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Research on Hybrid MIMO Channel Estimation based on Multivariate Training Sequence

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Abstract. Channel estimation has always been one of the key points in the research of multiple input multiple output (MIMO) communication systems. This paper proposes a hybrid MIMO channel estimation algorithm based on multiple training sequences which combine sequential insertion mode and superposition mode. In this algorithm, a channel estimation model based on multiple training sequences is proposed. Using the periodic superposition of multiple training sequences, the training sequence signal is enhanced and the state estimation of the channel is realized. At the same time, the channel estimation is improved by using the excellent autocorrelation function of the multiple training sequences and the lower peak average power bit. By combining the channel estimation model of the timing insertion mode and the channel estimation model of the superposition mode, the power of the training sequence and the length of the training sequence can be adjusted flexibly, and the spectrum utilization of the MIMO communication system can be improved. The experimental results show that this algorithm is more suitable for flexible channel environment.

Keywords: channel estimation, MIMO, training sequence, superimposed algorithm

1 Introduction

The multiple-input and multiple-output (MIMO) is a modern wireless communication system with strong capacity and high diversity gain. The performance of the system directly hinges on the channel state information (CSI) [1-3]. As a result, channel estimation has attracted much attention in the research of MIMO. One of the popular channel estimation methods is based on a training sequence, which is either in the time domain or superimposed. The time-domain training sequence-based method (hereinafter referred to as the time-domain method) achieves a high signal-to-noise ratio (SNR) by transmitting the training sequence in a separate timeslot [4], while the superimposed training sequence-based method (hereinafter referred to as the superimposed method) can save a certain amount of spectrum resources for the training sequence is superimposed with the data information for transmission [5-6].

For both methods, the design of the training sequence has been the research focus of MIMO channel estimation [7-10]. For instance, Reference [9] puts forward a MIMO channel estimation model for the superimposed method; Instead of occupying extra signal bandwidth, the proposed model can derive the channel estimation error, the lower limit of channel capacity and a compact Cramér–Rao bound (CRB) through the least squares (LS) method. Reference [10] integrates the zero-correlation zone (ZCZ) sequence to the superimposed method, creating a new estimation method for MIMO-frequency selective channels; the new method eliminates the DC offset with the equilibrium property of the ZCZ sequence. In order to improve the performance of the channel estimation, the characteristics of channel environment

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are also been researched in [11-15]. Reference [11] tackles MIMO channels with a certain spatial correlation, and explores how to determine the optimal length of the training sequence based on relevant channel information. Reference [12] designs an effective training sequence generation (TSG) algorithm for multi-carrier communication based on the offset quadrature amplitude modulation (OQAM); the TSG algorithm proposes a new type of training sequences through the cascading of two ZCZ sequences, whose auto-correlation and cross-correlation are both zero at the same position around the time-shifted window. References [13-14] optimize the design of training sequences for MIMO channel estimation considering the spatial fading correlation, and propose the estimation mean square error (MMSE) method; the results show that the addition of spatial correlation can enhance the estimation accuracy and shorten the training time. Focusing on sparse channels, [15] investigates the time-domain method by compressive sensing, presents several optimization criteria for the design of time-domain training sequences, and suggests that the optimized design of training sequences for MIMO channel estimation, which depends on channel features like type of fading and channel noise model. The training sequence methioned above are designed in binary sequence, in order to expand the field of training sequence, this paper uses the multivariate training sequence to estimate the channel information.

Based on the above research, this paper adopts the multivariate training sequence as the training sequence for MIMO channel estimation according to the optimal design criteria, and puts forward a mixed channel estimation method based on time-domain method and superimposed method (hereinafter referred to as the “mixed channel estimation method”). The purpose is to further enhance the performance of the MIMO communication system with the excellent correlation and good secrecy of the multivariate training sequence and the merits of the two training sequence-based methods.

The rest of this paper is organized as follows. In Section Two, the concept of multivariate training sequence is given and we also give the peak-to-average power ratio (PAPR) of the training sequence. In Section Three, multivariate time-domain method will be given. Next, multivariate superimposed method will be deduced. Section Five gives mixed channel estimation method. Section Six gives the simulation and the analysis of the results. Finally, conclusions are drawn in Section Seven.

2 Multivariate Training Sequence

Let **A** be a family of P multivariate training sequences, each of which contains of K sub-sequences. Suppose each sub-sequence is L in length. Then, **A** can be described as **A**(P,K,L) with the matrix below.

$$\mathbf{A}=\left[\mathbf{A}_1,\mathbf{A}_2,\cdots,\mathbf{A}_P\right]^T=\begin{bmatrix}\mathbf{A}_1^1 & \mathbf{A}_1^2 & \cdots & \mathbf{A}_1^K\\ \mathbf{A}_2^1 & \mathbf{A}_2^2 & \cdots & \mathbf{A}_2^K\\ \vdots & \vdots & \ddots & \vdots\\ \mathbf{A}_P^1 & \mathbf{A}_P^2 & \cdots & \mathbf{A}_P^K\end{bmatrix} \tag{1}$$

Thus, the length of each $\mathbf{A}_p^k (1\le p\le P, 1\le k\le K)$ is L, and the sub-sequence $\mathbf{A}_p^k$ contains elements $\mathbf{A}_p^{k,l}(1\le l\le L)\in\{1,j,-1,-j\}$. In this case, **A** can be called a quaternary sequence. If the sequences in **A** satisfy the following conditions, then **A** can be called a quaternary orthogonal sequence.

