Fundamental Study on Blind MIMO Transmission by using ICA

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1. Introduction

MIMO is one of the broadband communication techniques, which utilizes multiple antennas in both transmitter and receiver. In the MIMO system, transmitted streams are multiplexed spatially at the same frequency. This causes inter-stream interference at the receiver. Therefore, equalization/decoding method is necessary. Least Squares Channel Estimation (LSCE) [1] is often used as the method. However, overhead in throughput due to training symbols for the channel estimation is a problem for effective transmission. In this report, we focus on Independent Component Analysis (ICA) [2] [3] as a blind method without the training symbols for the channel estimation. We have reported effectiveness of the ICA for the blind equalizer in the MIMO with QPSK and DQPSK modulation [4]. In this report, we evaluate performance of the ICA equalization for the MIMO transmission modulated with QAM. Computer simulation results are shown to demonstrate availability of the method.

2. Data Model

We consider a MIMO system consisting of N_t transmitting antennas and N_r receiving antennas. The received vector, $\boldsymbol{x}(t) = [x_1(t) \quad x_2(t) \quad \cdots \quad x_{N_r}(t)]^T$, at the receiver can be given by

$$\boldsymbol{x}(t) = \boldsymbol{H}\boldsymbol{s}(t) + \boldsymbol{n}(t), \tag{1}$$

where $\boldsymbol{H}$ denotes the $N_r \times N_t$ MIMO channel matrix, $\boldsymbol{s}(t) = [s_1(t) \quad s_2(t) \quad \cdots \quad s_{N_t}(t)]^T$ is the transmitted symbols vector, and $\boldsymbol{n}(t) = [n_1(t) \quad n_2(t) \quad \cdots \quad n_{N_r}(t)]^T$ is the complex valued Gaussian noise vector. Furthermore, when we define the received signal matrix $\boldsymbol{X}$ whose column corresponds to the received data symbols at each time, it can be written by

$$\boldsymbol{X} = \boldsymbol{H}\boldsymbol{S} + \boldsymbol{N}, \tag{2}$$

where

$$\boldsymbol{S} = [\boldsymbol{s}(1) \quad \boldsymbol{s}(2) \quad \cdots \quad \boldsymbol{s}(N_s)] \in C^{N_t \times N_s}, \tag{3}$$

$$\boldsymbol{X} = [\boldsymbol{x}(1) \quad \boldsymbol{x}(2) \quad \cdots \quad \boldsymbol{x}(N_s)] \in C^{N_r \times N_s}, \tag{4}$$

$$\boldsymbol{N} = [\boldsymbol{n}(1) \quad \boldsymbol{n}(2) \quad \cdots \quad \boldsymbol{n}(N_s)] \in C^{N_r \times N_s}, \tag{5}$$

where N_s is the number of the symbols.

3. EQUALIZATION ESTIMATION METHOD

3.1 LSCE

Let us denote the training symbols by $\hat{\boldsymbol{S}}$. The estimated MIMO channel matrix $\hat{\boldsymbol{H}}$ of the LSCE, which is one of the conventional equalizing technique, is given by

$$\hat{\boldsymbol{H}} = \boldsymbol{X}\hat{\boldsymbol{S}}^H(\hat{\boldsymbol{S}}\hat{\boldsymbol{S}}^H)^{-1} \tag{6}$$

where ^{H} is the conjugate transpose. When the $\hat{\boldsymbol{H}}$ is estimated, the transmitted signals ($\boldsymbol{S}$) can be easily recovered by applying the (general) inverse of $\hat{\boldsymbol{H}}$ to the received signals.

3.2 ICA

When the transmitted signals from each antenna are mutually independent from each other, the transmitted signals can be separated from the observed signal by using the ICA.

Independent component matrix $\boldsymbol{Y}$ of the ICA is given by

$$\boldsymbol{Y} = \boldsymbol{W}\boldsymbol{X}, \quad (7)$$

where

$$\boldsymbol{Y} = [\boldsymbol{y}(1) \quad \boldsymbol{y}(2) \quad \cdots \quad \boldsymbol{y}(N_s)] \in C^{N_r \times N_s}, \quad (8)$$

$$\boldsymbol{W} = [\boldsymbol{w}_1 \quad \boldsymbol{w}_2 \quad \cdots \quad \boldsymbol{w}_{N_t}]^T \in C^{N_t \times N_r}, \quad (9)$$

In this report, we employ the FastICA [2] [3] which is a popular technique as the ICA algorithm. As shown below, the transmitted signals ($\boldsymbol{S}$) can be recovered without estimating $\hat{\boldsymbol{H}}$.

