

Large MIMO Channel Estimation Study Based on Independent Component Analysis

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Abstract— MIMO systems, which consist of multiple transmitting and receiving antennas, are used as a method for effective use of frequency bandwidth. In general, signal separation in MIMO requires a known channel matrix. However, using Independent Components Analysis, signal separation is possible even when the channel matrix is unknown. On the other hand, if the channel matrix is known, MIMO technology may be efficiently utilized by precoding in the reverse direction line of TDD. In this study, we examined whether ICA can be used for signal separation and channel information estimation. We report that signal detection and channel estimation in large-scale MIMO can be performed without any problems.

Keywords— Large-scale MIMO, Channel Estimation, Independent Component Analysis, Blind Signal Separation

I. INTRODUCTION

In recent years, the demand for wireless communication technology has been expanding further, and technologies for efficient use of frequency bands are required to meet this demand. Among them, the technology to operate independent signals in the same frequency band is effective. MIMO (Multi-Input Multi-Output) systems consisting of multiple transmitting and receiving antennas are used as an effective method of utilizing frequency bands, and the importance of highly efficient intercommunication using large-scale MIMO communication technology is increasing. In large-scale MIMO systems, it is necessary to separate and detect multiple signals synthesized in space at the receiver side, which generally requires estimation of the channel matrix. Conventionally, the least-squares estimation method using training symbols is widely used to estimate the channel matrix [1]. However, in some cases, the overhead of training symbols required for channel matrix estimation is a problem. In addition, for separating spatially multiplexed signals, it is necessary to estimate the Channel State Information (CSI) using training symbols and apply spatial filtering based on the CSI[2][3]. In principle, when the number of spatial multiplexes becomes large, it is necessary to increase the length of training symbols for the CSI estimation. However, it is undesirable, from the viewpoint of transmission efficiency, to use a long training symbol length for small data packets [4]. Under these circumstances, it has been proposed to apply Independent Components Analysis (ICA) [5] to MIMO systems [1] [6]. Considering the use of ICA in the uplink, Blind Signal

Separation (BSS), which does not require estimation of the channel matrix, is possible, but phase uncertainties remain in the separated signals. In addition, since the correspondence between the separated signal series and the original signal series cannot be determined, reordering is required after the separation [1]. These problems can be addressed by using pilots (preambles) of a few symbols for phase rotation compensation and sequencing. Using this scheme, signal separation can be performed with a relatively short preamble compared to the conventional training symbols for estimating the channel matrix [7]. In this way, when signal separation is performed on the uplink, hard values of the data are obtained. The baseband signal regenerated from the hard values can be used as a new preamble sequence for channel estimation. Since the data sequence is sufficiently long compared to the preamble sequence, the estimation accuracy of CSI is expected to be improved. Moreover, if the channel matrix is known, the MIMO technique may be used efficiently in the reverse direction of TDD by means of precoding and so on. This study examines whether ICA can be used for signal separation and channel information estimation. We evaluate signal detection and channel estimation in large-scale MIMO by computer simulations.

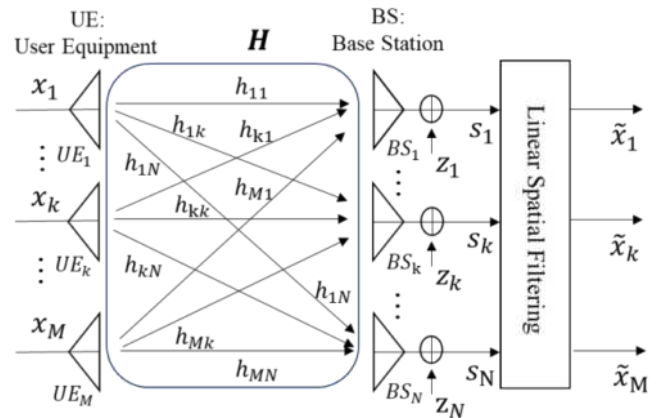


Figure 1. Uplink MIMO channel model

II. MIMO

In this study, we consider a large-scale MIMO transmission consisting of the base station (BS) with N antennas and M terminals (User Equipment: UE) with one antenna. As a