Autocorrelation function:

$$\begin{gathered}\begin{cases}R_{A_1^1,A_1^1}+R_{A_1^2,A_1^2}+\cdots+R_{A_1^K,A_1^K}=KL & (\tau=0)\\ R_{A_1^1,A_1^1}+R_{A_1^2,A_1^2}+\cdots+R_{A_1^K,A_1^K}=0 & (\tau=others)\end{cases}\\ \begin{cases}R_{A_2^1,A_2^1}+R_{A_2^2,A_2^2}+\cdots+R_{A_2^K,A_2^K}=KL & (\tau=0)\\ R_{A_2^1,A_2^1}+R_{A_2^2,A_2^2}+\cdots+R_{A_2^K,A_2^K}=0 & (\tau=others)\end{cases}\\ \vdots\\ \begin{cases}R_{A_P^1,A_P^1}+R_{A_P^2,A_P^2}+\cdots+R_{A_P^K,A_P^K}=KL & (\tau=0)\\ R_{A_P^1,A_P^1}+R_{A_P^2,A_P^2}+\cdots+R_{A_P^K,A_P^K}=0 & (\tau=others)\end{cases}\end{gathered} \tag{2}$$

Cross-correlation function:

$$R_{A^1_{p1},A^1_{p2}} + R_{A^2_{p1},A^2_{p2}} + \cdots + R_{A^Q_{p1},A^Q_{p2}} = 0 \qquad (\tau = any \quad delay) \tag{3}$$

where $R(\cdot)$ is the correlation function ($1 \le p1, p2 \le P$, $p1 \ne p2$); τ is the time delay. The $R(\cdot)$ is an autocorrelation function if the two sequences are the same, and a cross-correlation function if otherwise. The sequence family **A** is an orthogonal sequence if it satisfies the above autocorrelation function and cross-correlation function.

Fig. 1 and Fig. 2 show the PAPR between without pre-coding and multivariate orthogonal sequence, respectively. As shown in Fig. 1 and Fig. 2, the PAPR of multivariate orthogonal sequence is 9db smaller than that without pre-coding.

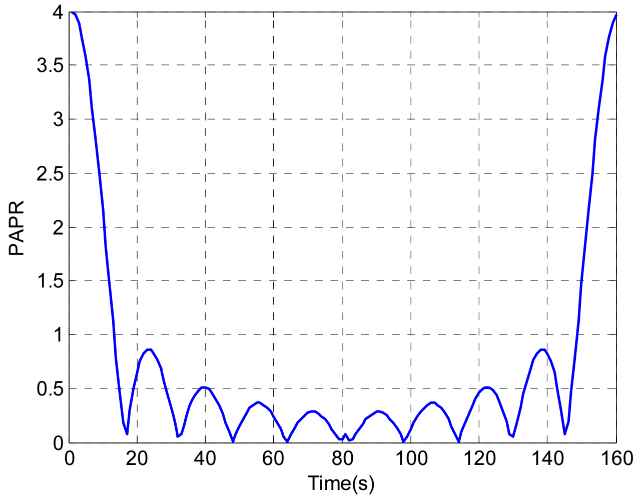

Fig. 1. PAPR without pre-coding

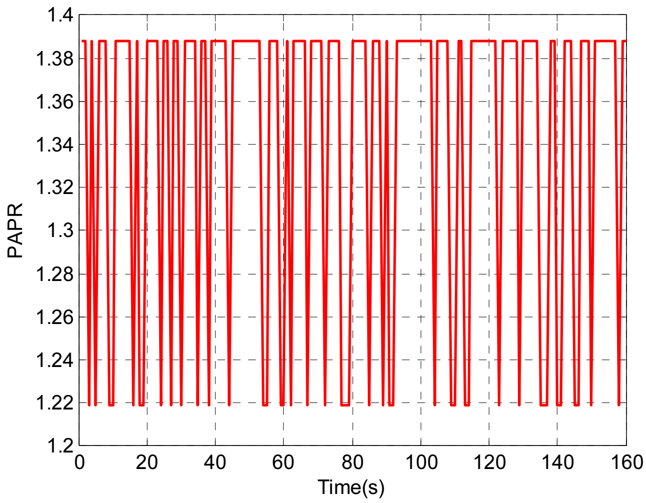

Fig. 2. PAPR of multivariate orthogonal sequence

3 Multivariate Time-domain Method

A MIMO communication system with time-domain training sequence transmits signals alternatively in different timeslots at the same frequency. This communication method is known for channel reciprocity. Thanks to this feature, the accurate channel information can be acquired solely based on the training sequence of the uplink.

Fig. 3 shows a channel estimation model based on multivariate time-domain training sequence. In this model, the multivariate orthogonal sequence is K=2, i.e. each sequence contains two sub-sequences.

