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Kalman filter based channel estimation method in wireless communication and its performance optimization

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ABSTRACT

In this paper, with the help of the real-time state observation property of the Kalman filter method, we propose to use the Kalman filter method for channel estimation of OFDM wireless communication system. The linear interpolation method is used to deal with the fading process of data symbol positions, and the Kalman filter estimation expression of the fading process is obtained. And considering the computational complexity of the channel estimation algorithm, the channel estimation is optimized by adding the 1st order AR model into the channel model. The Doppler frequency is used as the simulation parameter to analyze the operational performance of the Kalman filter channel estimation method under different Doppler frequencies. To further broaden the applicability of the proposed method in this paper, a MIMO-OFDM system is introduced, and numerical simulations are conducted to analyze the relationship curves between the outage probability and the SNR performance under the OFDM channel processing module for both the random channel and the random channel with OFDM modulation. In the massive MIMO multipath random transmission channel, the better the SNR performance of the channel, the smaller the probability of generating interruptions. Meanwhile, in the presence of the same non-ideal factors (hardware impairments, interference noise) interruption probability impairments of the channel, the SNR in OFDM-ideal state is about 10 dB more than the OFDM-hardware impairments simulation value.

Keywords: Kalman filtering, 1st order AR model, MIMO-OFDM system, channel estimation, Doppler frequency

1. Introduction

In wireless communication networks, channel estimation is a key technique, which is used to estimate the state and parameters of the wireless channel, and its plays a vital role in improving both data transmission rate and reliability. The channel in a wireless communication system can be viewed as the combined effect of various interferences and fading to which the signal is subjected during

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transmission [1-4]. Accurate estimation of the state and parameters of the channel can help the receiver to recover during demodulation and detection and improve the capacity and signal quality of the system, and Kalman filtering based is an important method to achieve this goal [5-8].

With the increasing popularity of mobile communication devices and the continuous development of network technology, channel estimation and optimization techniques have been improved and innovated. In channel estimation, the commonly used techniques include least squares, Kalman filter, wavelet transform, etc [9-12]. Among them, the least squares method is a widely used linear algorithm, which can obtain the frequency response of the channel by demodulating the received signal. Kalman filtering, on the other hand, can accurately control the changes of the channel by estimating the state of the channel [13-16]. Kalman filtering is a recursive filtering method, which estimates the channel state and parameters through a state-space model, and can be iteratively updated based on a priori and observation information, which is suitable for dynamic channels and nonlinear systems. It is very important to select appropriate channel estimation methods for different channel conditions and application scenarios [17-20].

Liao,Y. et al [21] proposed a high speed channel estimation algorithm based on nonlinear Kalman filtering, channel interpolation algorithm based on EKF, introduced UKF algorithm,and used BEM to eliminate ICI.The results showed that the channel estimation accuracy of BEM-UKF was improved compared to BEM-EKF and the effect of PD was smaller, which further improved the robustness of the algorithm. Tang,R. et al [22] proposed a KF-based channel estimation method for 2×2 and 4×4 STBCMIMO-OFDM systems, emphasizing that the method has better BER and NMSE performance, and is able to effectively adapt to the dynamic multipath propagation conditions with different low- and high-order modulations.Jellali,Z. et al [23] proposed a delayed subspace by Kalman filtering for the space for non-joint continuous tracking and thus tracking of CIR structures, which outperforms sparsity-independent Kalman tracking algorithms and performs similarly to the best benchmark algorithms based on perfect knowledge of the CIR structure.Salam,A.O.A. et al [24] introduced an automatic modulation classification model combining the KF with the IMM and a method utilizing the singular value decomposition algorithm. The IMM-KF structure was revealed to be advantageous in achieving the targeted optimal performance and reducing the computational complexity load.Siebert,A. et al [25] mentioned hybrid architecture SKF and combined the power of KF and neural networks to benefit from adaptive KF.It was revealed that in a time-varying channel estimation environment with abrupt Doppler frequency variations, the SKF is superior to the 5dB at SNR, and to the LS algorithm at high SNR and better than LS algorithm 3dB.Almamori,A. et al [26] proposed a channel state information estimation method based on detection data, Kalman filtering, and a priori knowledge of the channel, which relies comparatively less on channel statistics and is able to be used without any loss of reachability.Dalwadi,D.C. et al [27] introduced an extended Kalman filter for channel estimation in MIMO-OFDM systems and by comparing it is able to improve the performance in terms of BER and has improved in terms of BER and has achieved the lowest BER.Jain,R.[28] explored the channel tracking problem for time varying channels and proposed the Kalman filter. The excellent performance of Kalman filter as a tracker and predictor with fast convergence of mean square error was emphasized and applied in channel tracking for OFDM systems.Shaw et al [29] used KF for estimation of VLC channel with application of ACO-OFDM and DCOOFD.It was revealed that the KF estimator shows better performance performance with respect to other conventional estimators.Ali,K .S. et al [30] investigated the channel estimation problem for MIMO communication systems in mmWave. And proposed SBLkf based scheme for estimating sparse channel vectors for hybrid mmWave MIMO structures. It is expressed that the SBL-kf algorithm has less estimation error compared to existing algorithms such as SBL and is suitable for implementation in efficient millimeter-wave MIMO systems.Sadr,M.A.M. et al [31] explored the joint problem of recursive channel estimation and robust beamformer design for peer-to-peer communication in a network of time-varying radio channel repeaters. The effectiveness of the recursive CSI estimation method is verified by centralized estimation of CSI using EKF or CKF.Lien,P.H. et al [32] Algorithm for combining channel estimation and CFO estimation in mobile OFDM systems. And the BER performance of the algorithm was emphasized by improving the channel estimation algorithm for better performance.

In summary, Kalman filtering is not only widely used in the estimation of wireless communication channels, but it performs better than other methods, but the current research results are more in expressing the advantages of Kalman filtering, failing to reflect its shortcomings, which has some blindness to the future or other corresponding applications and research.

