

Research Article

An Improved Channel Estimation Algorithm Based on WD-DDA in OFDM System

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Channel estimation is the key technology to ensure reliable transmission in orthogonal frequency division multiplexing (OFDM) system. In order to improve the accuracy of the channel estimation algorithm in a low signal-to-noise ratio (SNR) channel environment, in this paper, we proposed an improved channel estimation algorithm based on the transform domain. The improved algorithm with wavelet denoising (WD) and distance decision analysis (DDA) to perform secondary denoising on the channel estimation algorithm based on the transform domain is proposed. First, after the least-squares (LS) algorithm, WD is used to denoise for the first time, then the DDA is used to further suppress the residual noise in the transform domain, and the important channel taps are screened out. Simulation results show that the proposed algorithm can improve the detection performance of existing channel estimation algorithms based on transform domain in low SNR.

1. Introduction

In recent years, orthogonal frequency division multiplexing (OFDM) has been widely used in the wireless channel to improve spectrum utilization, transmission rate, and frequency-selective fading [1–3]. Due to the uncontrollable and random nature of the wireless channel, the communication quality can be greatly affected, and subsequent critical steps such as data demodulation require accurate channel parameters [4]. Therefore, the accuracy of channel estimation plays a crucial role in the performance of the whole system [5]. Channel estimation techniques for OFDM-based systems can be grouped into two main categories: blind and nonblind. The blind channel estimation methods exploit the statistical behavior of the received signals and require a large amount of data [5]. The nonblind channel estimation methods exploit the known information such as pilot. In this article, only the pilot-assisted channel estimation method will be investigated.

Some classical channel estimation algorithms have been proposed by many scholars. Least squares (LS) [6] is the simplest channel estimation algorithm that utilizes the least-

squares criterion with a simple structure and low computational complexity, but the LS algorithm ignores the effect of the noise term on the results and is easily affected by the noise. Another classical algorithm is the linear minimum mean square error (LMMSE) algorithm [7], which requires a priori statistical information of the channel. Although the LMMSE algorithm has a low bit error rate (BER) and mean square error (MSE) under low signal-to-noise ratio (SNR) conditions, it requires a large number of matrix inversion operations, which has high computational complexity and is not easy to implement. In order to make a tradeoff between the LS algorithm and the LMMSE algorithm, an improved LS algorithm based on the transform domain has gradually come into focus. The performance, as well as the computational complexity of the channel estimation algorithm based on discrete Fourier transform (DFT) [8], is between the LS algorithm and the LMMSE algorithm. The DFT-based channel estimation algorithm is easy to implement and is a widely used channel estimation algorithm with a complexity and performance tradeoff [9]. The DFT-based algorithm mainly exploits the fact that the channel power is concentrated on a relatively small number of channel impulse

response (CIR) samples, while the noise power is equally distributed over the entire sample, and the algorithm performance is improved by reducing the impact of noise in the time domain [10]. However, the traditional DFT-based channel estimation algorithm does not consider the noise in the cyclic prefix (CP) length of the CIR, and eliminating the noise in the CP length of the CIR can further improve the performance of the DFT-based channel estimation algorithm. In [11], a threshold-based DFT channel estimation algorithm is proposed, which improves the performance of the traditional DFT-based channel estimation algorithm, but the choice of the threshold value has a significant impact on the performance of the algorithm. Cruz-Roldán et al. [12] proposed a channel estimation algorithm based on discrete cosine transform (DCT). Compared with the DFT-based channel estimation algorithm, the DCT-based channel estimation algorithm can reduce the high-frequency components in the transform domain, reduce the aliasing error, and obtain better performance than the DFT-based channel estimation algorithm. It is suitable for a channel environment in which the channel delay is a noninteger multiple of the sampling period. The improved algorithms of DFT-based and DCT-based channel estimation algorithms are basically to eliminate the noise within CP length in CIR by setting the threshold in the transform domain. Wang et al. [13] propose a way to improve the performance of the LS algorithm using wavelet transform to eliminate noise. After the LS algorithm, the channel information obtained for the first time is decomposed, denoised, and reconstructed by wavelet, and the channel estimation after noise removal is obtained. He [14] proposes a method that uses K-means clustering analysis to distinguish noise from signal and selects significant taps to remove the noise. The computational complexity of the algorithm is very high, and it is difficult to implement in applications. But it provides a way to eliminate noise and improve the performance of the algorithm by classifying the noise and the important taps.

The existing algorithms are mainly improved on the basis of LS, and the performance of the algorithm is improved by removing noise interference. Therefore, in order to improve the channel estimation accuracy of OFDM systems and achieve ultrareliable transmission, it is significant to study efficient and robust channel estimation algorithms. To solve this problem, this study mainly improves the channel estimation based on the transform domain. After the estimation value of the channel estimation is obtained by the LS algorithm, wavelet denoising (WD) is performed first to suppress the noise, and then distance decision analysis (DDA) is used in the transform domain to select the significant channel taps to further suppress the interference of noise and filter out the significant channel tap. The simulation results show that the algorithm effectively suppresses the noise in samples, with better performance and lower BER.

