EFFECT OF BLIND SOURCE SEPARATION FOR ANALOG MODULATION

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ABSTRACT. We investigated the effect of blind source separation for analog modulation. The proposed separating model can separate the mixed signals to a certain extent. We estimated the efficacy of the method in the Radio Anechoic Chamber experiment. In the blind source separation, independent component analysis can estimate unknown source signals from their mixtures under the assumption that the source signals are statistically independent. The experimental results suggested that the blind source separation is effective in radio communication.

 ${\bf Keywords:}$ Blind source separation, Analog modulation, Anechoic Chamber experiment

1. Introduction. The BSS (Blind Source Separation) has been researched in the field of acoustics [1]. Under the situation that some sound sources are observed by microphones, BSS is a method for estimating the sound sources by the observed mixture signals without using the information about the sources and the transfer functions. For BSS, ICA (Independent Component Analysis) can separate the sources from their mixtures if they are statistically independent each other.

For BSS in radio communication, blind carrier frequency offset and channel using ICA in QAM-OFDM systems have been proposed [2]. However, the effect of direct BSS for analog modulation is not investigated. Therefore, we investigated the effect of the BSS in radio communication [3]. In this study, we create a signal separation model including the analog modulation and demodulation. It is found that our method based on natural gradient algorithm can estimate the original source signals. This method can be effectively utilized for analog modulation occupied bandwidth [4] because this method can use the same modulation frequency.

2. Blind Source Separation for Radio Communication. Consider the case where sound sources are observed by sensors. We assume the observed mixture signals $\boldsymbol{x} = [x_1, \ldots, x_m, \ldots, x_M]^T$. They are generated a linear mixture of the sources as

$$\boldsymbol{x} = A\boldsymbol{s} \tag{1}$$

where $\boldsymbol{s} = [s_1, \ldots, s_n, \ldots, s_N]^T$ denotes unknown source signals, N denotes the number of the sources, M denotes the number of the mixtures and A denotes an unknown mixing matrix whose elements are a_{mn} . ICA can estimate the sources \boldsymbol{s} except for indeterminacy of scaling and permutation under the assumption that each component of \boldsymbol{s} is statistically independent. The indeterminacy of scaling is that the scale of the separated signals is not equal to that of the source signals. The indeterminacy of permutation is that the order of the separated signals is not equal to that of the source signals. The separated signals $\boldsymbol{y} = [y_1, \ldots, y_n, \ldots, y_N]^T$, the estimated of the source signals are expressed as

$$\boldsymbol{y} = W\boldsymbol{x} \tag{2}$$

where W denotes a demixing matrix. The matrix W is estimated by ICA algorithms such as the Natural Gradient.

The Natural Gradient is a gradient method based on finding a minimum of the Kullback-Leibler divergence $I(\boldsymbol{y})$ of the separated signals \boldsymbol{y} . The Kullback-Leibler divergence $I(\boldsymbol{y})$ using entropy $H(\boldsymbol{y})$ of the separated signals \boldsymbol{y} with density $p(\boldsymbol{y})$ is defined as follows.

$$I(\boldsymbol{y}) = \int p(\boldsymbol{y}) \log \left(p(\boldsymbol{y}) / \Pi p(y_n) \right) d\boldsymbol{y}$$
(3)

$$=\Sigma H(y_n) - H(\boldsymbol{y}) \tag{4}$$

$$H(\boldsymbol{y}) = \int p(\boldsymbol{y}) \log p(\boldsymbol{y}) d\boldsymbol{y}$$
(5)

The Natural Gradient algorithm is formulated as

$$W + \Delta W = W - \eta \left(\partial I(\boldsymbol{y}) / \partial W \right) W^{\mathrm{T}} W$$
(6)

$$= W + \eta \mathbf{E} \left[I - \varphi(\mathbf{y}) \mathbf{y}^{\mathrm{T}} \right] W$$
(7)

where $\varphi(\boldsymbol{y})$ denotes a nonlinear function, η denotes a learning parameter and I denotes unit matrix.