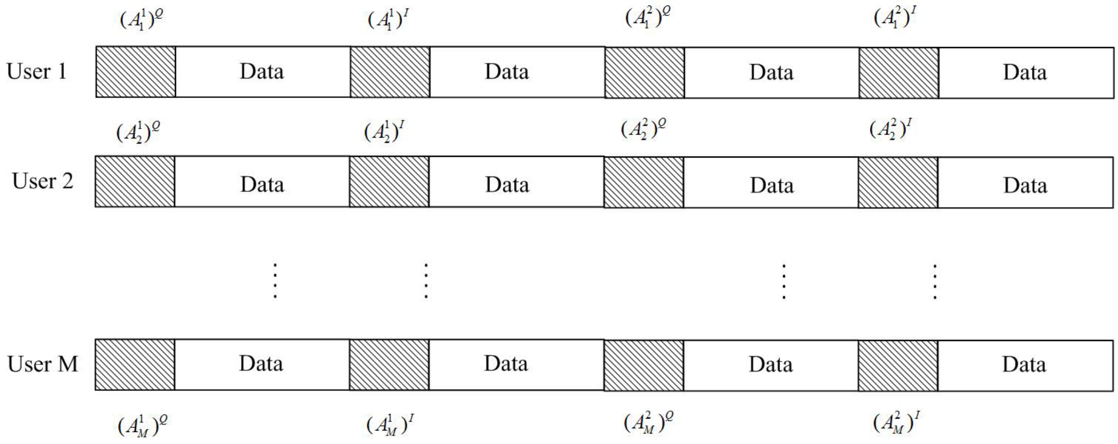

Fig. 3. MIMO channel estimation model based on multivariate time-domain training sequence

In light of Fig. 1, it was assumed that there are M users and N base stations. Then, M sequences were selected from the family of P sequences to serve as the training sequence for the MIMO system. Hence, M must be equal to or smaller than P. Let $\mathbf{A}_m$ be the multivariate training sequence for user m, $(\mathbf{A}_m^k)^Q$ be the real part of the multivariate training sequence $(\mathbf{A}_m^k)$, and $(\mathbf{A}_m^k)^I$ be the imaginary part of $(\mathbf{A}_m^k)$ ($1 \le m \le M$). Since K=2, we have k=1, 2.

Next, the LS was been introduced to estimate the CSI of the MIMO communication system. The signal model at the receiving end of the MIMO system can be expressed as:

$$\mathbf{Y} = \sqrt{\frac{\rho}{M}}\mathbf{H}\mathbf{X} + \mathbf{V} \tag{4}$$

where ρ is the transmitted pilot power (it is assumed that all users share the same pilot power); $\mathbf{H}$ is the channel coefficient matrix; $\mathbf{X}$ is the transmitted training sequence matrix; $\mathbf{V}$ is the additive white Gaussian noise matrix (mean value: zero). Let $\hat{\mathbf{H}}_{LS}$ be the estimated CSI of channel $\mathbf{H}$. Then, the objective function of LS estimation can be expressed as:

$$\begin{aligned} E(\hat{\mathbf{H}}_{LS}) &= \left(\mathbf{Y} - \sqrt{\frac{\rho}{M}}\hat{\mathbf{Y}}\right)^H \left(\mathbf{Y} - \sqrt{\frac{\rho}{M}}\hat{\mathbf{Y}}\right) \\ &= \left(\mathbf{Y} - \sqrt{\frac{\rho}{M}}\hat{\mathbf{H}}_{LS}\mathbf{X}\right)^H \left(\mathbf{Y} - \sqrt{\frac{\rho}{M}}\hat{\mathbf{H}}_{LS}\mathbf{X}\right) \end{aligned} \tag{5}$$

where $(\cdot)^H$ is the conjugate transpose operation; $\mathbf{Y}$ is the matrix of the signals received at the receiving end; $\hat{\mathbf{Y}}=\hat{\mathbf{H}}_{LS}\mathbf{X}$ is the training sequence output signal matrix obtained after channel estimation. According to equation (5), the LS algorithm aims to estimate the CSI when the partial derivative of the objective function relative to $\hat{\mathbf{H}}_{LS}$ is zero, that is:

$$\frac{\partial\left\{\left(\mathbf{Y} - \sqrt{\frac{\rho}{M}}\hat{\mathbf{H}}_{LS}\mathbf{X}\right)^H \left(\mathbf{Y} - \sqrt{\frac{\rho}{M}}\hat{\mathbf{H}}_{LS}\mathbf{X}\right)\right\}}{\partial\hat{\mathbf{H}}_{LS}}=0 \tag{6}$$

By solving equation (6), we have the channel estimation:

$$\hat{\mathbf{H}}_{LS}=\sqrt{\frac{M}{\rho}}\mathbf{Y}\mathbf{X}^H\left(\mathbf{X}\mathbf{X}^H\right)^{-1} \tag{7}$$

expressed as follows according to equation (1):

$$\mathbf{X}=\begin{bmatrix}\mathbf{A}_1^1 & \mathbf{A}_1^2\\ \mathbf{A}_2^1 & \mathbf{A}_2^2\\ \vdots & \vdots\\ \mathbf{A}_M^1 & \mathbf{A}_M^2\end{bmatrix} \quad \mathbf{(8)}$$