2. OFDM System Model

We consider an OFDM system that consists of N subcarriers, and each subcarrier consists of data symbol $X(k)$.

$X(k)$ is the frequency-domain symbol which is modulated on the k th subcarrier. Then the transmitted OFDM signal can be expressed as

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) \exp\left(j2\pi \frac{nk}{N}\right), \quad 0 \leq n \leq N-1, \quad (1)$$

where n is the time-domain sample index of an OFDM signal.

In OFDM systems, the last L samples of each OFDM symbol are copied and placed before the symbol as a CP, which is used to maintain intersymbol orthogonality and avoid intercarrier interference (ICI). It is assumed that the guard interval is longer than the channel maximum delay and that the synchronization is perfect. As the signal may be subject to multipath fading and additive white Gaussian noise (AWGN) pollution during transmission, at the receiver side, the time-domain OFDM symbol obtained by removing CP from the received signal can be expressed as

$$y(n) = x(n) \otimes h(n) + \omega(n), \quad 0 \leq n \leq N-1, \quad (2)$$

where \otimes denotes cyclic convolution, $h(n) = \sum_{l=0}^{L_D-1} \alpha_l \delta(n - \tau_l)$ denotes the time CIR, L_D is the length of the CIR, α_l represents complex gain that is complex Gaussian, and τ_l denotes the delay of the l th path.

In the frequency domain, the received signal can be expressed as

$$Y(k) = X(k)H(k) + W(k), \quad 0 \leq k \leq N-1, \quad (3)$$

where $X(k)$ is the transmitted signal, $Y(k)$ is the received signal, $H(k)$ is the channel frequency response (CFR) of the multipath channel, and $W(k)$ is the additive white Gaussian noise.

3. Channel Estimation

3.1. LS Channel Estimation. LS channel estimation is the simplest channel estimation algorithm, which does not need any prior information about the channel. It can be known from equation (3) that, in order to obtain the CFR of the pilot signal $X(k)$ in the signal transmission process, the LS algorithm can obtain $H_{LS}(k)$ by

$$H_{LS}(k) = \frac{Y(k)}{X(k)} = H(k) + \frac{W(k)}{X(k)}. \quad (4)$$

From equation (4), it can be seen that the LS algorithm does not take into account the interference of noise on the results, which leads to the large MSE of the LS algorithm. Therefore, the LS algorithm is only suitable for the channel environment with large SNR.

The individual MSE of k th subcarrier [5, 10] is

$$\text{MSE}_{LS}(k) = \frac{\beta}{\text{SNR}}, \quad (5)$$

where $\text{SNR} = E(|X(k)|^2)/\sigma_{\omega}^2$ is the average SNR, $\beta = E(|X(k)|^2)E(|X(k)|^{-2})$ is a constant depending on signal constellation (e.g., $\beta = 1$ for QPSK and $\beta = 17/9$ for 16-QAM), and $E(\cdot)$ denotes expectation operation.

3.2. Transform Domain-Based Channel Estimation. Transform domain-based channel estimation mainly includes DFT-based channel estimation and DCT-based channel estimation. Transform domain-based channel estimation exploits the property that the CIR energy is mainly concentrated in the first few sample points and the length generally takes CP length L [10]. Therefore, the interference of noise on channel estimation can be reduced by directly nulling the noise component beyond the CP length in the transform domain, which is the reason that the estimation accuracy of the transform domain-based channel estimation algorithm is higher than that of the LS algorithm [15]. However, the traditional transform domain-based channel estimation does not consider the noise interference within the CP length.

For that channel estimation algorithm based on DFT, due to the implicit periodicity of DFT, i.e., when the original data are discontinuous, performing DFT operation can generate additional high-order component, which can easily cause aliasing in the subsequent interpolation process. In order to reduce these high-order components, the original data can be symmetrically processed before DFT to construct an even symmetric signal. Using the even symmetry property of DFT, the DFT operation is carried out for the dual symmetric signal. Except for the boundary junction, no new high-order components are added in the even symmetric processing, which can well inhibit the energy spectrum leakage generated by the DFT processing [16]. DCT-based channel estimation is proposed based on the above principle, which can concentrate the signal energy in the low-frequency part, reduce the influence of the high-

frequency term, and effectively suppress energy leakage [17]. This method is mainly designed to obtain better channel estimation results when the channel delay is a noninteger multiple of the sampling period.

In the transform domain, the basic block diagram of the algorithm is shown in Figure 1.