This paper analyzes the strategic deployment location of channel estimation module in OFDM system as well as the operation of channel estimation through OFDM structure diagram representation. The process of Kalman filtering is analyzed and the OFDM channel estimation method based on Kalman filtering is proposed. Setting the simulation experiment parameters, the Kalman filtering channel estimation method based on comb-guided frequency proposed in this paper is subjected to performance experiments with different Doppler frequency values. The channel frequency response mean-square errors of LS estimation, LMMSE estimation, and the estimation method of this paper are analyzed in different SNR environments when the Doppler frequencies are the same. And the method of this paper is brought into MIMO-OFDM system to check the applicability of this paper's method under different channel schemes.

2. Kalman filter-based channel estimation

2.1. Channel estimation module

Orthogonal Frequency Division Multiplexing (OFDM) wireless communication system reduces the impact of inter-channel interference and inter-code crosstalk suffered by parallel transmission of information-carrying signal waveforms through orthogonal frequency division multiplexing. Saving the computational overhead of channel estimation and equalization modules is a key technology for the development of 4G LTE and 5G NR networks. In order to recover the transmitted signal accurately at the receiver, OFDM needs to obtain the channel state information (CSI) at the receiver when the signal passes through the channel, and channel estimation based on the guide frequency is one of the effective methods to obtain the CSI.

With the development of wireless communication application scenarios, the application scenarios of OFDM are more complex and diversified, and the wireless channel transmission environment is more severe, which puts forward higher requirements for the channel estimation accuracy of OFDM.

The OFDM wireless communication system adopts the scheme of modulating the serial time-domain information stream into multiple low-speed parallel frequency-domain sub-data streams and assigning them to each orthogonal subcarrier channel for independent sending and transmission. The scheme has outstanding resistance to multipath fading and supports large-scale user access.

Channel estimation is the basis for signal detection, demodulation and channel equalization and helps the receiver to eliminate inter-code crosstalk and channel interference from the received signal [33]. The estimation process will provide the CSI of the transmitted signal for channel equalization, signal demodulation, and channel decoding, and improve the accuracy of the receiver's final recovery of bits.The OFDM architecture is shown in Fig. 1, and the channel estimation module is usually deployed at the receiver side in OFDM.

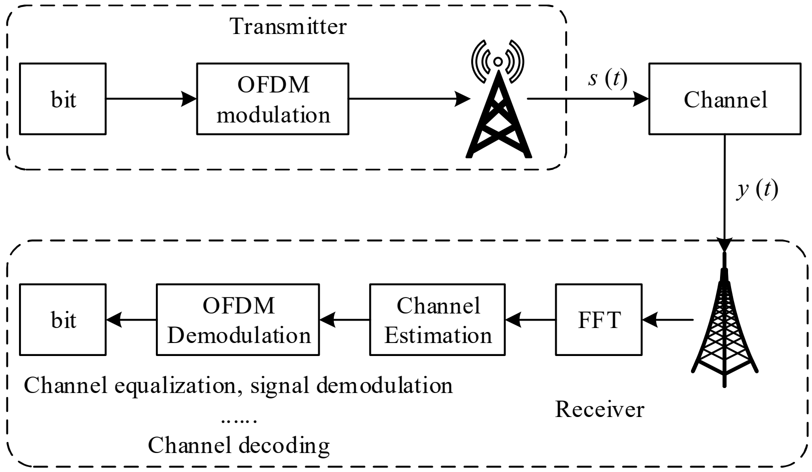

Fig. 1. OFDM structure

2.2. Kalman Filter

Kalman filtering is a more mature estimation method in the field of state estimation, which is best characterized by accurate estimation and low complexity [34-35].

Theoretically, the biggest disadvantage of Wiener filtering is that it needs to use all the historical observation data when filtering, which requires a lot of hardware resources for storage and computation in practical systems. Moreover, when new observations are obtained, a reasonable recursion cannot be utilized. It is difficult to obtain satisfactory filtering results for systems with non-stable environmental conditions. It is difficult to be used for state estimation in non-stationary environments without a suitable recursive method.

The introduction of Kalman filter theory can effectively solve the above problems, which aims at minimizing the mean square error and estimating the unknown variables by recursion. The basic idea is to first establish the state equation and observation equation containing signal and noise according to the actual system. Then a series of related recursive operations are performed. Finally, the estimated value of the previous moment and the observed value of the current moment are combined to make predictions and corrections, and then the state estimate is obtained.

In Kalman filtering, state estimation is one of the most important parts. In a general sense, the quantitative inference of a random variable based on the observed data independently or jointly with the previous data is the estimation. In practice, some systems with time-varying states have high real-time requirements, in which case fast and effective state estimation is very important to ensure the overall performance.

2.2.1. Equations of state and observation.Let the non-smooth vector sequences x_{k-1} and y_{k-1} be described by the following dynamic equations:

$$\begin{cases} x_k = \Phi_{k,k-1} x_{k-1} + w_{k-1} \\ y_k = C_k x_k + v_k \end{cases} (k \geq 0) \tag{1}$$

x_k is the state vector, y_k is the observation vector, w_k is the input noise, v_k is the observation noise, and $\Phi_{k,k-1}$ is the state transfer matrix from moment $k-1$ to moment k. The above dynamic equations can be obtained either by mechanistic derivation of the system or by identification of experimental data, which is assumed to be known here.

The following assumptions are made:

1) w_k and v_k are zero-mean white noise viz:

$$\begin{cases} E[w_k]=0, Cov[w_k, w_j]=E(w_k w_j^T)=Q_k\delta_{kj} \\ E[v_k]=0, Cov[v_k, v_j]=E(v_k v_j^T)=R_k\delta_{kj} \end{cases} \tag{2}$$

Where Q_k is the variance array of the system input noise vector sequence w_k, symmetric non-negative definite. R_k is the variance array of the system observation noise vector sequence v_k, symmetric positive definite. δ_{kj} is the Kronecker δ function:

$$\delta_{kj}=\begin{cases} 0 & k\neq j \\ 1 & k=j \end{cases} \tag{3}$$

2) w_k and v_k are not related, i.e:

$$Cov[w_k, v_j]=E(w_k v_j^T)=0(\forall k, j) \tag{4}$$

3) The initial state x_0 is a random vector of some known distribution or normal distribution and is uncorrelated with w_k and v_k, i.e:

$$\begin{cases} Cov[x_0, w_k]=E[(x_0-Ex_0)w_k^T]=0 \\ Cov[x_0, v_k]=E[(x_0-Ex_0)v_k^T]=0 \end{cases} \tag{5}$$

Kalman filtering means that after establishing the dynamic equation (1) (state and observation equations) which is close to the actual system characteristics, the value of a random sequence of sample-states x_k is estimated by using the sample observation $y_k, y_{k-1}, \cdots$ at each moment, and its estimated value can be noted as $\hat{x}_k$.