precondition, we use TDD in which the CSI of the uplink and downlink are the same. Figure 1 shows the transmission model of large-scale MIMO for the uplink. For the uplink, signal detection is important to separate the spatially multiplexed signals in the BS. If the transmitted signal from the UE at time k is $\mathbf{x}[k]$,

$$\mathbf{s}[k] = \mathbf{H}\mathbf{x}[k] + \mathbf{z}[k] \quad (1)$$

denotes the received signal $\mathbf{s}[k]$ at the BS. Where the boldface type denotes a vector or matrix and $\mathbf{z}[k]$ is an additive white Gaussian noise vector. $\mathbf{H}$ is defined as an $N \times M$ channel matrix, of which the (n, m) th element h_{nm} denotes the channel coefficients between the m -th UE antenna and the n -th BS antenna. As the propagation environment, we assume Rayleigh fading following a complex Gaussian distribution. For uplink signal detection, from the viewpoint of computational complexity, we use signal processing based on linear spatial estimation [7], in which the received signal $\mathbf{s}[k]$ is multiplied by a weight matrix $\mathbf{W}$ to obtain an estimate $\tilde{\mathbf{x}}[k]$ of the transmission vector $\mathbf{x}[k]$ of:

$$\tilde{\mathbf{x}}[k] = \mathbf{W}\mathbf{s}[k]. \quad (2)$$

Using the Least Square (LS) norm to derive the solution, the transmitted symbols are estimated to satisfy:

$$\tilde{\mathbf{x}}[k] = \underset{\mathbf{x}}{\operatorname{argmin}} \mathbb{E}\{\|\mathbf{y}[k] - \mathbf{H}\mathbf{x}\|^2\}. \quad (3)$$

Where $\mathbb{E}\{\cdot\}$ means the expected value. Comparing equation (2) and (3), the weight matrix $\mathbf{W}$ can be obtained in:

$$\mathbf{W} = \mathbf{H}^\dagger = [\mathbf{H}^H \mathbf{H}]^{-1} \mathbf{H}^H \quad (4)$$

by using the inverse matrix operation.

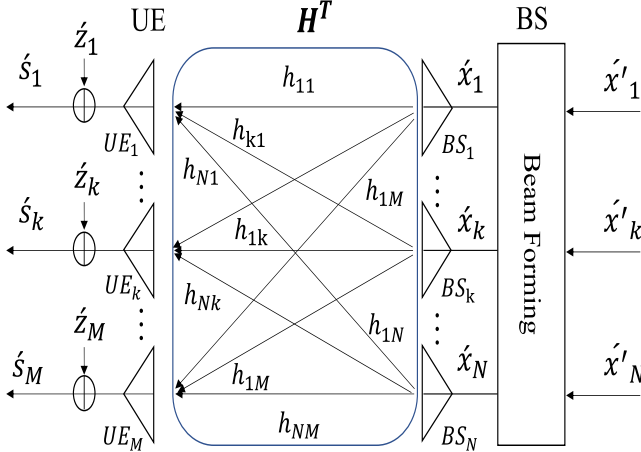


Figure 2. Downlink MIMO channel model

III. CHANNEL ESTIMATION

Considering a frame of K symbols, the spatial-temporal matrices $\mathbf{X}(M \times K)$, $\mathbf{Y}(N \times K)$, $\mathbf{Z}(N \times K)$ can be defined as:

$$\mathbf{X} = [\mathbf{x}[1], \dots, \mathbf{x}[k], \dots, \mathbf{x}[K]] \quad (5)$$

$$\mathbf{Y} = [\mathbf{y}[1], \dots, \mathbf{y}[k], \dots, \mathbf{y}[K]] \quad (6)$$

$$\mathbf{Z} = [\mathbf{z}[1], \dots, \mathbf{z}[k], \dots, \mathbf{z}[K]]. \quad (7)$$

Therefore, equation (1) can be extended to the spatial-temporal expression in:

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{Z}. \quad (8)$$

Where the time variation of $\mathbf{H}$ is assumed to be static in the interval $1 \leq k \leq K$. Each UE is assumed to form a frame consisting of K_p pilot symbols ($K_p = \{1, \dots, K_p\}$) and K_d data symbols ($K_d = \{K_p + 1, \dots, K\}$). The K symbols consist of $K = K_p + K_d$. In this case, the spatio-temporal matrix can be divided into a pilot part and a data part as in:

$$\mathbf{X} = [\mathbf{X}_p, \mathbf{X}_d] \quad \mathbf{X}_p: (M \times K_p), \mathbf{X}_d: (M \times K_d) \quad (9)$$

$$\mathbf{Y} = [\mathbf{Y}_p, \mathbf{Y}_d] \quad \mathbf{Y}_p: (N \times K_p), \mathbf{Y}_d: (N \times K_d) \quad (10)$$

$$\mathbf{Z} = [\mathbf{Z}_p, \mathbf{Z}_d] \quad \mathbf{Z}_p: (N \times K_p), \mathbf{Z}_d: (N \times K_d). \quad (11)$$

Using this data part, channel estimation based on the LS norm yields an estimate of:

$$\tilde{\mathbf{H}} = \underset{\mathbf{H}}{\operatorname{argmin}} \|\mathbf{Y}_d - \mathbf{H}\mathbf{X}_d\|_F^2 = \mathbf{Y}_d \mathbf{X}_d^\dagger. \quad (12)$$

However, $\mathbf{X}_p^\dagger = \mathbf{X}_p^H [\mathbf{X}_p \mathbf{X}_p^H]^{-1}$ is the Moore-Penrose pseudo-inverse.

IV. INDEPENDENT COMPONENTS ANALYSIS

Fig. 1 shows the transmission model of large-scale MIMO for the uplink. If the independent and unknown transmit signal is $\mathbf{x}$, the received signal is $\mathbf{s}$, and the unknown mixed variable matrix is $\mathbf{W}$, the model can be expressed as in:

$$\mathbf{s} = \mathbf{W}\mathbf{x}. \quad (13)$$

ICA can detect the unknown transmit vectors regardless of the form of the received vectors, provided that all the signal sources are non-Gaussian. Considering one independent component s_i of the transmitted signal vector, it is necessary to update the weight matrix $\mathbf{W}$ to maximize the non-Gaussianity to estimate s_i . As an algorithm for updating the matrix $\mathbf{W}$, we used negentropy as an evaluation method for non-Gaussian and the fixed-point iteration method as maximization method. Targeted orthogonalization is used to estimate multiple independent components, and $\mathbf{z}$ is the centered and whitened signal of the transmitted signal $\mathbf{s}$. The algorithm for updating the matrix $\mathbf{W}$ using these methods consists of:

$$\mathbf{w}_i \leftarrow E\{\mathbf{z}(\mathbf{w}_i^H \mathbf{z})^* |\mathbf{w}_i^H \mathbf{z}|^2\} - E\{2|\mathbf{w}_i^H \mathbf{z}|^2\} \mathbf{w}_i \quad (14)$$

$$\mathbf{W} \leftarrow (\mathbf{W}\mathbf{W}^H)^{-\frac{1}{2}} \mathbf{W}. \quad (15)$$

Here, in this study, time averages are used instead of expected values. In the updating procedure, the initial value of $\mathbf{w}_i$ is determined first, and then equation (14) is executed for each component. Then, the matrix is orthogonalized using Equation (15), and Equation (14) is repeated if the matrix $\mathbf{W}$ has not converged. If the signal detection is successful on the uplink line, there is no need to perform channel estimation. However, accurate channel information on the downlink is necessary for demodulation with precoding. Therefore, assuming TDD, channel estimation after the completion of signal detection is meaningful. In this study, the LS norm from Equation (12) is used to estimate the downlink channel as:

$$\tilde{\mathbf{H}} = \underset{\mathbf{H}}{\operatorname{argmin}} \|\mathbf{Y} - \mathbf{H}\mathbf{X}\|_F^2 = \mathbf{Y}\mathbf{X}^\dagger. \quad (16)$$