Thus,

$$\begin{aligned}\mathbf{XX}^H&=\begin{bmatrix}\mathbf{A}_1^1 & \mathbf{A}_1^2\\ \mathbf{A}_2^1 & \mathbf{A}_2^2\\ \vdots & \vdots\\ \mathbf{A}_M^1 & \mathbf{A}_M^2\end{bmatrix}\begin{bmatrix}(\mathbf{A}_1^1)^* & (\mathbf{A}_2^1)^* & \cdots & (\mathbf{A}_M^1)^*\\ (\mathbf{A}_1^2)^* & (\mathbf{A}_2^2)^* & \cdots & (\mathbf{A}_M^2)^*\end{bmatrix}\\ &=\begin{bmatrix}\mathbf{A}_1^1(\mathbf{A}_1^1)^*+\mathbf{A}_1^2(\mathbf{A}_1^2)^* & \mathbf{A}_1^1(\mathbf{A}_2^1)^*+\mathbf{A}_1^2(\mathbf{A}_2^2)^* & \cdots & \mathbf{A}_1^1(\mathbf{A}_M^1)^*+\mathbf{A}_1^2(\mathbf{A}_M^2)^*\\ \mathbf{A}_2^1(\mathbf{A}_1^1)^*+\mathbf{A}_2^2(\mathbf{A}_1^2)^* & \mathbf{A}_2^1(\mathbf{A}_2^1)^*+\mathbf{A}_2^2(\mathbf{A}_2^2)^* & \cdots & \mathbf{A}_2^1(\mathbf{A}_M^1)^*+\mathbf{A}_2^2(\mathbf{A}_M^2)^*\\ \vdots & \vdots & \ddots & \vdots\\ \mathbf{A}_M^1(\mathbf{A}_M^1)^*+\mathbf{A}_M^2(\mathbf{A}_M^2)^* & \mathbf{A}_M^1(\mathbf{A}_2^1)^*+\mathbf{A}_M^2(\mathbf{A}_2^2)^* & \cdots & \mathbf{A}_M^1(\mathbf{A}_M^1)^*+\mathbf{A}_M^2(\mathbf{A}_M^2)^*\end{bmatrix}\end{aligned} \quad \mathbf{(9)}$$

The transmitted training sequence **X** is multivariate orthogonal sequence, (9) can be described in (10) according to the correlation functions (2)and (3):

$$\mathbf{XX}^H=\begin{bmatrix}2L & 0 & \cdots & 0\\ 0 & 2L & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & 2L\end{bmatrix}=KL\mathbf{I}_{M\times M} \quad \mathbf{(10)}$$

Hence, the channel estimation can be obtained from equation (7):

$$\hat{\mathbf{H}}_{LS}=\sqrt{\frac{M}{\rho}}\frac{1}{KL}\mathbf{YX}^H \quad \mathbf{(11)}$$

4 Multivariate Superimposed Method

In the time-domain method, the training sequence and data information are divided into different timeslots. This time division may lead to a waste of bandwidth resources, and affect the accuracy of channel estimation when the channel state is changing fast with the time. To solve the problems, the superimposed method comes into being. This method superimposes the training sequence and the data information in the same timeslot for transmission. At the receiving end, the received signals are statistically cycle-stationary, making it possible to make statistical channel estimation. Since the training sequence is hidden in data information, less spectrum resources are consumed and the spectrum efficiency is enhanced. Fig. 4 illustrates a channel estimation model based on multivariate superimposed training sequence.

Suppose there are M transmitting antennas and N receiving antennas. Then, the data received by antenna n at time t can be expressed as:

$$\mathbf{Y}_n(t)=\sqrt{\rho_m}\mathbf{H}\left[\mathbf{S}_m(t)+\mathbf{X}_m(t)\right]+\mathbf{V}_n(t) \quad \mathbf{(12)}$$

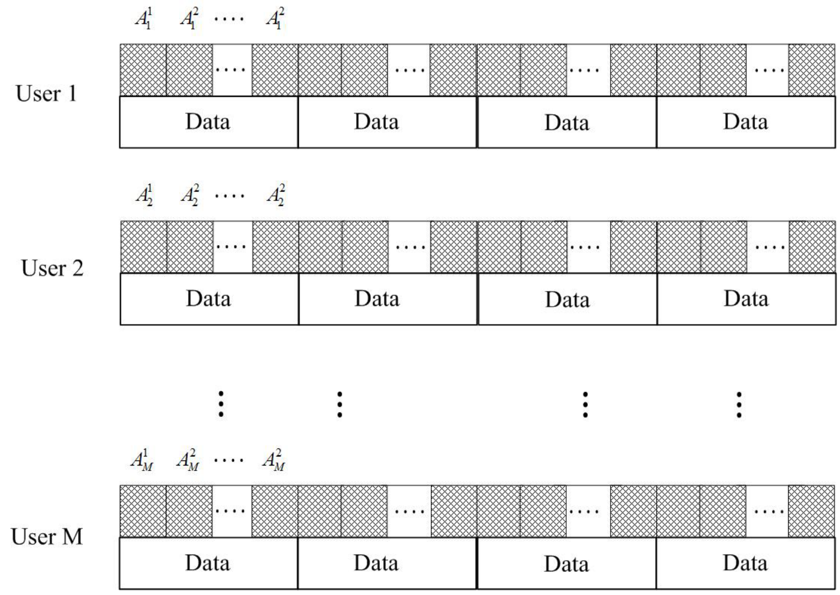

Fig. 4. MIMO channel estimation based on multivariate superimposed training sequence