Observing the dynamic equation, if there is no observation noise, it can be obtained directly from y_k to x_k. If there is no input noise, it can be obtained directly from x_{k-1} to x_k. However, since w_k and v_k are not zero in practice, the equation (1) cannot be solved directly.

2.2.2. **Calculation process**.In channel estimation of a communication system, the concern is whether the receiver can accurately receive and recover the originally sent data. However, during the communication process, the measurements are often inaccurate due to the effects of noise and the inevitable errors of the measurement instruments themselves. The Kalman filter utilizes this dynamic information-the current moment's observation and the correlation of the time-varying channel at different moments. The Kalman gain coefficients are chosen to minimize the effect of noise, resulting in a more accurate estimate of the channel coefficients. The process of Kalman filtering is shown below.

In a linear system, from moment $k-1$ to moment k, the system state prediction equation can be described as follows:

$$X_k = AX_{k-1} + Bu_k + w_k \tag{6}$$

System state observation equations:

$$Z_k = HX_k + v_k \tag{7}$$

where X_k denotes the current state of the system and A denotes the state transfer matrix. u_k denotes the control signal, i.e., the system input vector. B denotes the weighting of the control signal, i.e., the input gain matrix. w_k denotes the process noise with mean 0, covariance Q and following a normal distribution. It is not generated by observations or measurements, but is an inherent part of the system process. Z_k is the current observation of the system, and H denotes the measurement matrix. v_k is the measured value of the current noise, which is normally distributed with a mean of 0 and a covariance matrix of R, with the initial state X_0 and the noise at each moment $\{X_0, w_1, w_2, \ldots, w_k, v_1, v_2, \ldots, v_k\}$ independent of each other.

In real systems, many truly dynamic systems do not exactly fit this model, but the process described by Eq. (6) and Eq. (7) takes into account the effects of process noise w_k and measurement noise v_k. Therefore many real systems including channel estimation can apply this model.

The goal of Kalman filtering is to obtain the state X_k from the observations Z_k by rewriting Eq. (7) as:

$$X_k = H^{-1}\left(Z_k - v_k\right) \tag{8}$$

From Eq. (8), it can be seen that the biggest problem in solving for the current state is not knowing the current noise. Because the noise is unpredictable. Kalman proposes that the current state $\hat{X}_k$ can be estimated from the current observation Z_k and prediction $\hat{X}'_k$. Based on equation (9):

$$\hat{X}_k = \hat{X}'_k + K_k\left(Z_k - H\hat{X}'_k\right) \tag{9}$$

From the above equation, it can be seen that Kalman filtering consists of two processes, prediction and correction. In the prediction stage, the Kalman filter utilizes the estimation of the previous state to make a prediction of the current system state. In the correction phase, the filter uses the observations of the current state to correct the prediction obtained in the prediction phase to obtain a new estimate that is more closely aligned with the true value.The computational process of Kalman filtering can be expressed as follows:

Prediction phase:

$$\hat{X}'_k = A\hat{X}_{k-1} + Bu_k \tag{10}$$

$$P'_k = AP_{k-1}A^T + Q \tag{11}$$

Calibration phase:

$$\Delta_k = Z_k - H\hat{X}'_k \tag{12}$$

$$K_k = P'_k H^T\left(HP'_k H^T + R\right)^{-1} \tag{13}$$

$$\hat{X}_k = \hat{X}'_k + K_k\Delta_k \tag{14}$$

Update covariance estimates:

$$P_k = \left(I - K_k H\right)P'_k \tag{15}$$

Where, $\hat{X}_k$ denotes the predicted value of the current moment state obtained from the previous moment state estimation result. $\hat{X}_k$ denotes the estimated value of the state of the system after Kalman filtering. P_k denotes the prediction error covariance matrix, P_k denotes the Kalman estimation error covariance matrix, and K_k denotes the Kalman gain.

2.3. Kalman filter based OFDM channel estimation

Kalman filtering method is an estimation method that can be used to estimate the real-time state. Kalman filtering uses state equations to describe the state variables without knowing all the past values and is suitable for time-varying systems. The basic idea of channel estimation based on Kalman filtering, the state space model consists of the system receiving equations and the channel model. Each state variable is updated according to the channel estimate at the previous moment and the signal observation at this moment to get the channel estimate at this moment.

Using Kalman filter for channel estimation, the estimation of the fading process $h_k(n)$ of the n nd OFDM symbol on the k st subcarrier will be performed in two steps. First, the fading process at the pilot symbol location is estimated using the Kalman filter $h_k(n)$. Second, the fading process at the data symbol location will be estimated by using some interpolation methods. Linear, spline or low-pass interpolation, and in this paper linear interpolation is used.

When a comb lead frequency distribution is used, the N_p lead frequencies are inserted uniformly $x_k(n)$ in the following manner:

$$x_k(n) = x_{uL+i}(n) = \begin{cases} x_{uL,pilot}(n), i = 0 \\ x_{uL,i,data}(n), i = 1, 2, \cdots, L-1 \end{cases} \tag{16}$$

where $x_{n,pilot}(n)$ is the guide frequency symbol, $u = 0, 1, \cdots, N_p - 1$, $L = M / N_p$ are the guide frequency intervals, and M is the number of subcarriers.

In this paper, a Kalman filter based on a Kalman filter with known guide frequency symbols is used to estimate the fading process on the n th OFDM symbol on the k th subcarrier $h_k(n)$. The frequency indexes are deleted for brevity and clarity of presentation. Therefore, the fading process $h_k(n)$ is represented by h_n. The Kalman filter estimation procedure for the fading process is as follows. Define the state vector as follows:

$$h_n = \begin{bmatrix} h_n & h_{n-1} & \cdots & h_{n-p+1} \end{bmatrix}^T \tag{17}$$

Equation (17) can then be written in the following state-space form:

$$h_n = \Phi h_{n-1} + g v_n \tag{18}$$

where $\Phi = \begin{bmatrix} -a_1 & -a_2 & \cdots & -a_p \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 1 & 0 \end{bmatrix}$, $g = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix}^T$.