For the BSS in radio communication, we create a signal separation model including the modulation and demodulation as shown in Figure 1. Source signals s_n are audio signals that are input to the transmitter. Each of the source signals is modulated to transmission signal t_n using a carrier wave. It is assumed that the modulation frequency of all t_n has the same value. Transmission signals t_n are transmitted from the transmitter. Transmitted signals are mixed in a space, and the received signals r_n are observed by the receiver. Therefore, the demodulated signals are mixture signals x_n by the source signals. Then we estimate the original source signals using x_n based on the Natural Gradient algorithm Equation (7).



FIGURE 1. Signal separation model including the modulation and demodulation

3. Experiment Method. Figure 2 shows the illustration of the location of Transmitters and Receivers in an experimental room (anechoic chamber) and Table 1 shows the condition of the source signals. We send AM or FM signal from 2 Transmitters. Transmitter-1 sends the source signal-1 (sine wave, 1 kHz) and Transmitter-2 sends the source signal-2 (sine wave, 2 kHz). The source signals are mixed on the propagation path and are received by 2 Receivers. We apply the BSS to the mixed signals and estimate the effect of blind source separation in radio communication by comparing the source signals and the separated signals. Figure 3 shows the photograph of the experimental condition in the anechoic chamber.



FIGURE 2. Illustration of the experiment



FIGURE 3. Photograph of the experiment

TABLE 1. Condition of source signals

	Frequency	Input voltage	Modulation frequency	Waveform
Source 1	1 kHz	1Vp-p	$145 \mathrm{~MHz}$	sine wave
Source 2	2 kHz			

4. **Results.** In this section, we present the result about effect of blind source separation for AM and FM.

4.1. Effect of blind source separation for AM. Figure 4 shows the comparison between the source signals and the separated signals for AM. Figure 4(a) compared the source signal-1 (1 kHz) and the separated signal-1, and Figure 4(b) compared the source signal-2 (2 kHz) and the separated signal-2. The separated signal-1's waveform is deformation but frequency nearly matched that of the source signal-1 (1.002 kHz). The separated signal-2's waveform and frequency nearly matched (2.004 kHz) those of the source signal-2.

4.2. Effect of blind source separation for FM. Figure 5 shows the comparison between the source signals and the separated signals for FM. Figure 5(a) compared the source signal-1 (1 kHz) and the separated signal-1, and Figure 5(b) compared the source signal-2 (2 kHz) and the separated signal-2. The separated signal-1's waveform nearly



1.5 urce signal arated signal 1 0.5 voltage[mV] 0 -0.5 -1 -1.5 4.001 4.0015 4.002 4 4,0005 4.0025 4.003 time[s]

(a) Comparison between source signal-1 and separated signal-1

(b) Comparison between source signal-2 and separated signal-2

FIGURE 4. Comparison between source signal and separated signal for AM

matched that of the source signal-1 but frequency error is larger than AM. The separated signal-2 nearly matched the source signal-2.

5. **Discussion.** In this section, we discuss the causes of the deformation of the AM signal's waveform and the FM signal's frequency error. It is considered that the cause of the waveform deformation is a transmitter-incurred nonlinear inter-modulation distortion. Furthermore, Figure 6 shows the comparison between the mixed signal-1 and the mixed signal-2 for FM. The frequency of the mixed signal-1 nearly matched that of the mixed signal-2. We considered that the frequency error in the case of applying BSS to FM is the cause of that. However, we can separate mixed signals. The results suggested that the BSS is effective in radio communication.

6. **Conclusions.** We investigated the applicability of blind source separation for AM and FM. In AM mode, the separated signal-1's waveform is deformation but frequency nearly matched that of the source signal-1. The separated signal-2's waveform and frequency





(a) Comparison between source signal-1 and separated signal-1

(b) Comparison between source signal-2 and separated signal-2

FIGURE 5. Comparison between source signal and separated signal for FM



FIGURE 6. Comparison between mixed signals for FM

nearly matched those of the source signal-2. In FM mode, the separated signal-1's waveform is nearly matched that of the source signal-1 but frequency error is larger than AM. The separated signal-2 is nearly matched the source signal-2. The proposed separating model can separate the mixed signals. These results suggested that the blind source separation is effective in radio communication. In future work, we will apply this proposed separating model for digital modulation.

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