H is the channel fading coefficient between the transmitting and receiving antennas:

$$\mathbf{H} = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1M} \\ h_{21} & h_{22} & \cdots & h_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ h_{N1} & h_{N2} & \cdots & h_{NM} \end{bmatrix} \tag{13}$$

where $\mathbf{S}_n(t)$ is the baseband information sequence sent at time *t*; $\mathbf{X}_n(t)$ is the training sequence sent at time *t*; $\mathbf{V}_n(t)$ is the noise information received at time *t* (mean value: zero; variance: δ_v^2). The matrix form of equation (12) can be expressed as:

$$\mathbf{Y}(t) = \sqrt{\rho_m}\mathbf{H}\left[\mathbf{S}(t)+\mathbf{X}(t)\right] + \mathbf{V}(t) \tag{14}$$

Whereas the training sequence is superimposed on each antenna, the normalized data information power is $\frac{\rho}{M}$ if the mean value of transmitted data information $\mathbf{S}_n(t)$ is 0 and the data information power is 1. Whereas

$$E\{\mathbf{Y}(t)\} = \sqrt{\frac{\rho}{M}}\mathbf{H}\mathbf{X}(t) \tag{15}$$

Let T_s be the transmission cycle of the data information and the training sequence. The data received at the receiving end are observed at integral multiples of the transmission cycle. Let us denote the integer as *T*. Note that *T* must be equal to RT_s and *R* must be a positive integer for a common training sequence. In our research, the multivariate orthogonal sequence involves multiple groups of sub-sequences. Thus, the length of observation data must be related to the number of sub-sequences:

$$T = RKT_s \tag{16}$$

Therefore, when the training sequence is a quaternary orthogonal sequence, the data information at the receiving end in time *T* is:

$$\mathbf{Y}_T(t) = \left[\mathbf{Y}(t) \quad \mathbf{Y}(t+2T_s) \quad \cdots \quad \mathbf{Y}(t+rKT_s)\right] \qquad (r=1,2,\cdots,R, \qquad K=2) \tag{17}$$

The mathematical expectation is:

$$\begin{aligned} E\left[\mathbf{Y}_T(t)\right] &= \sqrt{\frac{\rho}{M}}\frac{1}{RK}\sum_{r=1}^{R}\mathbf{Y}(t+rKT) \\ &= \sqrt{\frac{\rho}{M}}\mathbf{H}\left[\mathbf{X}(t) \quad \mathbf{X}(t+2T_s) \ \cdots \ \mathbf{X}(t+rKT_s)\right] \\ &= \sqrt{\frac{\rho}{M}}\mathbf{HX} \end{aligned} \tag{18}$$

Through the LS estimation of equation (18), we have:

$$\hat{\mathbf{H}}_{LS} = \sqrt{\frac{\rho}{M}}\frac{1}{RK}\left[\sum_{r=1}^{R}\mathbf{Y}(t+rKT)\right]\mathbf{X}^H(\mathbf{XX}^H)^{-1} \tag{19}$$

Since:

$$\begin{aligned} \mathbf{XX}^H &= \begin{bmatrix} \overrightarrow{\mathbf{A}_1^1 \quad \mathbf{A}_1^2} & \overrightarrow{\mathbf{A}_1^1 \quad \mathbf{A}_1^2} & & \overrightarrow{\mathbf{A}_1^1 \quad \mathbf{A}_1^2} \\ \mathbf{A}_2^1 \quad \mathbf{A}_2^2 & \mathbf{A}_2^1 \quad \mathbf{A}_2^2 & \cdots & \mathbf{A}_2^1 \quad \mathbf{A}_2^2 \\ \vdots \qquad \vdots & \vdots \qquad \vdots & & \vdots \qquad \vdots \\ \mathbf{A}_M^1 \quad \mathbf{A}_M^2 & \mathbf{A}_M^1 \quad \mathbf{A}_M^2 & & \mathbf{A}_M^1 \quad \mathbf{A}_M^2 \end{bmatrix} \begin{bmatrix} (\mathbf{A}_1^1)^* & (\mathbf{A}_2^1)^* & \cdots & (\mathbf{A}_M^1)^* \\ (\mathbf{A}_1^2)^* & (\mathbf{A}_2^2)^* & \cdots & (\mathbf{A}_M^2)^* \\ (\mathbf{A}_1^1)^* & (\mathbf{A}_2^1)^* & \cdots & (\mathbf{A}_M^1)^* \\ (\mathbf{A}_1^2)^* & (\mathbf{A}_2^2)^* & \cdots & (\mathbf{A}_M^2)^* \\ & \vdots & & \\ (\mathbf{A}_1^1)^* & (\mathbf{A}_2^1)^* & \cdots & (\mathbf{A}_M^1)^* \\ (\mathbf{A}_1^2)^* & (\mathbf{A}_2^2)^* & \cdots & (\mathbf{A}_M^2)^* \end{bmatrix} \\ &= \begin{bmatrix} 2RL & 0 & \cdots & 0 \\ 0 & 2RL & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 2RL \end{bmatrix} = KRL\mathbf{I}_{M\times M} \end{aligned} \tag{20}$$