Combining equations (17) and (18) results in the following:

$$y_n = x_n^T h_n + \eta_n \tag{19}$$

where $x_n = \begin{bmatrix} x_{n,pilot} & 0 & \cdots & 0 \end{bmatrix}^T$.

Thus, Eqs. (17) and (18) represent the state space model of the n rd OFDM symbol fading channel system on the k nd subcarrier. The standard Kalman filtering algorithm can then be performed to provide an estimate $\hat{h}_{n|n}$ of the state vector h_n given the set of observations $\{y_i\}$.

The core of the standard Kalman filtering algorithm is the "prediction-correction" process, which predicts the value of moment k based on the filtered estimate of moment $k-1$. The error between the true observed value and the predicted value at moment k is calculated, and this error is used to correct the predicted value to obtain the filtered estimate at moment k. In this process, the error between the true observed value and the predicted value is called "new interest". The "new interest" reflects the inaccuracy of the filtered estimate, and when the "new interest" is zero, the filtered estimate is the true state at moment k.

Considering the computational complexity of the channel estimation algorithm, the channel model in this paper adopts the 1st order AR model for channel estimation.

From the Jakes fading channel model, the variance of the fading parameter a and the process noise v_n in Eq. (18) can be expressed by the Yule-Walker equation as follows:

$$a = J_0\left(2\pi f_d T_s\right) \tag{20}$$

$$\sigma_v^2 = \left(1 - a^2\right)\sigma_i^2(n) \tag{21}$$

$\sigma_{\hat{h}}^2(n)$ in Eq. (21) is the variance of h_n.

3. Kalman filter channel estimation simulation

3.1. Fixed Doppler frequency

3.1.1. OFDM system parameters.Here the above proposed Kalman filter channel estimation method based on comb pilot is simulated and analyzed using MATLAB and its performance is compared with other algorithms. In simulation OFDM system parameters are shown in Table 1.

Table 1. OFDM system simulation parameters

Parameter	Specific value
FFT length (N)	64
OFDM Sign cycle	0.45ms
Protection interval length	20
Pilot interval	1/10
Symbol modulation mode	6QAM
Channel model	Rayleigh fading channel jakes model
Channel multipath (N)	12
Maximum delay	0.050ms

Since this chapter focuses on channel estimation algorithms under time-varying channels, the channel Doppler frequency f_d = 500 Hz. the number of channel paths is 12 in units of μs. The per-path attenuation amplitude is: $\{0,-2,-5,-10,-15,-20,-25,-30\}$ in units of dB. In order to better compare the performances of the various channel estimation methods, it is assumed that the received signals are perfectly synchronized. The length of the guard interval is also chosen to be greater than the maximum delay extension to avoid inter-symbol interference.

3.1.2. Simulation results.The channel frequency response mean square error-SNR curves obtained by various channel estimation methods are shown in Fig. 2.

At different SNRs, the channel frequency response mean square error obtained by the various methods is different.LS estimation is the simplest, but the performance is poorer.LMMSE estimation improves the channel estimation mean square error performance by 3~7 dB compared with LS at higher SNRs. However, both methods show the so-called floor effect at higher signal-to-noise ratios. The mean square error performance of the curves flattens out at S/N ratios of 27.5~35 dB. Even if the signal-to-noise ratio of the received signal is increased further, the estimation error does not decrease significantly. Therefore, both methods are not well suited for time-varying channels with fast fading. This is mainly due to the fact that in the fast fading environment, the Doppler shift disrupts the orthogonality between subcarriers, leading to inter-subchannel interference (ICI), and the usual estimation methods, such as LS and LMMSE, are able to effectively overcome the effect of AWGN, but are less resistant to ICI interference of the channel.

Compared to the usual estimation methods, the Kalman filtered channel estimation method based on comb-conductance proposed in this paper provides a large improvement in the estimated MSE. At an MSE of -4.0$\times 10^3$, the signal-to-noise ratio performance improvement is more than 10 dB compared to LS. Especially at higher SNR, the floor effect, which cannot be avoided by LS and LMMSE, is effectively overcome and the estimation error of the channel is effectively improved. This is mainly due to the fact that Kalman filtering computes the estimation error at iteration time and adjusts the estimate for the next iteration. Therefore the estimation error decreases as the number of iterations increases, and the estimate of the frequency bias gets closer to the actual value.

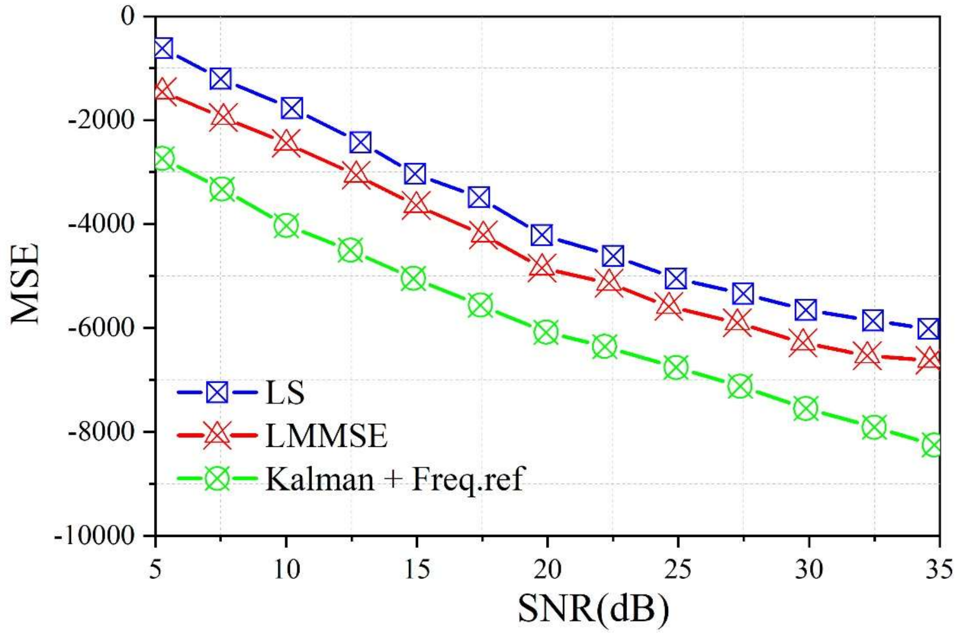

Fig. 2. Several estimation methods compare the MSE-SNR curve

The BER-SNR curves of different estimation methods for different channel environments are shown in Fig. 3. The BER-SNR performance of LS and Kalman filter-based channel estimation methods for different values of Doppler shift are compared.