In this study, the mean square error (MSE) of the estimated values of the channel coefficients is evaluated. Let h_{nm} be an element of the channel coefficient matrix and $\tilde{h}_{nm}$ be an element of the estimated channel coefficient matrix [7], the MSE is given by:

$$\text{MSE} = \mathbb{E}\{|\tilde{h}_{nm} - h_{nm}|^2\}. \quad (17)$$

V. SIMULATION METHOD AND RESULTS

A. Simulation In Uplink

Simulations of signal detection and channel estimation using ICA were conducted on the uplink line. Each channel coefficient follows a complex Gaussian distribution with mean 0 and variance 1. Focusing on the number of antennas at the UE side 16, 16 symbols, which are equivalent to the number of rows in the channel matrix, are required for channel estimation by inverse matrix operations. However, using ICA, 5 symbols are sufficient for the preamble part. Therefore, about 99.6% of the total symbols can be used as the data part. In addition, it is necessary to repeat the process of equations (14) and (15) to converge the weight matrix $\mathbf{W}$. In this study, 30 iterations of iterative processing of the weight matrix were sufficient to converge the weight matrix.

Fig.3 shows the BER characteristics of the signal $x_1[k]$ when the number of terminals (UEs) is set to 16. The signal detection accuracy using ICA is evaluated in terms of Bit Error Rate (BER). The ideal characteristics for the case where the channel matrix is known are derived using equation (5) and are shown as the BER characteristics of the signal $x_1[k]$ by MMSE. Fig.3 shows that the signal detection using ICA is successfully performed on the uplink when the number of transmit antennas is set to 16. Compared with MMSE, the signal detection using ICA has a required SNR degradation of about 12dB for $N=16$ and $N=24$, focusing on $\text{BER}=10^{-3}$, while the required SNR degradation for $N=24$ is about 10dB for MMSE. 24, and for $\text{BER}=10^{-5}$, the required SNR degradation for $N=24$ is about 1.5dB. Compared with the very good BER characteristics of MMSE with a known channel matrix, the signal detection and BER characteristics using ICA are highly accurate. In addition, the diversity effect is confirmed by increasing the number of base station (BS) antennas, and the accuracy of signal detection is improved. This performs a result of the diversity effect in MIMO. Therefore, it can be said that uplink signal detection using ICA is effective in a large-scale MIMO environment.

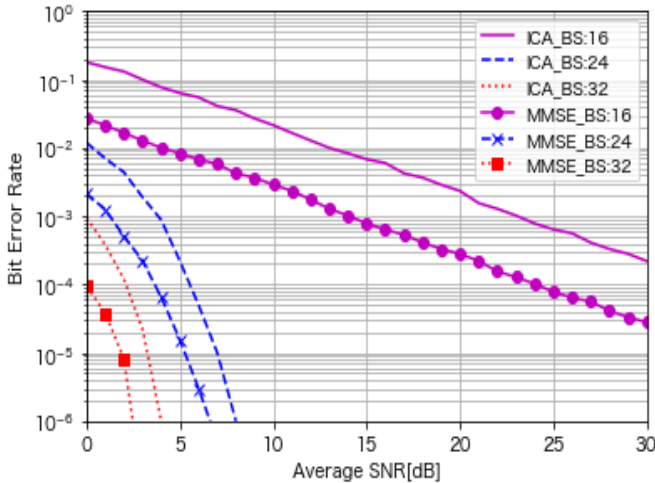


Figure 3. Bit Error Rate Performance of $x_1[k]$ in Uplink

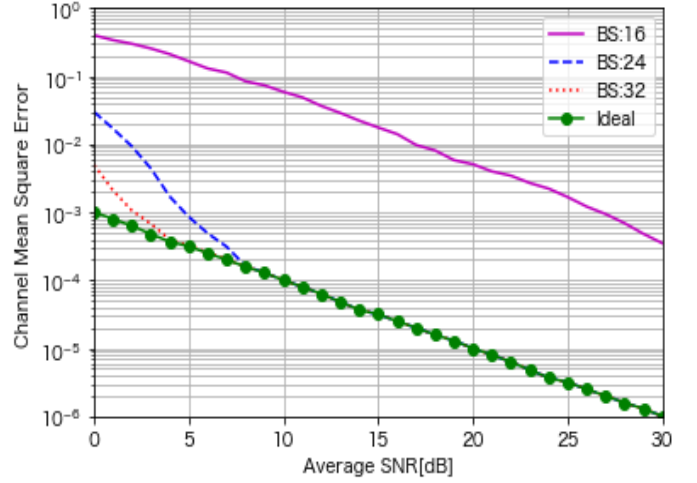


Figure 4. Mean Square Error of Channel Estimation

TABLE 1. SIMULATION PAREMETERS IN UPLINK

UE	Number of Users	16
	Number of Antennas	1
	Number of Symbols	1,280
	Number of Preambles	5 symbols
	Modulation	QPSK
BS	Number of Antennas	16,24,32
	Signal Separation	fast ICA
	Number of Iterations	30
Channel	Rayleigh Fading	