Substituting equation (20) into equation (19), we have:

$$\hat{\mathbf{H}}_{LS} = \sqrt{\frac{M}{\rho}}\frac{1}{KL}\mathbf{YX}^H \tag{21}$$

Equations (11) and (21) show that the time-domain method yields the same channel estimation with the superimposed method, provided that the same multivariate orthogonal sequence is adopted as the training sequence. However, the superimposed method boasts higher spectrum efficiency.

5 Mixed Channel Estimation Method

Fig. 5 presents the frame structure of the mixed channel estimation method. As shown in the figure, the training sequence is partially transmitted in a separate timeslot and partially superimposed with data information for transmission. The mixed pattern combines the simplicity of the time-domain method and the high spectrum efficiency of the superimposed method.

The mixed channel estimation method starts from the energy distribution. Suppose the energy ratio between the training sequence and data information is η. Then, we have:

$$\mathbf{y}_{rL+n} = \mathbf{h}_n\mathbf{s}_{rL+n} + \eta\mathbf{x}_n\mathbf{h}_n + \mathbf{v}_n \tag{22}$$

where $\mathbf{y}$ is the sum of the received data and the training sequence; $\mathbf{s}$ is the data information; $\mathbf{x}$ is the training sequence; $r \in [1,2,\cdots,R]$ with R being the number of training sequences being superimposed; $n \in [1,2,\cdots,L]$ with L being one cycle length of the time-domain training sequence. From the above figure, it can be seen that the length of data information $\mathbf{S}$ is RL and the length of the received signals $\mathbf{Y}$ is $(R+1)L$. The matrix form of the length of the received signals can be expressed as:

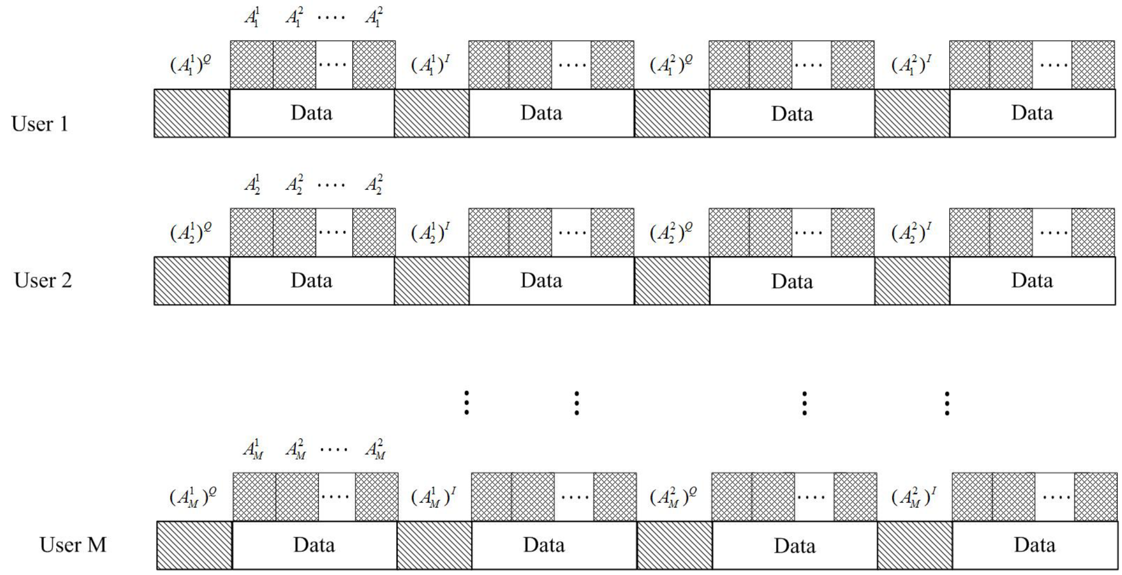

Fig. 5. Structure of mixed channel estimation method

$$\mathbf{Y}_r = \mathbf{H}(\mathbf{S}_{r\text{-}1} + \eta\mathbf{X}_r) + \mathbf{V} \quad \textbf{(23)}$$

When r=0, the received data only contain the training sequence; when r=R, the data of one complete frame is:

$$\mathbf{Y} = \sum_{r=0}^{R}\mathbf{Y}_r = \mathbf{H}\left[\sum_{r=1}^{R}\mathbf{S}_{r\text{-}1} + (K+1)\eta\mathbf{X}\right] + \mathbf{V} \quad \textbf{(24)}$$

Assuming that the transmitted data **S** are independent and identically distributed and averaged at zero, $\sum_{r=1}^{R}\mathbf{S}_{r\text{-}1}$ approximates zero when R is relatively large. Hence, the above equation can be written as:

$$\overline{\mathbf{Y}} = \mathbf{H}(R+1)\eta\mathbf{X} + \overline{\mathbf{V}} = (R+1)\eta\mathbf{H}\begin{bmatrix} \mathbf{A}_1^1 & \mathbf{A}_1^2 \\ \mathbf{A}_2^1 & \mathbf{A}_2^2 \\ \vdots & \vdots \\ \mathbf{A}_M^1 & \mathbf{A}_M^2 \end{bmatrix} + \overline{\mathbf{V}} \quad \textbf{(25)}$$