From the figure, it can be seen that the BER-SNR performance of the Kalman filter estimation algorithm proposed in this paper outperforms the LS estimation in two completely different channel environments, namely, faster and slower channel fading. It can also be seen from the figure that the overall BER-SNR performance of the Kalman filter-based channel estimation algorithm decreases when the Doppler shift increases. This is mainly due to the fact that this paper uses a first-order AR model in order to reduce the computational complexity when modeling the channel. This limits the estimation accuracy when the change of the channel is accelerated. If the estimation accuracy is to be further mentioned, the AR model order can be increased to better adapt to the channel variations.

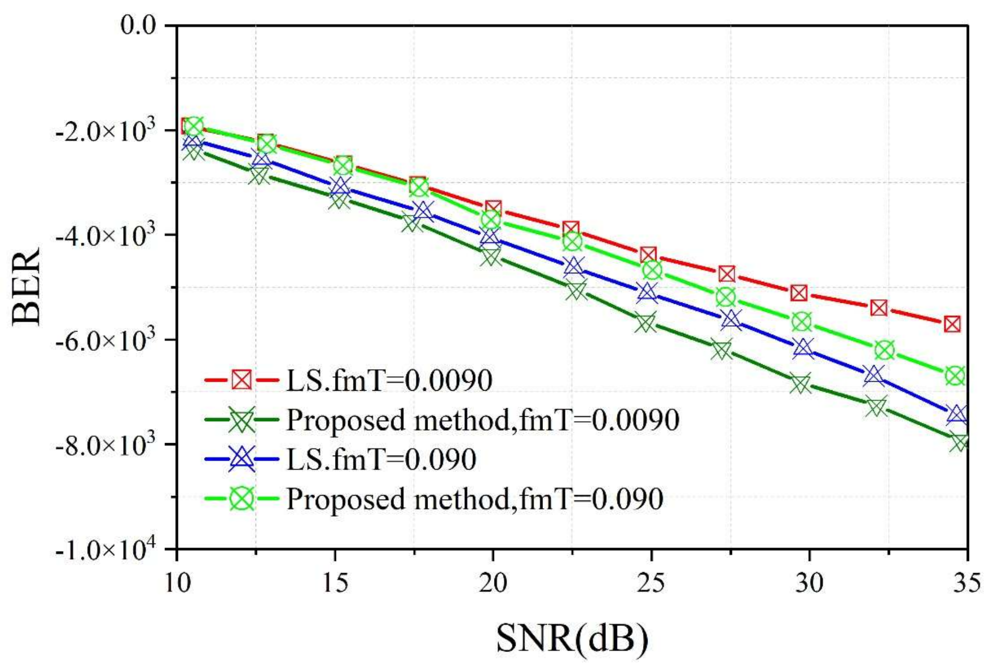

Fig. 3. The different estimation method of the SNR curve

3.2. Different Doppler frequencies

Assume that the channel estimation of the guide auxiliary sequence is performed using Kalman filtering when the noise variance is known.

Fix the frequency-guided auxiliary sequence to be a Gray's complement sequence of length 8192 and transmit power 1. Set the Doppler frequency to be 15 Hz and the channel to be a single-path fading channel.

The Doppler frequencies are set to be 0 Hz, 15 Hz, 45 Hz, and 90 Hz. The channel is set to be a 2-path, and the interval between the two paths is 2 each symbol period. The measure uses the mean square error between the actual channel response on each symbol and the channel estimation result, i.e:

$$\rho = \frac{1}{N}\sum_{n=0}^{N-1}\left(\hat{h}_n - h_n\right)^2 \tag{22}$$

The results of the variation of the mean square error with the signal-to-noise ratio at different Doppler frequencies are shown in Fig. 4, where the range of the simulated signal-to-noise ratio is set lower. It can be seen that channel estimation using Kalman filtering can lead to more accurate channel estimation results.

When the Doppler frequency is 0Hz, the performance of the two is basically the same. When the Doppler frequency is not 0Hz, the channel estimation based on Kalman filtering can make the performance get a significant improvement. The higher the Doppler frequency, the more the performance is improved compared with the traditional channel estimation with the help of guide frequency sequence. At the same time, since the channel estimation result is affected by the signal power when the SNR increases, the error will be larger at higher SNR if the ML method is used. When the Doppler frequency reaches 90 Hz, the performance of Kalman filter-based channel estimation can be improved by one order of magnitude at 0 dB, which is also good at low SNR. In summary, Kalman filter-based channel estimation can make the results of channel estimation follow the channel changes more accurately.