Fig.4 shows the channel estimates for the cases with 16, 24, and 32 BS antennas, respectively. The channel estimation accuracy is evaluated using the MSE of the channel estimates. In addition, when $\mathbf{X} = \hat{\mathbf{X}}$ is satisfied in equation (4) and (12), the state of ideal signal detection is defined as the ideal state of signal detection, which is shown in Fig. 4. Here, the channel MSE shown in Fig.4 is the average of the estimated values of all the elements ($h_{11}, h_{12}, h_{21}, h_{22}$) of the channel coefficient matrix. From Fig. 4, we can confirm that the accuracy of channel estimation improves as the SNR value increases. In addition, when the number of BS antennas is increased up to 24, it can be read that the estimation accuracy is equivalent to that of the ideal characteristics when the SNR is 8dB or higher. Furthermore, when the number of BS antennas is increased up to 32, the estimation accuracy is found to be equivalent to that of the ideal characteristics when the SNR value is 4 dB or higher. In conclusion, it can be confirmed that channel estimation accuracy improves in a system with many UE antennas connected simultaneously, i.e., a large-scale MIMO system, and channel estimation using ICA would be effective.

B. Simulation In Downlink

TABLE 2. SIMULATION PAREMETERS IN DOWNLINK

UE	Number of Users	16
	Number of Antennas	1
	SNR[dB]	0,20
BS	Number of Antennas	16,24,32
	Number of Symbols	1,280
	Number of Iterations	30
Channel	Rayleigh Fading	

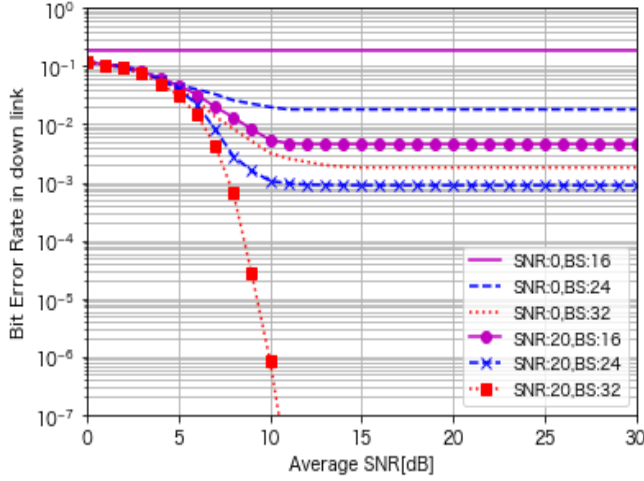


Figure 5. Bit Error Rate Performance of $\hat{s}_1[k]$ in Downlink

The channel coefficients estimated for the uplink were applied to the downlink to simulate the communication with precoding. First, 0 dB and 20 dB signals are transmitted on the uplink and downlink, respectively. Next, signals are detected on the uplink using ICA, and the estimated matrix of channel coefficients, $\hat{\mathbf{X}}$, is obtained using Equation (16).

Fig. 5 shows the BER characteristics of $\hat{s}_1[k]$ for 16 UEs. The effect of interference is sufficiently reduced in the downlink except for the cases where the transmitted signal in the uplink becomes extremely small (0 dB) and $N = M$. This indicates that ICA-based intercommunication is effective in large-scale MIMO systems except for the cases where the situation is extremely bad.

VI. SUMMARY

It is demonstrated that the ICA-based signal detection is feasible in a large-scale MIMO system without using many preambles. We also studied a method of channel estimation by regenerating the hard-coded values of the data obtained from the ICA signal detection to the baseband signal. It is shown that the accuracy of the method is improved by increasing the number of BS antennas.

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