Since $\mathbf{X}\mathbf{X}^H = \mathbf{I}_M$, we have:

$$\hat{\mathbf{H}} = \frac{1}{(R+1)\eta}\overline{\mathbf{Y}}\begin{bmatrix} (\mathbf{A}_1^1)^* & (\mathbf{A}_2^1)^* & \cdots & (\mathbf{A}_M^1)^* \\ (\mathbf{A}_1^2)^* & (\mathbf{A}_2^2)^* & \cdots & (\mathbf{A}_M^2)^* \end{bmatrix} \quad \textbf{(26)}$$

The error of channel estimation was measured by the normalized mean square error (NMSE), which is defined as follows:

$$NMSE = \frac{1}{N_m}\sum_{i=1}^{N_m}\left\|\mathbf{H} - \hat{\mathbf{H}}\right\|_2^2 \quad \textbf{(27)}$$

where $\|\cdot\|_2$ is the bound norm; N_m is the number of Monte-Carlo simulations.

6 Simulation and Result Analysis

We set a MIMO communication system, and the number of transmitting antennas is 4 and the number of receiving antennas is also 4. The simulation parameters are displayed in Table 1.

Table 1. Simulation parameters

Name of parameter	Value
Number of transmitting antennas	4
Number of receiving antennas	4
Carrier frequency	3G
Modulation method	BPSK
Number of frame data blocks	10
Length of multivariate orthogonal sequence	20, 40
Sampling interval	50ns
Number of Monte-Carlo simulations	500

The simulation results of the proposed mixed channel estimation method, the time-domain method, superimposed method and the mixed channel estimation method are shown in Fig. 6 to Fig. 9, respectively.

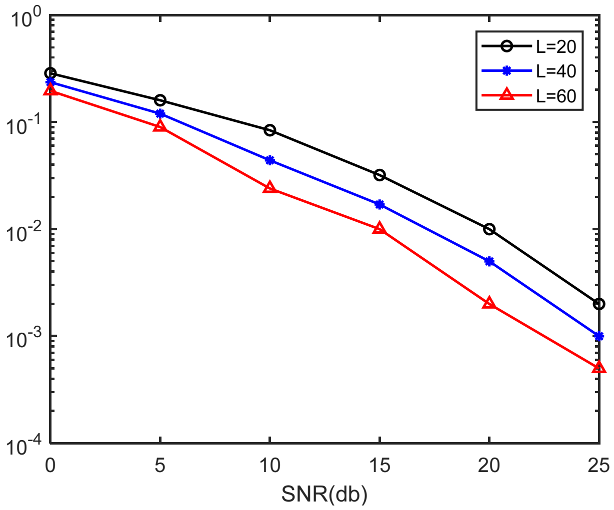

Fig. 6. Simulation results of multivariate time-domain method (at different lengths of the training sequence)

Fig. 6 shows the simulation results of multivariate time-domain method. From Fig.6, we can see that the performance under L=60 is better than the results with L=40 and L=20. With the increase in the length of training sequence, the channel estimation performance gradually improved, but the improvement of the NMSE exhibited a gradual declining trend.

Fig. 7 displays the simulation results of multivariate superimposed method. It can be seen that the channel estimation performance gradually improved with the increase of the superimposition power, while the improvement of the NMSE showed a gradual declining trend. The trends are the same with those of the multivariate time-domain method.

The increase in the length of training sequence in the time-domain method reveals the growth in power to a certain extent, which indicates the increase of the power ratio between the training sequence and the data information. The power ratio is negatively correlated with the transmitting power for data information, and positively with the bit error rate at the receiving end. If the power ratio is too high, the system performance will be severely undermined. Thus, it is necessary to choose a proper power for training sequence in the superimposed method.

The time-domain method had a lower data transmission rate than the superimposed method, because it must spend some time in transmitting the training sequence. As shown in Fig. 8, the superimposed method consumed less time in channel estimation than the time-domain method, as long as the training sequence length remained the same. This finding has great practical significance.

In order to compare the channel estimation performance of mixed method with other methods, we simulate the NMSE in mixed method. The results are shown in Fig. 9 and Fig. 10.