Convert $\hat{H}_{LS}(k)$ to the time domain by IDFT and IDCT, respectively,

$$\begin{aligned}\hat{h}_{LS}(n) &= \text{IDFT}\{\hat{H}_{LS}(k)\} \text{ or } \text{IDCT}\{\hat{H}_{LS}(k)\} \\ &= h(n) + \tilde{w}(n), \quad 0 \leq n \leq N-1,\end{aligned}\quad (6)$$

where $\text{IDFT}\{\cdot\}$ denotes N -point IDFT and $\text{IDCT}\{\cdot\}$ denotes N -point IDCT.

$\hat{h}_{LS}(n)$ obtained by formula (6) can be divided into two parts: significant channel taps and noise mixing within the CP length and noise-only portions outside the CP length

$$\hat{h}_{LS}(n) = \begin{cases} h(n) + \tilde{w}(n), & 0 \leq n \leq L, \\ \tilde{w}(n), & \text{else.} \end{cases}\quad (7)$$

From equation (7), for the noise component outside the CP length in CIR, we eliminate the noise by directly setting it to zero

$$\hat{h}'_{\text{Tran}}(n) = \begin{cases} \hat{h}_{LS}(n), & 0 \leq n \leq L, \\ 0, & \text{else.} \end{cases}\quad (8)$$

The transform domain-based channel estimation is denoted as

$$\hat{H}_{\text{Tran}}(k) = \text{DFT}_N\{\hat{h}'_{\text{Tran}}(n)\} \text{ or } \text{DCT}_N\{\hat{h}'_{\text{Tran}}(n)\}, \quad 0 \leq k \leq N-1.\quad (9)$$

The individual MSE of the transform domain-based channel estimation is given as [4]

$$\text{MSE}_{\text{Tran}}(k) = \frac{L}{N} \frac{\beta}{\text{SNR}}.\quad (10)$$

It can be seen that the traditional channel estimation algorithm based on the transform domain does not consider eliminating the noise term within CP length. An improved threshold-based DFT channel estimation algorithm is proposed in [10]. The noise estimated outside the CP length in CIR is used to reduce the noise interference inside the CP length in CIR. The selection of the threshold greatly affects the algorithm. In the following section, we propose a method of screening important taps which is different from the threshold method.

4. Proposed Channel Estimation

Through the previous detailed description of the existing algorithms, it can be found that, for the channel estimation algorithm based on the transform domain, the key to improve the performance of the algorithm is to better remove

the noise component in the transform domain. In this part, we propose an improved algorithm based on WD and DDA to remove the noise in CP length in CIR, which is based on the transform domain channel estimation algorithm. In order to better reduce the interference of noise on the channel estimation algorithm, after completing the LS algorithm, we first perform WD on $\hat{H}_{LS}(k)$. Then, the channel estimation in the transform domain is performed, and DDA is used to further remove the residual noise in the transform domain.

4.1. Wavelet Denoising (WD). Compared with DFT, discrete wavelet transform (DWT) has the ability to represent local characteristics of channels in both frequency domain and time domain [18]. The main process of the wavelet threshold denoising method is shown in Figure 2. Using the multi-resolution analysis characteristics of wavelet, appropriate wavelet bases are selected, and the signals are subjected to wavelet decomposition at different scales to obtain the corresponding scale coefficients and wavelet coefficients. The appropriate threshold and threshold functions are selected

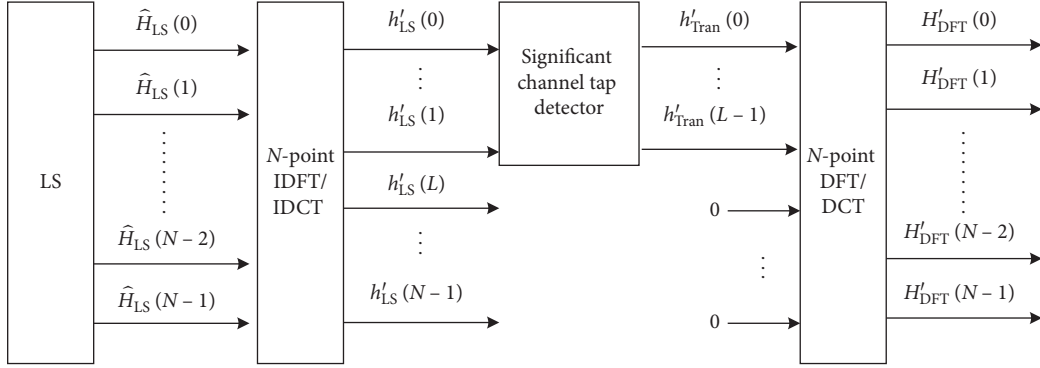


FIGURE 1: Transform domain-based channel estimation.