The ICA is the method which can decompose mixed signals into individual signal components when the original signals are independent. Received signals have Gaussian distribution than the original source signals. Therefore, when we obtain the weight matrix which maximizes the non-Gaussian property of the received signals, we can recover the transmitted signals by the matrix. As the criterion of non-Gaussian distribution, the kurtosis is often used. When the absolute value of the kurtosis is maximum, non-Gaussian property of the signals becomes maximum. In other words, the ICA is the method which calculates the weight matrix $\boldsymbol{W}$ to maximize the absolute value of the kurtosis of $\boldsymbol{y}(t)$.

Before using the ICA, whitening processing for the received signals is necessary. The whitened matrix $\boldsymbol{V}$ is given by

$$\boldsymbol{V} = \boldsymbol{D}^{-\frac{1}{2}} \boldsymbol{P}^H, \quad (10)$$

$$\boldsymbol{D} = \mathrm{diag}\{\lambda_1 , \lambda_2 , \cdots , \lambda_{N_t}\}, \quad (11)$$

$$\boldsymbol{P} = [\boldsymbol{p}_1, \boldsymbol{p}_2, \cdots , \boldsymbol{p}_{N_t}], \quad (12)$$

where λ_k $(k = 1, 2, \cdots , N_t)$ is the k-th large eigenvalue of the received data correlation matrix, and $\boldsymbol{p}_k$ is the eigenvector corresponds to λ_k. The whitened received signal vector $\boldsymbol{z}(t)$ is given by

$$\boldsymbol{z}(t) = [z_1, z_2, \cdots , z_{N_t}]^T, \quad (13)$$

$$= \boldsymbol{V}\boldsymbol{x}(t), \quad (14)$$

The goal of the ICA processing is derivation of the independent component vector $\boldsymbol{y}$ which holds $\boldsymbol{y}(= \boldsymbol{W}\boldsymbol{z}) \propto \boldsymbol{s}$. Standard cost function for the ICA is given by

$$J_{\mathrm{ica}} = \sum_{k=1}^{N_t} \mathrm{E}[|\boldsymbol{w}_k \boldsymbol{z}|^4] \quad (15)$$

where $\boldsymbol{w}_k$ is the k-th row vector of $\boldsymbol{W}$.

The FastICA is one of realization for the ICA by using a fast fixed-point algorithm, and it has fast convergence characteristic. Procedure of the complex FastICA algorithm is summarized below:

Step.1 Set the initial value of p to 0.

Step.2 Initialize $\boldsymbol{W}$ ($\boldsymbol{W}^{(p)} = \boldsymbol{I}$).

Step.3 Increment p; $(p = p + 1)$.

Step.4 Set $k = 1$.

Step.5 Compute $\boldsymbol{w}_k^{(p)} = E[\boldsymbol{z}(t)(\boldsymbol{w}^{(p-1)}\boldsymbol{z}(t))^* |\boldsymbol{w}^{(p-1)}\boldsymbol{z}(t)|^2] - E[2|\boldsymbol{w}^{(p-1)}\boldsymbol{z}(t)|^2]\boldsymbol{w}^{(p-1)H}$.

Step.6 If $k < N_t$, then set $k = k + 1$ and return to Step.5.

Step.7 Compute $\boldsymbol{W}^{(p)} = (\boldsymbol{W}^{(p)}\boldsymbol{W}^{(p)H})^{-1/2}\boldsymbol{W}^{(p)}$.

Step.8 If $\| \boldsymbol{W}^{(p)}\boldsymbol{W}^{(p-1)H} - \boldsymbol{I} \|_F$ is not converged, then return to Step.3.

Step.9 Estimate the channel matrix $\hat{\boldsymbol{H}} = \boldsymbol{W}^{(p)H}(\boldsymbol{W}^{(p)}\boldsymbol{W}^{(p)H})^{-1}$.

where $\| \cdot \|_F$ denotes the Frobenius norm and $\boldsymbol{I}$ is the unit matrix. Note that phase of evaluated channel matrix would be rotated by this estimation. To compensate these phase ambiguity, estimation of the phase value by a few known/training symbols is necessary even for the ICA.

4. Simulation Example

In the simulation, Rayleigh fading environment based on the Jakes model having 20 random scattering points is assumed. Received wave from each scattering point is assumed as a plane wave. The SNR in this report is defined by the ratio of overall transmitting power to noise.

In this report, we investigate channel capacity and BER(Bit Error Rate) of the MIMO transmission with the ICA and LSCE, respectively. Theoretical value with perfect channel information is also plotted as a reference. We considered a MIMO system with $N_t = 4$ and $N_r = 4$, and the modulation scheme was 16QAM. At first, we demonstrate performance on training symbols. The model parameters in the simulations are listed on Table 1. Figure 1 shows the results of the number of the training symbols vs. channel capacity. As shown in this figure, capacity of the ICA is high with little number of training symbols compared with that of the LSCE. Note that the training symbols for the ICA is only used for phase bias estimation described in Sec.3, not for channel estimation. Since the LSCE is the method using training symbols, correct channel estimation is difficult with the little number of training symbols. Figure 2 shows the results of the number of the training symbols vs. BER. As well as the results shown in Fig.1, the ICA shows good result with the little number of training symbols compared with that of the LSCE. Therefore, the ICA is effective with a few training symbols.