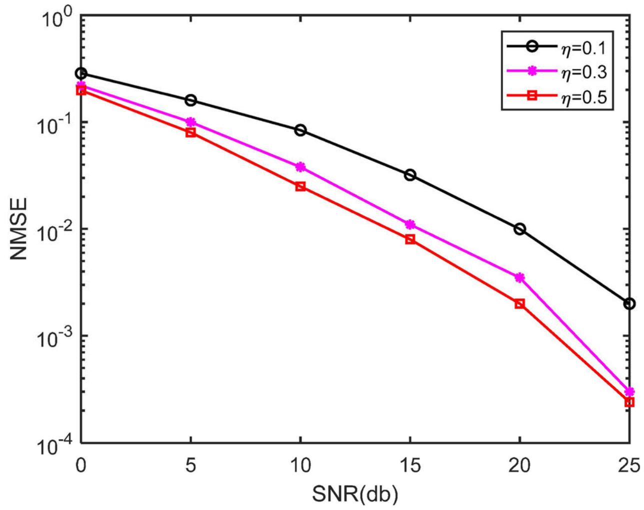

Fig. 7. Simulation results of multivariate superimposed method
(at different superimposition powers of the training sequence)

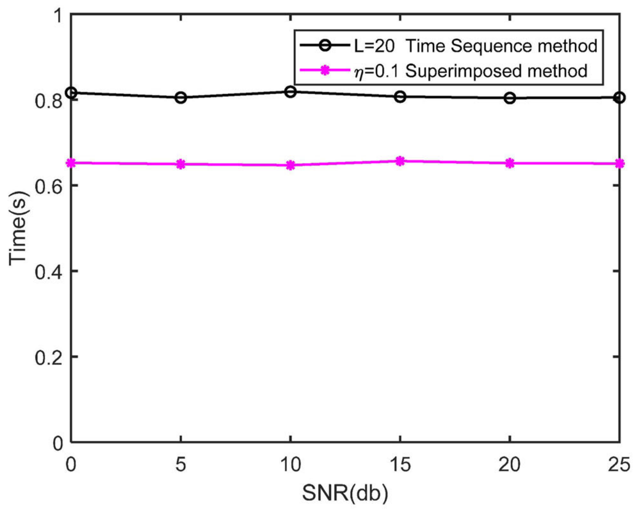

Fig. 8. System running time for the time-domain method and the superimposed method

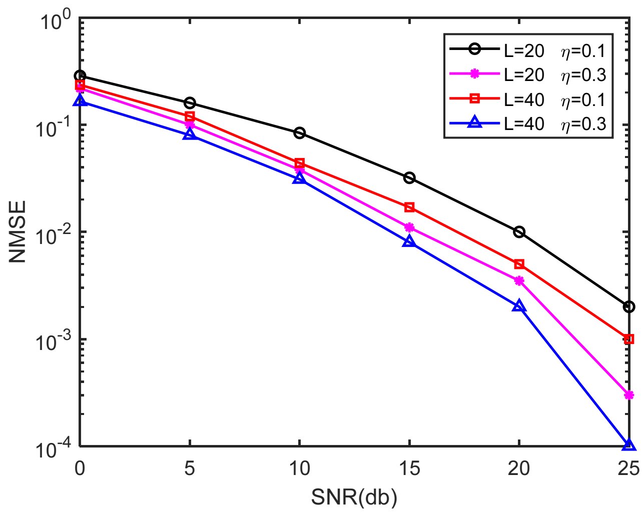

Fig. 9. Simulation results of the mixed channel estimation method
(at different lengths and superimposition power of the training sequence)

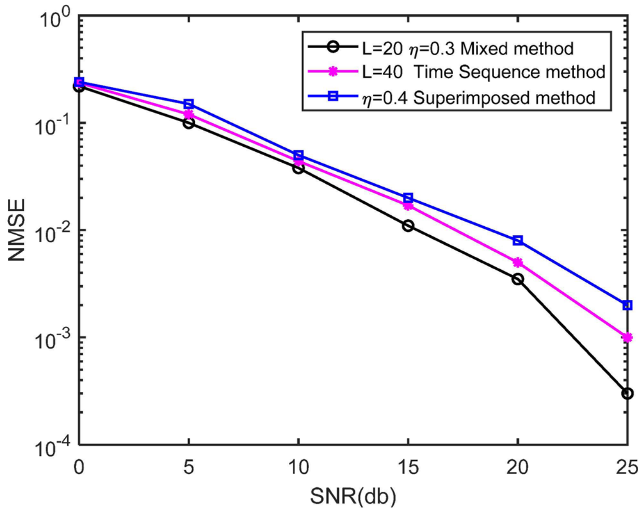

Fig. 10. Simulation results of the different channel estimation methods

Fig. 9 exhibits the channel estimation performance of the mixed channel estimation method. It is clear that the mixed channel estimation method achieved the same performance with the time-domain or superimposed methods although its training sequence was relatively short. The good performance is attributed to the performance compensation through the superimposition of the training sequence. Fig. 10 shows the performance comparisons of the above mentioned methods. From the results, we can see that the mixed channel estimation method has a better performance than the other two methods under the same simulation condition.

7 Conclusions

This paper combines the time-domain method and superimposed method into a new mixed channel estimation method. Considering that training sequence usually enjoys a high PAPR, the multivariate orthogonal sequence was introduced as the training sequence in the mixed channel estimation method, which lowered the PAPR and the NMSE in MIMO system. By means of simulations between different lengths of training sequences and different distributions of power, mixed method has the performance gain about 1db than the time-domain method and superimposed method, so it was shown to be capable of outperforming the other two methods.

In our future research, we will expand the concept of MIMO to massive MIMO system, in which we can obtain better performance gain by increasing the number of antennas. Hence, how to improve the channel estimation performance in massive MIMO system schemes will be more challenging.

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