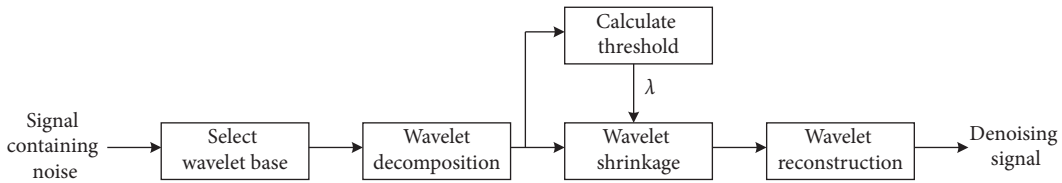


FIGURE 2: Diagram of wavelet denoising.

to process the wavelet coefficients and filter the noise. Finally, wavelet reconstruction is performed to obtain the denoised signal.

The basic steps of wavelet threshold denoising are as follows:

Step 1: selecting an appropriate wavelet base to carry out DWT on the noisy signal

Step 2: wavelet decomposition is performed, and the appropriate threshold is selected for the detailed coefficients decomposed by wavelet to denoise with wavelet shrinkage

Step 3: based on the denoised detail coefficient and the scale coefficient, wavelet reconstruction is carried out to obtain a denoised signal

In the decomposition and reconstruction process, we choose to use the Mallat algorithm [19], which is shown in Figure 3.

In Figure 3 $\downarrow 2$ indicates downsampling 2 times and $\uparrow 2$ indicates up-sampling 2 times. The HPF is a high-pass filter, and the LPF is a low-pass filter. $C(n-1)$ denotes an approximation component, and $D(n-1)$ denotes a detail component. In wavelet analysis, the approximate component is low-frequency information and the detailed component is high-frequency information. For a signal containing noise, the noise component is mainly concentrated in the detail component.

In the process of wavelet denoising, there are two parameters that hinder its performance: (1) the choice of wavelet basis function and (2) setting of threshold function [20]. In the selection of wavelet basis function, Haar wavelet which is suitable for signal continuity is chosen in this study. Wavelet shrinkage is used to denoise the high-frequency coefficient components with threshold [21].

$$\lambda = \sigma \sqrt{2 \log N}, \quad (11)$$

where $\sigma = \text{MAD}/0.6745$, in which MAD is the middle value of the absolute value of the first-level wavelet decomposition coefficient. The threshold function selects the traditional hard threshold [22] to distinguish the detailed coefficients

$$D'(n-1) = \begin{cases} D(n-1) - \lambda, & |D(n-1)| > \lambda, \\ 0, & \text{else.} \end{cases} \quad (12)$$

We use WD to denoise $\hat{H}_{LS}(k)$ which was obtained from the LS algorithm in equation (4) and get $\hat{H}_{WD}(k)$ after denoising. Then, $\hat{h}_{WD_DFT}(n)$ or $\hat{h}_{WD_DCT}(n)$ can be obtained through IDFT or IDCT transform by $\hat{H}_{WD}(k)$, respectively, and significant channel taps are screened in the transform domain.

4.2. Distance Decision Analysis (DDA). In Section 3.2, we discuss some denoising methods in channel estimation algorithm based on transform domain, which is mainly to set that threshold to remove the noise, but using CIR power out of CP length as the threshold is not accurate enough. Decision analysis is a typical multivariate statistical analysis method for classification studies, which usually uses a certain “distance” for classification [23]. For the selection of significant channel taps in channel estimation, we consider that if the Euclidean distance is used for classification, the single factor is considered, so we propose to use the Mahalanobis distance for DDA, replacing the threshold set by the mean value of the CIR power beyond the CP length. The Mahalanobis distance was proposed by the Indian statistician Mahalanobis (P. C. Mahalanobis) and represented the covariance distance of the data [24]. It is calculated as follows:

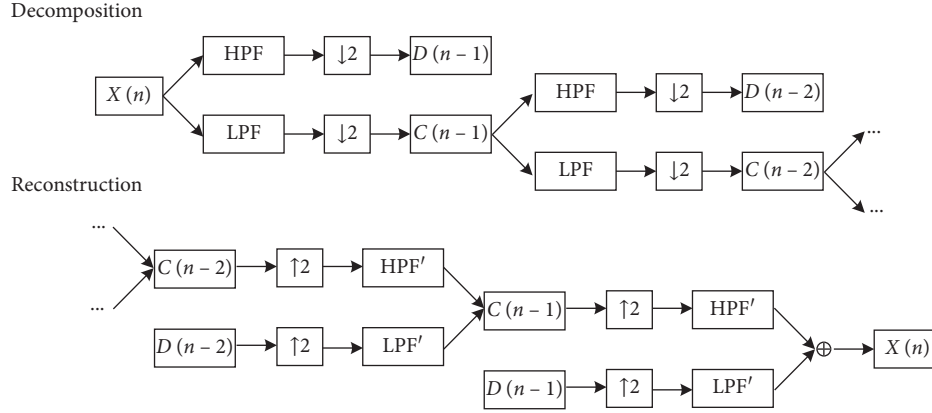


FIGURE 3: Two-level decomposition and reconstruction of the signal.

$$d^2(x) = (x - \mu)^T \sum^{-1} (x - \mu), \quad (13)$$

where \sum denotes covariance matrix, x is the variable to be studied, and $\mu = \text{mean}(x)$.