Table 1: Simulation parameters 1

Number of data symbols	1024
Number of training symbols	1~32
SNR	30

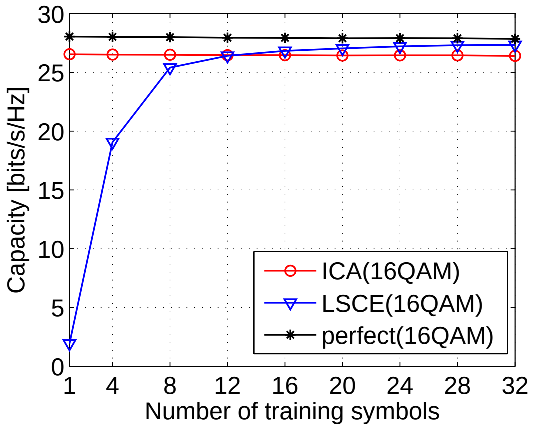

Figure 1: Number of training symbols vs. channel capacity

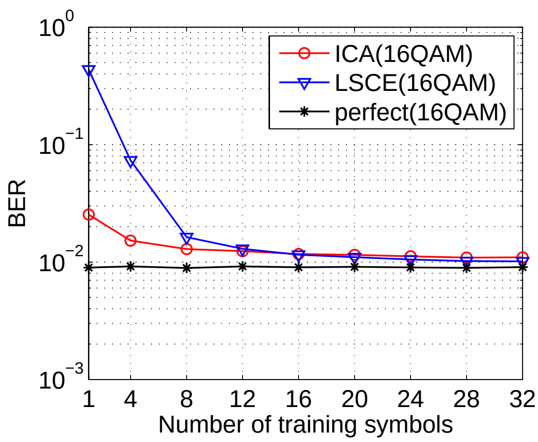

Figure 2: Number of training symbols vs. BER

Next, we demonstrate the performance on SNR. The model parameters in the simulations are listed on the Table 2. Figure 3 shows the results of SNR vs. channel capacity, and Figure 4 shows the results of SNR vs. BER. As shown in these figures, even when the SNR is high, the performance cannot be improved by the LSCE. On the other hand, good and stable performance can be realized by the ICA.

Table 2: Simulation parameters 2

Number of data symbols	1024
Number of training symbols	4
SNR	0~30

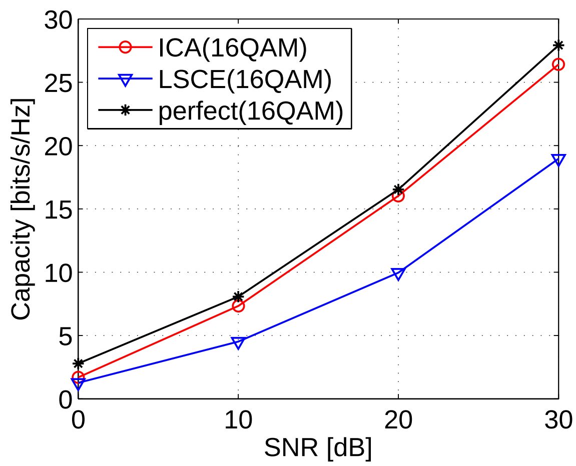

Figure 3: SNR vs. channel capacity

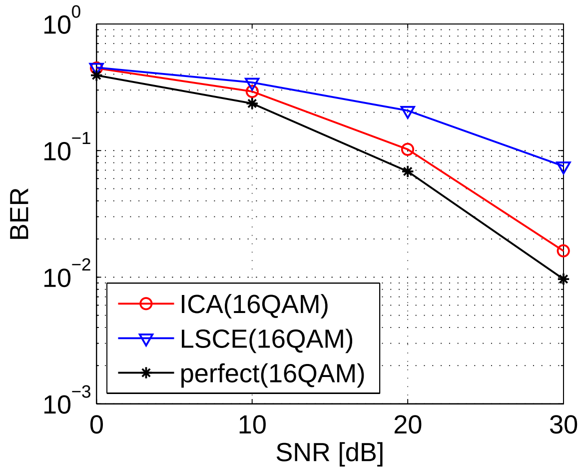

Figure 4: SNR vs. BER

5. Conclusions

In this report, we show performance of the blind MIMO transmission with the ICA. The channel and BER property for 16QAM are evaluated by the computer simulation. These results showed that the ICA has advantages with transmission in a few training symbols in comparison with the LSCE.

Acknowledgment

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