PAPER

MLICA-Based Separation Algorithm for Complex Sinusoidal Signals with PDF Parameter Optimization

Tetsuhiro OKANO[†], Shouhei KIDERA[††a)], *and* Tetsuo KIRIMOTO[††], *Members*

SUMMARY Blind source separation (BSS) techniques are required for various signal decomposing issues. Independent component analysis (ICA), assuming only a statistical independence among stochastic source signals, is one of the most useful BSS tools because it does not need *a priori* information on each source. However, there are many requirements for decomposing multiple deterministic signals such as complex sinusoidal signals with different frequencies. These requirements may include pulse compression or clutter rejection. It has been theoretically shown that an ICA algorithm based on maximizing non-Gaussianity successfully decomposes such deterministic signals. However, this ICA algorithm does not maintain a sufficient separation performance when the frequency difference of the sinusoidal waves becomes less than a nominal frequency resolution. To solve this problem, this paper proposes a super-resolution algorithm for complex sinusoidal signals by extending the maximum likelihood ICA, where the probability density function (PDF) of a complex sinusoidal signal is exploited as *a priori* knowledge, in which the PDF of the signal amplitude is approximated as a Gaussian distribution with an extremely small standard deviation. Furthermore, we introduce an optimization process for this standard deviation to avoid divergence in updating the reconstruction matrix. Numerical simulations verify that our proposed algorithm remarkably enhances the separation performance compared to the conventional one, and accomplishes a super-resolution separation even in noisy situations.

key words: *radar signal processing, maximum likelihood independent component analysis (MLICA), complex sinusoidal signals, PDF parameter optimization*

1. Introduction

Blind source separation (BSS), exploiting only the statistical feature of the observed signal, is often used for various signal decomposing issues. Various complex-valued independent component analysis (ICA) algorithms, such as FastICA [1] and maximum-likelihood ICA (MLICA) [2], have been developed for such diverse signal processing as noise-robust speech recognition [3] and electroencephalogram analysis [4]. A distinct advantage of an ICA is that it assumes only that each source signal is statistically independent. It does not need any *a priori* knowledge of the desired signals, allowing uncertainty in the scale and permutation shifts of the decomposed signal. However, typical radar signal processing issues such as pulse compression [5] and clutter rejection in Doppler radar systems [6] require deterministic source signals such as complex sinusoidal forms to be accurately decomposed. It has recently been theoretically shown that an ICA successfully decomposes the multiple deterministic signals into complex sinusoidal waves with different frequencies [7]. However, its separation performance seriously degrades when the difference of the complex sinusoidal signal frequencies is less than the nominal frequency resolution determined by the maximum data length. Since general radar issues such as time of arrival (TOA) estimation or clutter rejection in Doppler radar often entail the above situations, a super-resolution separation algorithm has a significant demand in this field.

To solve these problems, this paper proposes a new ICA algorithm extending the maximum-likelihood approach [2], which exploits the probability density function (PDF) of each source signal. Most conventional maximum-likelihood ICAs [8], [9] determine the likelihood function from some typical PDFs. Then, the separation performance of these algorithms seriously depends on the selected PDF. To educe the maximum performance of MLICA, the proposed ICA algorithm uses *a priori* information of the PDF of the complex sinusoidal signals to determine the likelihood function. Since the PDF of the amplitude of a complex sinusoidal signal is expressed as a Dirac delta function assuming in a uniform phase distribution, it is difficult to numerically calculate the score function PDF because one needs the super function's partial derivative. To avoid this difficulty, we approximate the above PDF as a Gaussian function with an extremely small standard deviation. Moreover, to avoid the numerical divergence in updating the reconstruction matrix, the standard deviation of the Gaussian PDF is optimized by measuring the likelihood function. Numerical simulations verify that the separation performance of the proposed algorithm is remarkably superior to that achieved by the conventional ICA algorithm, and can considerably reduce the lower limit of frequency resolution.