The centroids of noise variance and significant channel taps variance are different, and the distance between the unclassified point and the centroids of the two is calculated to distinguish and classify. Before the first DDA, the length of CP in CIR is considered as the initialization significant channel taps, and the rest is considered as noise.

The main steps are as follows:

Step 1: define an average of noise $\mu_{\text{WT}} = 1/(N-L) \sum_{n=L}^{N-1} |h_{\text{WD_Tran}}(n)|$ and an average of important taps $\mu_{\text{ST}}^0 = 1/L \sum_{N=0}^{L-1} |\hat{h}_{\text{WD_Tran}}(n)|$, respectively.

Step 2: after obtaining the above parameters, they are substituted into equation (13) and we can obtain

$$\begin{aligned} d_{\text{ST}}^2(\hat{h}_{\text{WD_Tran}}(l)) &= (\hat{h}_{\text{WD_Tran}}(l) - \mu_{\text{ST}})^T \sum^{-1} (\hat{h}_{\text{WD_Tran}}(l) - \mu_{\text{ST}}), \\ d_{\text{WT}}^2(\hat{h}_{\text{WD_Tran}}(l)) &= (\hat{h}_{\text{WD_Tran}}(l) - \mu_{\text{WT}})^T \sum^{-1} (\hat{h}_{\text{WD_Tran}}(l) - \mu_{\text{WT}}). \end{aligned} \quad (14)$$

To determine whether the value of l ($0 \leq l \leq L-1$) is a significant channel tap, we define a decision function

$$A(l) = d_{\text{ST}}^2(l) - d_{\text{WT}}^2(l). \quad (15)$$

If $A(l) < 0$, it is a significant channel tap. If $A(l) > 0$, it belongs to the noise class. Record the significant channel tap positions.

Step 3: update the covariance matrix and the average, and return to Step 2 to traverse l

$$\mu_{\text{ST}}^{i+1} = \frac{1}{L^{i+1}} \left(\mu_{\text{ST}}^i \cdot L^i - |\hat{h}_{\text{WD_Tran}}(l)| \right), \quad (16)$$

where $L^{i+1} = L^i - 1$.

Step 4: when all l have been traversed, the following judgment condition is executed, i.e., setting the non-significant taps to zero.

$$\hat{h}_{\text{WD_Tran_DDA}}(n) = \begin{cases} \hat{h}_{\text{WD_Tran}}(n), & n \in \text{ST}, \\ 0, & n \notin \text{ST}, \end{cases} \quad 0 \leq n \leq N-1. \quad (17)$$

Step 5: transform the result of time domain to frequency domain.

4.3. WD-DDA-Based Channel Estimation in the Transform Domain. In this section, we present an improved channel estimation algorithm in the transform domain based on WD and DDA. The principal block diagram of the improved algorithm is shown in Figure 4.

After the LS algorithm, WD is added. $\hat{H}_{\text{LS}}(k)$ is decomposed by wavelet denoising algorithm, and high-frequency components are denoised by threshold. Then wavelet reconstruction is performed to complete the initial denoising of $\hat{H}_{\text{LS}}(k)$, and $\hat{H}_{\text{WD}}(k)$ is obtained. IDFT or IDCT is then performed to complete the transform domain channel estimation. In the transform domain, we propose an improved algorithm based on DDA, which applies the

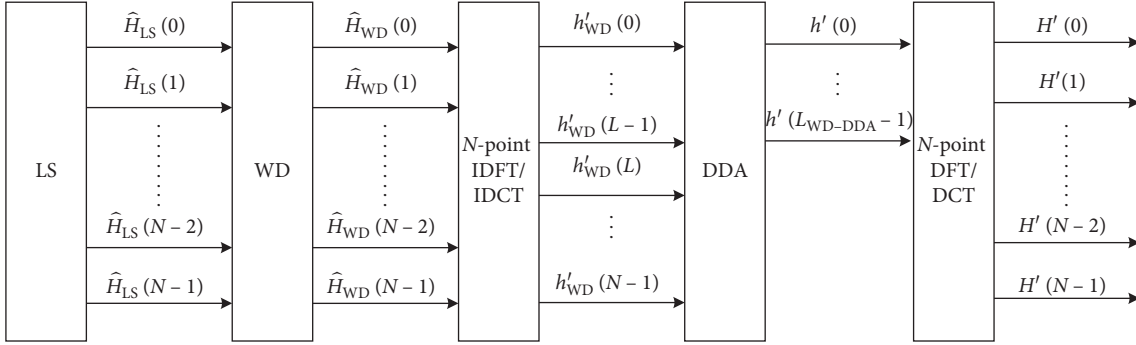


FIGURE 4: Block diagram of the proposed algorithm.