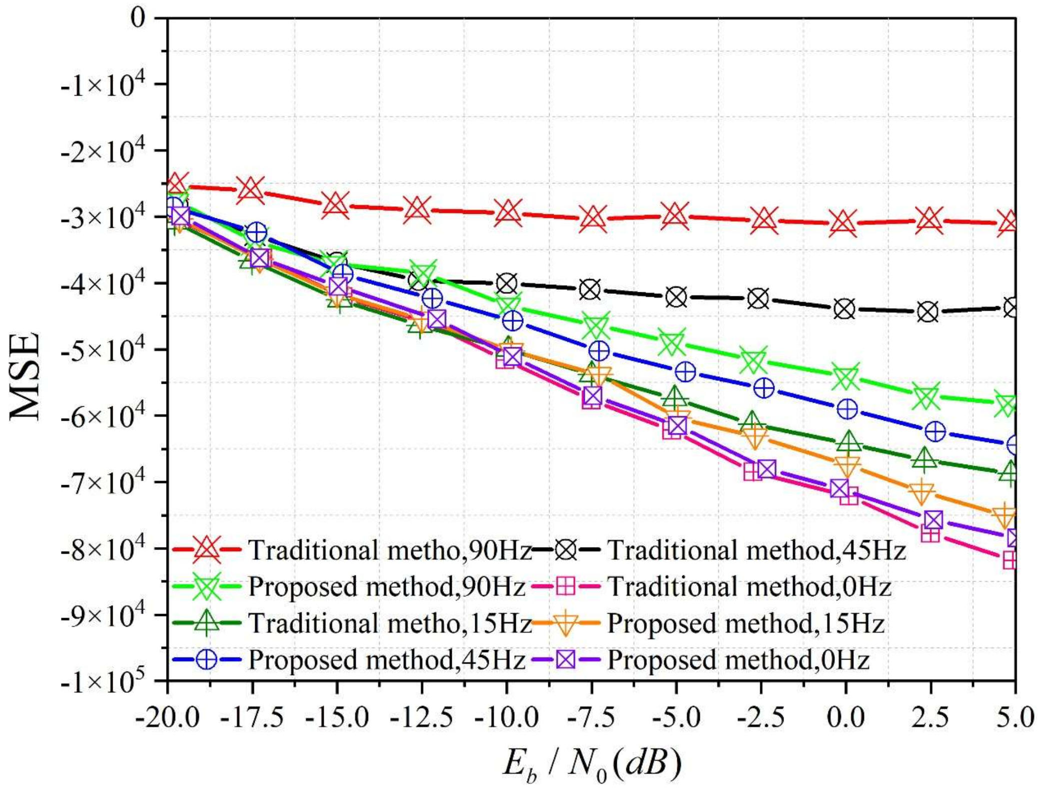

Fig. 4. The results of the variation of the average error in different doppler frequencies

4. Kalman filter-based OFDM-MIMO channel simulation

The OFDM modulation structure model based on Kalman filtering solves as many problems as possible such as antenna RF end coupling, antenna gain calibration, phase noise interference and antenna unit coupling. At the same time in the transmission module to amplify the gain characteristics of the peak control end of the linear characteristics and energy consumption, etc., are module design should be considered.

In large-scale multipath channel transmission, considering the economic cost of deployment of scenario applications, a large number of antenna units are used as analog components, but this also introduces the non-ideal characteristics of the analog front-end. Thereby, distortion and interference are generated during information reception and processing, which directly leads to the deviation of the signal transmitted by the transceiver system (base station). Therefore, it is crucial to model these non-ideal components in a reasonable way.

In this chapter, the analog channel simulation is analyzed by the large-scale multiple-input multiple-output (MIMO) fast processing module. Numerical simulation analysis is carried out for the relay selection scheme random channel and the random channel using OFDM modulation. In order to visualize and analyze the outage probability and its SNR performance of the OFDM channel processing module under Kalman filtering based in scale random channel. In this case, when the channel diversity order (number of channels) is large, the transmission characteristics and performance of the multipath channel decreases accordingly and the value of the outage probability increases exponentially. Since there is an estimated component of channel distortion noise and channel performance, the Kalman filtering algorithm provides a more reliable information transmission channel for the channel.

4.1. Large-scale MIMO-OFDM systems

4.1.1. MIMO technology.MIMO technology can improve the performance or channel capacity of a communication system by employing multiple antenna arrays at the transmitter or receiver end.

MIMO systems can provide two types of gain, spatial diversity gain and spatial multiplexing gain.

Spatial diversity improves the reliability of communication in fading channels by sending the same data at different antennas. Spatial multiplexing improves the effectiveness of communication by sending different data at different antennas.

The basic idea of spatial diversity technique is to make multiple copies of the transmitted signal to counter channel fading through independent fading propagation paths. At the receiving end, multiple independent fading copies of the transmitted data signal are coherently combined for more reliable reception. Smart antenna techniques and Alamouti coding techniques are well known spatial diversity techniques. If spatial diversity is a means to combat fading, spatial multiplexing is an effective way to increase the capacity of MIMO systems. Essentially, if the path gains between individual transmit antenna pairs are independently faded such that the channel matrix is well-conditioned. Then the data rate can be increased by creating multiple parallel spatial channels by sending multiple data streams through the spatial channel.

4.1.2. MIMO-OFDM System Composition. The massive MIMO-OFDM system contains N_t transmit antenna and N_r receive antennas. Therefore, the massive MIMO channel consists of $N_t \times N_r$ propagation sub-channels. At moment n, the input data can be expressed as:

$$x[n,k]=\left[x^{(1)}[n,k]x^{(2)}[n,k]\cdots x^{(N_1)}[n,k]\right]^T, k=1,2\cdots K \tag{23}$$

Where $x^{(i)}[n,k]$ denotes the moment n the i rd transmitting antenna, the transmit symbol of the k th subcarrier, K is the number of subcarriers, and the superscript "T" denotes the transpose operator.

OFDM uses the discrete Fourier inverse transform (IDFT) to modulate the transmit signal. Correspondingly, Discrete Fourier Transform (DFT) is used at the receiver side to demodulate the received signal. Inserting a cyclic prefix (CP) of length L_{CP}, the antenna frequency domain signal received at the u th receiving antenna can be expressed as:

$$y^{(u)}[n,k]=\sum_{v=1}^{N_t} H^{(uv)}[n,k]x^{(u)}[n,k]+v^{(u)}[n,k] \tag{24}$$

where $H^{(uv)}[n,k]$, $v^{(u)}[n,k]$ represent the frequency response and additive Gaussian white noise from the v rd transmitting antenna to the u th receiving antenna at the k th subcarrier, respectively.

