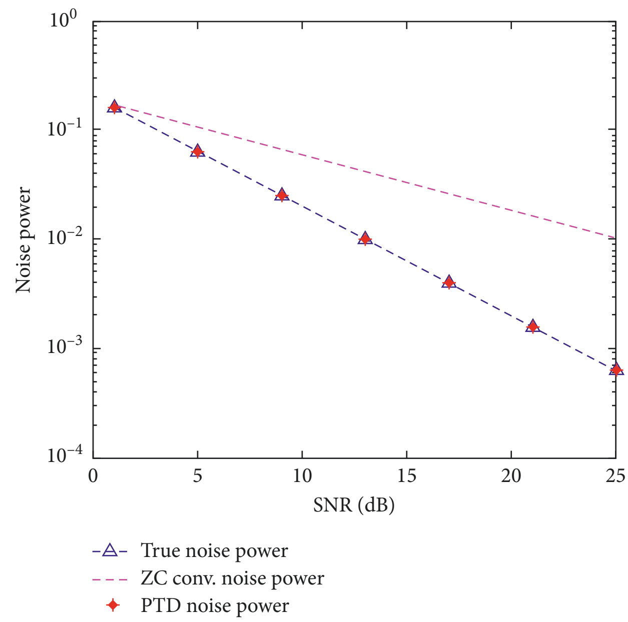

FIGURE 8: Comparison of the noise power estimator with true noise power.

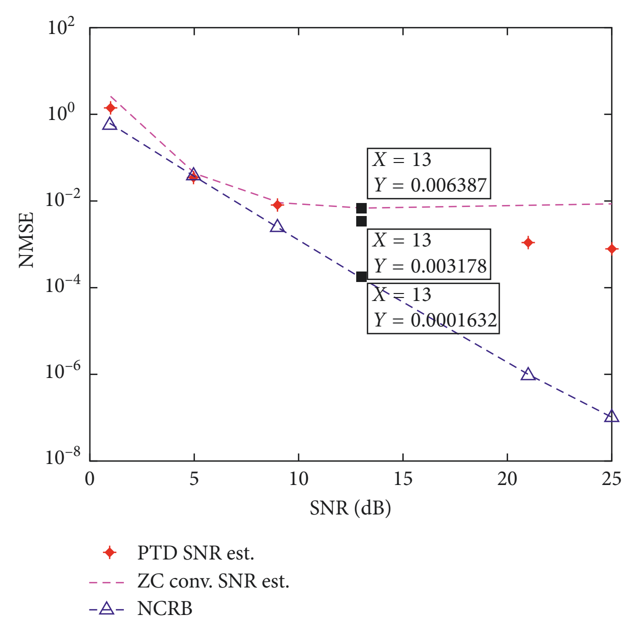

FIGURE 9: Comparison of the PTD SNR estimator in terms of NMSE.

The performance of the PTD noise power estimator is compared with preamble-based ZC noise power estimator in Figure 8. Here, ZC SNR estimator is chosen because it outperforms the conventional estimators without high computational complexity [25]. The comparison shows that the estimation of noise power in the PTD scheme is far better than the ZC-based scheme. The estimation in the PTD scheme is also seen to be close to true noise power at various values of SNR. This is due to the utilization of pilot subcarriers available in each data symbol that facilitates to track the noise variation symbol-by-symbol.

Figure 9 compares the NMSE performance of the PTD SNR estimator with the conventional ZC preamble-based time domain estimator. Moreover, the NMSE of the PTD estimator is compared with the minimum unbiased variance estimator Normalized Cramer-Rao Bound (NCRB) as shown in Equation (24) of [31]. It is seen that both estimators perform well in a low SNR regime. However, at a high SNR, the NMSE is larger than the NCRB. This can be explained by the following observation. In the PTD SNR estimator, the SNR is obtained primarily from noise power estimation, as shown in (21). It can be observed that the signal power is obtained from the difference of total received symbol power and the noise power. Therefore, at a high SNR, when the total received symbol power and noise power are nearly of the same order, the SNR estimation error increases.

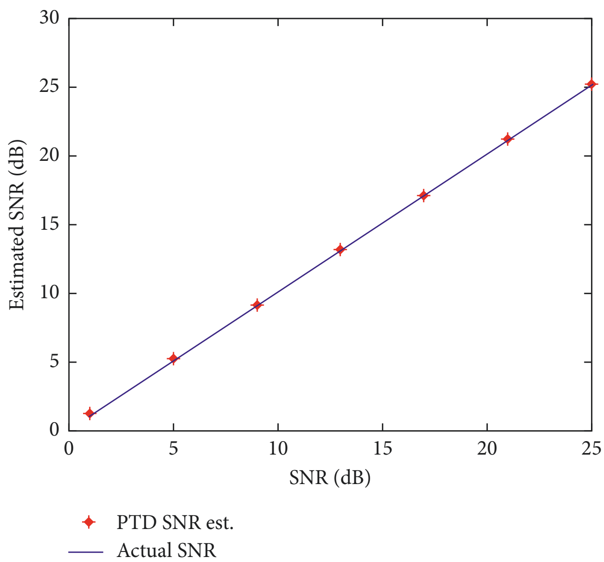

Figure 10: Estimated SNR versus actual SNR.

It can be seen in Figure 9 that at 13 dB of SNR, the NMSE of the PTD estimator improves approximately by 50.24% $(0.006387 - 0.003178/0.006387) \times 100$ with respect to ZC estimator and 3.01E–3 away from NCRB. In Figure 10, the estimated SNR is plotted against the actual SNR. It can be seen that the estimated SNR has less bias and is close to the actual SNR. Hence, it is verified that the PTD SNR estimator achieves a similar performance to the actual SNR at a much lower computational complexity, whilst its implementation is more feasible. Moreover, it utilizes the time domain estimation; therefore, it is robust enough for carrier frequency offset (CFO) [25].

8. Conclusion

In this study, a novel pilot-based SNR estimation algorithm is presented for broadcasting OFDM systems. At the receiver, pilot subcarriers of data symbol are used for SNR estimation. The simulation shows that the NMSE of the proposed algorithm is better than the other conventional scheme. The advantages of the proposed estimation scheme are that (a) it is less sensitive to tracking errors as compared to preamble-based estimation methods for highly time-varying frequency-selective channels, (b) the number of floating point operations per second involved is also fewer than the conventional preamble-based scheme, and (c) it is capable of providing high accuracy even at a low density of pilots subcarriers because it is independent of time/frequency interpolation.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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