Mahalanobis distance to DDA, divides $h'_{WD}(n)$ into noise class and important tap class, and makes a decision to get $h'(n)$. And finally, perform DFT or DCT to obtain the channel estimation $H'(k)$.

The MSE of the improved algorithm is

$$\text{MSE}_{\text{WD-DDA}}(k) = \frac{L_{\text{WD-DDA}}}{N} \frac{\beta}{\text{SNR}}, \quad (18)$$

where $L_{\text{WD-DDA}}$ is the number of significant channel taps selected by the improved algorithm and $L_{\text{WD-DDA}} < L$.

By comparing equations (5), (10), and (18), we can get

$$\text{MSE}_{\text{WD-DDA}}(k) < \text{MSE}_{\text{Tran}}(k) < \text{MSE}_{\text{LS}}(k). \quad (19)$$

Compared with the threshold-based channel estimation algorithm in the transform domain, the improved algorithm proposed in this study can distinguish the noises better and filter the residual noises by constantly updating the centroids (average of variances) of the two classes when making the decision analysis of noises and important taps for the sampling points in CP length in CIR.

5. Simulation Results

In this study, Matlab is used as a simulation platform to verify the proposed algorithm, and the simulation parameters are shown in Table 1. In order to reflect the performance of the improved algorithm in the wireless channel more realistically, the whole simulation environment is built by simulating the actual Physical Broadcast Channel (PBCH) in 5G new radio (NR) under the tapped delay line (TDL-A) [25] channel environment. The channel parameters of TDL-A are shown in Table 2. In the simulation environment of Table 1, the abovementioned value of β is 1, and $L = 288$ is the length of CP. However, $L_{\text{WD-DDA}}$ of the improved algorithm is not fixed. It will float with the change of the channel environment. When the channel environment is good, the noise within the CP length can be filtered better. When the channel environment is poor, the noise-filtering effect within the CP length will be reduced. However, the floating range of the number of selected important channel taps is generally between $L/3$ and L .

TABLE 1: Simulation parameters.

Parameter	Value
Numerology (μ)	3
Carrier frequency	4 GHz
Channel bandwidth	100 MHz
Sampling frequency	122.88 MHz
Modulation	QPSK
FFT size (N)	4096
Cell ID	4
CP	Normal
E_b/N_0	0 to 20 dB
Channel model	TDL-A
Wavelet base type	Haar
β	1
L	288

TABLE 2: Power delay profile of TDL-A channel [24].

Normalized delay	Power in dB	Fading distribution
0.0000	-13.4	Rayleigh
0.3819	0	Rayleigh
0.4025	-2.2	Rayleigh
0.5868	-4	Rayleigh
0.4610	-6	Rayleigh
0.5375	-8.2	Rayleigh
0.6708	-9.9	Rayleigh
0.5750	-10.5	Rayleigh
0.7618	-7.5	Rayleigh
1.5375	-15.9	Rayleigh
1.8978	-6.6	Rayleigh
2.2242	-16.7	Rayleigh
2.1718	-12.4	Rayleigh
2.4942	-15.2	Rayleigh
2.5119	-10.8	Rayleigh
3.0582	-11.3	Rayleigh
4.0810	-12.7	Rayleigh
4.4579	-16.2	Rayleigh
4.5695	-18.3	Rayleigh
4.7966	-18.9	Rayleigh
5.0066	-16.6	Rayleigh
5.3043	-19.9	Rayleigh
9.6586	-29.7	Rayleigh

Because this study studies the channel estimation algorithm of the OFDM system, we assume in the simulation that the synchronization process in the previous step of the receiver is perfect. For wavelet denoising, 2 layers are selected for wavelet decomposition level. For the simulation results, the MSE and BER are chosen as the measurement criteria. Simulations were carried out to compare the LS algorithm, the threshold-based DFT channel estimation, and the threshold-based DCT channel estimation.

Figures 5 and 6 are the MSE performance curves and BER performance curves of the five algorithms in the TDL-A channel environment, respectively. It can be clearly seen that although the LS algorithm is simple to implement, the threshold-based transform domain channel estimation algorithm is superior to the LS algorithm in both MSE and BER. Moreover, the MSE and BER of the improved algorithm proposed in this article are significantly superior to the threshold-based channel estimation algorithm, and it can achieve better performance in the case of a poor channel environment. Simulation results verify that the performance of noise cancellation after WD and DDA processing is better than the performance of the threshold-based transform domain channel estimation algorithm. With the increase of SNR, the interference of noise decreases, and its performance gradually approaches that of the threshold-based transform-domain channel estimation algorithm.