Similar to the signal at the transmitting end, defined at moment n, the received signal, channel frequency response, and noise at the k th subcarrier are, respectively:

$$y[n,k]=\left[y^{(1)}[n,k]y^{(2)}[n,k]\cdots y^{(N_k)}[n,k]\right]^T \tag{25}$$

$$H[n,k]=\begin{bmatrix} H^{(11)}[n,k] & H^{(12)}[n,k] & \cdots & H^{(1N_1)}[n,k] \\ H^{(21)}[n,k] & H^{(22)}[n,k] & \cdots & H^{(2V_1)}[n,k] \\ \vdots & \vdots & \ddots & \vdots \\ H^{(N_r)}[n,k] & H^{(N_r)}[n,k] & \cdots & H^{(N_rN_1)}[n,k] \end{bmatrix} \tag{26}$$

$$v[n,k]=\left[v^{(1)}[n,k]v^{(2)}[n,k]\cdots v^{(N)}[n,k]\right]^T \tag{27}$$

Therefore, according to Eq. (23), the received signal can be written as:

$$y[n,k] = H[n,k]x[n,k] + v[n,k] \tag{28}$$

4.2. Simulation Analysis

4.2.1. Random channels.The parameters are set as follows: $a_{SR_n} = a_{R_nD} = 5$, $N_{SR_n} = N_{R_nD} = 2$, $\mu_{SR_n} = \mu_{R_nD} = \mu = 1$, $\sigma_{e_{SR_n}} = \sigma_{e_{R_nD}} = \sigma_{ei}$, $\kappa_{SR_n} = \kappa_{R_nD} = \kappa$. The corresponding performance outage probability shows a decreasing trend with increasing performance SNR, channel estimated transmission parameter σ_{ei} = 0.02, hardware impairment level $\kappa = 0.2$, and threshold rate of $\gamma_{th} = 50$ bits/channel. Meanwhile, the SNR of the channel decreases as the parameter μ of the fading channel increases.

The variation curve between the SNR performance of the channel and the interruption performance is shown in Fig. 5. In the massive MIMO multipath random transmission channel, the smaller the interruption probability is, and as the SNR performance of the channel becomes better, the smaller the probability of generating interruptions. Meanwhile, in the presence of the same non-ideal factors (hardware impairments, interference noise) interruption probability impairments in the channel, the SNR in the OFDM-ideal state is about 10 dB more than the OFDM-hardware impairments simulation value, and the simulation performance of the modulated channel with OFDM-MIMO is 10-18 dB worse than that of the simulation performance of the channel without the use of modulation detection.

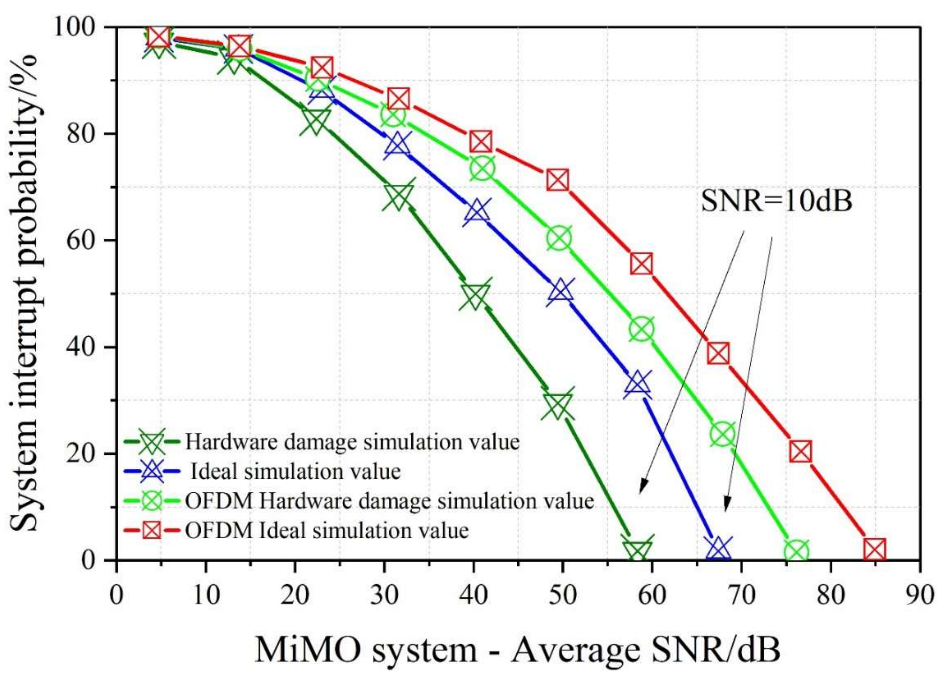

Fig. 5. The SNR performance and interrupt performance relationships of the channel

4.2.2. Random channel with OFDM modulation.When the Kalman filter structure is loaded into the OFDM scheme, the variation of random channel transmission performance SNR and interruption performance is shown in Fig. 6.

The simulation results in the above figure are compared with the simulation results here. In the case of scale multipath channel random transmission channel, after loading the Kalman filter structure at the antenna side in the OFDM -MIMO modulation scheme, its overall channel transmission SNR performance is 10 dB more than that of the channel transmission performance without loading the Kalman filter structure, while the interruption performance keeps the same change (compare its horizontal coordinate in dB decibels). That is, the Kalman filter has a greater improvement in the performance of the OFDM modulation scheme in the case of multipath channel transmission.

Therefore, both the interruption performance of the channel and the SNR performance of the channel are related to the modulation technique module processing used and are related to the distortion noise factor channel estimation parameters, fading coefficients, etc. of the channel. In other words, the SNR and interruption performance of the scale MIMO channel is related to the optimal filter (Kalman filter) detection structure.

For the optimal relay selection channel transmission scheme, it is related to the number of antennas R_n in addition to the selection and performance of the modulation scheme. In other words it is related to the number of relay forwarding sites N. In this simulation, the threshold of the system is set to $\gamma_{th} = 50$ bits/channel, and the hardware impairment level and channel parameter estimation errors are $\kappa = 0.2$ and $\sigma_{ei} = 0.3$. A clear and intuitive reflection of the variation of the interruption probability in the MIMO channel transmission scheme with respect to the number of nodes in the relaying stations can be seen in Fig. When the diversity order of the channel is increased, where the expression for the diversity order of the relay transmission channel is $min\left(\prod_{n=1}^{N} \alpha_{SR_n} \mu_{SR_n} / 2, \alpha_{R_nD} \mu_{R_nD} / 2\right)$, i.e., that is, when the number of relay channels is increased consequently, the outage probability of the system is already lost close to 20% when it exceeds N =500. It can be seen that the increase in the number of relays N affects the operation of the transmission system.