The 5G NR PBCH uses QPSK to modulate and demodulate the signal, and a comparison of the constellation diagrams of the received signal after equalization using different channel estimation algorithms is shown in Figure 7. It can be seen that, at SNR = 14 dB, the constellation diagram of the WD-DDA algorithm is more aggregated compared to the other two algorithms, allowing for a high-quality recovery of the data.

To quantify the performance gap between these algorithms, we performed a comparison by calculating error vector magnitude (EVM). The EVM is the difference between the ideal signal and the equalized measured signal [26]. The EVM value is proportional to the BER. Mathematically, we define the error vector E_k for the k th subcarrier as

$$E_k = (I_k - \hat{I}_k)^2 + (Q_k - \hat{Q}_k)^2, \quad (20)$$

where I_k and Q_k are the ideal in-phase and quadrature components of k th subcarrier, respectively, and \hat{I}_k and \hat{Q}_k are the measured versions.

For the demodulated QPSK signal, the equation for EVM can be defined as [27]

$$\text{EVM} = \sqrt{\frac{1/N \sum_{k=1}^N E_k}{1/N \sum_{k=1}^N (I_k^2 + Q_k^2)}}, \quad (21)$$

where N is the number of subcarriers.

After calculation and analysis, the EVM values of signals (b), (c), and (d) in Figure 7 are, respectively, 18.331%, 17.105%, and 15.919%. The larger the value of EVM, the higher the degree of signal degradation and the larger the

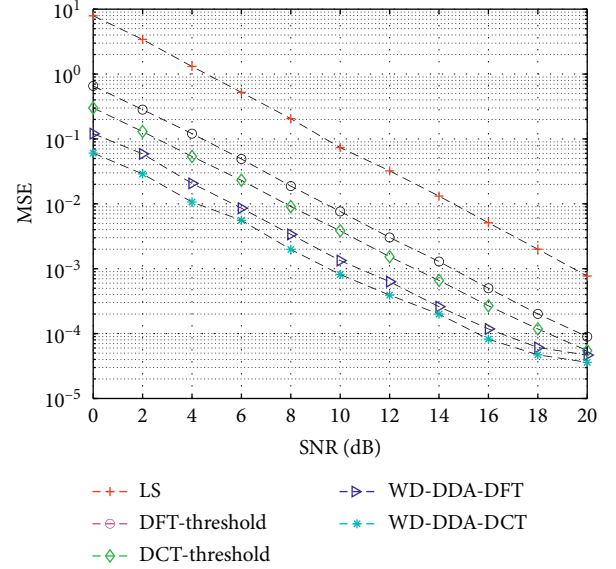


FIGURE 5: MSE performance of different algorithms.

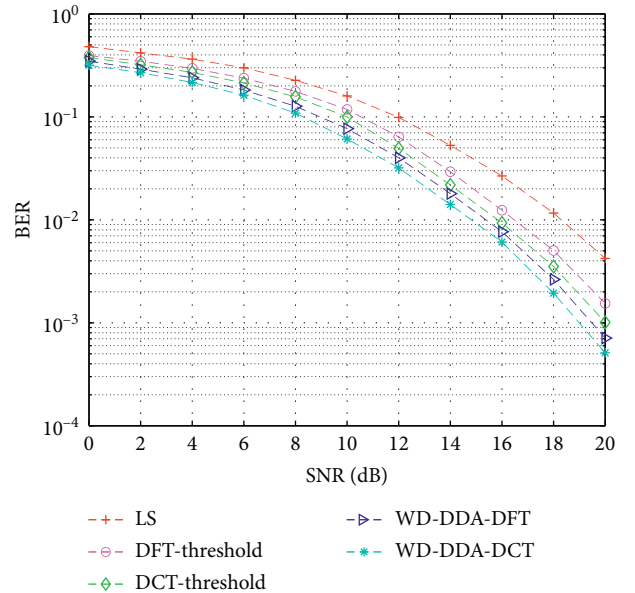


FIGURE 6: BER performance of different algorithms.

error of the recovered signal. On the contrary, the lower the degree of deterioration, the smaller the signal error. According to the constellation diagram, when the signal-to-noise ratio is fixed, the constellation diagram aggregation of LS algorithm is not strong, and the constellation diagram of DFT algorithm is relatively aggregated, while the constellation diagram aggregation is better when WD-DDA algorithm is adopted. From the perspective of EVM, an increase in the EVM value may result in overlapping states between symbols of different phases, which may lead to error codes. The EVM value of the improved algorithm proposed in this study is relatively smaller than that of the existing algorithm, and the antinoise performance is improved.