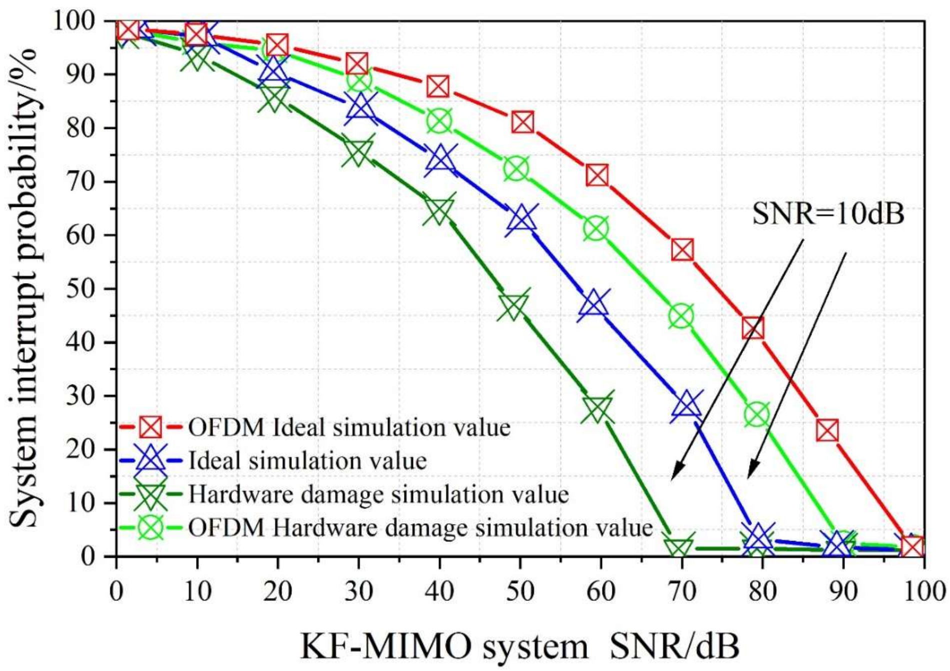

Fig. 6. KF-OFDM SNR performance and interrupt performance relationships

4.2.3. MIMO systems.The relationship between the number of MIMO-relay channel nodes and the outage probability performance is shown in Fig. 7, which shows the outage performance probability of the system obtained in four transmission channel simulation environments. In the case of ideal simulation channel state, its transmission channel is less affected by the number of relay channels than the random transmission channel with hardware impairments. The position of its curve is shifted to the right. When the channel is loaded with Kalman-based OFDM modulation filter structure, its hardware damage simulated channel state information is better than the channel performance without filter bank. And the transmission performance curve of the ideal state channel loaded with OFDM modulation filter is shifted to the right and the performance improvement is nearly 6% to 10%. Its channel transmission performance is 10% better than the channel transmission performance in the hardware damage case.

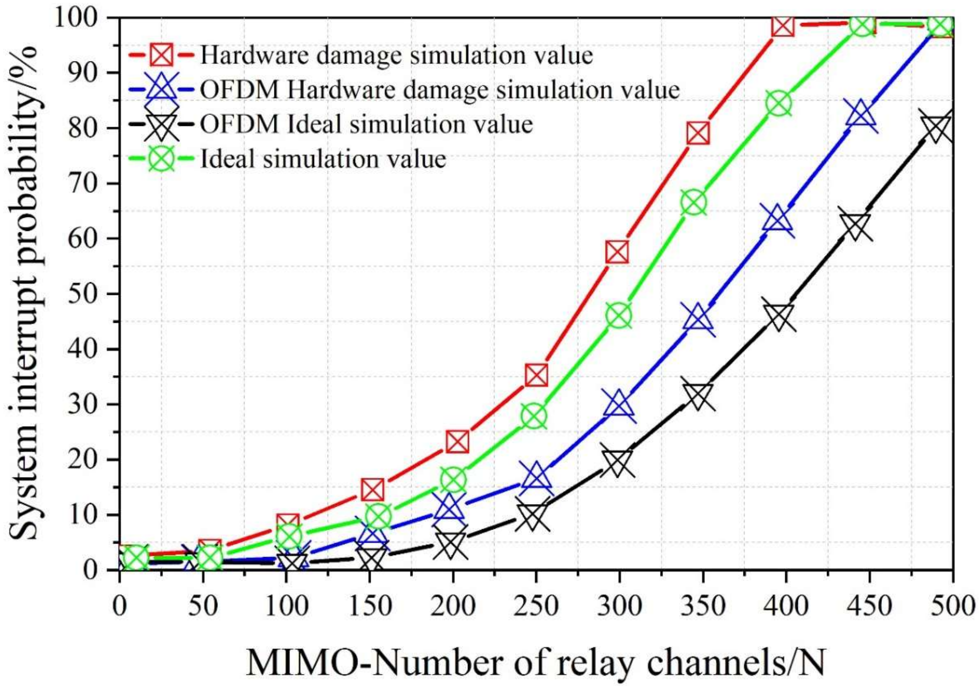

Fig. 7. The number and performance of the relay channel nodes

5. Conclusion

In this paper, the Kalman filter algorithm is applied to the channel estimation of OFDM wireless communication, and the Kalman filter channel estimation method based on comb-guided frequency is proposed. Simulation experiments are carried out to analyze the performance of Kalman filtering method in OFDM system and OFDM-MIMO system. Under the simulation experiment with limited Doppler frequency f_d =500Hz, the proposed Kalman filter channel estimation method based on comb-guide frequency can improve the MSE value of channel estimation. At MSE = -4.0×10^{3}, the signal-to-noise performance improvement compared to LS is more than 10 dB. Without limiting the Doppler frequency, the Kalman filtering-based channel estimation method is able to obtain more accurate channel estimation results in the low SNR range. The Kalman filter-based channel estimation method proposed in this paper is applied to large-scale MIMO-OFDM systems, and the simulation test shows that the method in this paper is able to obtain better performance in random channels, random channels using OFDM modulation, and MIMO systems.

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