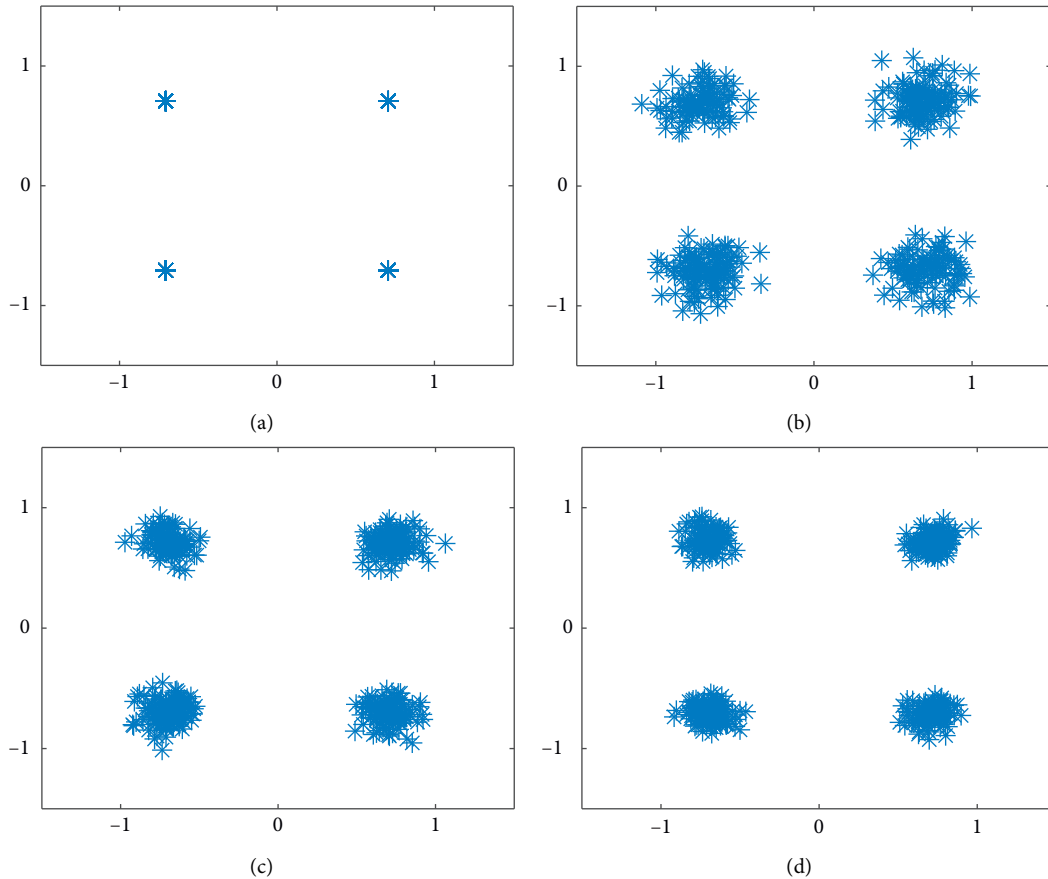


FIGURE 7: Comparison of constellation diagrams after equalization of different channel estimation algorithms: (a) original constellation diagram, (b) constellation diagram with LS algorithm, (c) constellation diagram with DFT-threshold, and (d) constellation diagram with WD-DDA.

The computational complexity of channel estimation based on transform domain is $O(NL)$ [13]. For DWT, IDWT, and the application of threshold function, the computational complexity is $O(N)$ [28], the algorithm proposed in this study only needs a simple operation to calculate the average value, standard deviation, and so on in the WD part and does not need complex calculus operation. The DDA part is also a single traversal, so the computational complexity required to improve the algorithm is $O(N(L+1)+L)$. Although the improved algorithm adds a small amount of computational complexity, it still has a performance gain of about 1 dB in the acceptable range.

6. Conclusion

In this study, the existing channel estimation algorithms in OFDM systems are discussed, and an improved channel estimation algorithm in the transform domain based on WD and DDA is proposed. Using WD and DDA for secondary filtering of noise within the CP length in CIR, the interference of noise on the selection of significant channel taps in the channel estimation algorithm is effectively suppressed. Simulation results and analysis also show that the proposed improved algorithm has lower BER compared to the threshold-based transform domain channel estimation algorithm at low signal-to-noise ratios.

Although the performance of the improved algorithm proposed in this study has been improved, in the WD part, only a relatively simple Haar wavelet basis function is selected to implement. In the follow-up work, more in-depth research may be conducted in this part of WD to explore whether there is room for performance improvement. At the same time, for the DDA part, the future work can consider whether to reduce some computational complexity as much as possible on the premise of ensuring performance.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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