This paper is organized as follows. The observation model and ICA processing are described in Sect. 2. Section 3 introduces the two conventional ICA algorithms, FastICA and MLICA, to compare algorithms. Section 4 describes the basic theory and detailed procedure of the proposed MLICA algorithm. In Sect. 5, numerical evaluations are done for some typical cases and discussed. Finally, Sect. 6 concludes our study, and suggests some directions for future work.

Manuscript received March 31, 2012.

[†]The author is with Hokkaido Electric Power Co., Sapporo-shi, 060-8677 Japan.

[††]The authors are with the Graduate School of Informatics and Engineering, The University of Electro-Communications, Chofu-shi, 182-8585 Japan.

a) E-mail: kidera@ee.uec.ac.jp

DOI: 10.1587/transcom.E95.B.3556

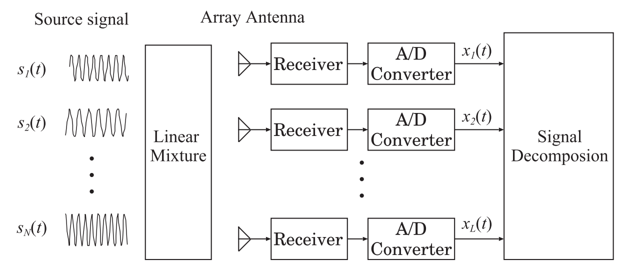

Fig. 1 System model.

2. Observation Model and ICA Processing

Figure 1 shows the system model. We assume array antennas for signal receiving, where L denotes the number of antennas. Each source signal is defined as $s_i(t) = A_i \exp(\mathrm{j}2\pi f_i t)$ $(i = 1, ..., N)$, where t is time, f is frequency, A is amplitude, and N is the number of sources. Here, we assume that $N \leq L$. The ICA model assumes that the observed signals are a linear mixture of the source signals. Then, observed signals $\boldsymbol{x}$ are given by

$$\boldsymbol{x} = \boldsymbol{B}\boldsymbol{s} + \boldsymbol{n}, \tag{1}$$

where $\boldsymbol{x} = [x_1(t), ..., x_L(t)]^T$, $\boldsymbol{s} = [s_1(t), ..., s_N(t)]^T$, $\boldsymbol{B}$ is called as mixing matrix, and $\boldsymbol{n} = [n_1(t), ..., n_L(t)]^T$ denotes the white Gaussian noise.

Principal component analysis (PCA) [10] is applied to obtain uncorrelated signals as $\hat{\boldsymbol{x}}$. PCA decomposes the observed signals into the uncorrelated signals using singular-value (SV) decomposition of $\boldsymbol{x}$. Basically, noisy components are eliminated by the PCA compression because the SVs of noises are, in general, relatively lower than those of sources. Then, uncorrelated signals $\hat{\boldsymbol{x}}$ are expressed as

$$\hat{\boldsymbol{x}} = \boldsymbol{M}\boldsymbol{x}, \tag{2}$$

where $\boldsymbol{M}$ is an $\hat{N} \times L$ matrix called the whitening matrix and $\hat{N}$ is the estimated number of source signals. Here, the number of sources can be estimated from the number of SVs, which have predominant values compared with other SVs. ICA reconstructs source signals as $\boldsymbol{u}$ using a reconstruction matrix $\boldsymbol{W}$:

$$\boldsymbol{u} = \boldsymbol{W}\hat{\boldsymbol{x}}. \tag{3}$$

Complete decomposition of the observed signals show satisfy the equation

$$\boldsymbol{W}\boldsymbol{M}\boldsymbol{B} = \boldsymbol{P}\boldsymbol{S}, \tag{4}$$

where $\boldsymbol{P}$ is a permutation matrix, and $\boldsymbol{S}$ is a diagonal matrix whose diagonal elements are equal to $ae^{\mathrm{j}\phi}$ $(0 \leq \phi \leq 2\pi)$, where a is a constant.

3. Conventional Algorithm

Several ICA algorithms have been already proposed based on maximizing the non-Gaussianity [1] or the likelihood criteria [2]. In addition, a FastICA-based algorithm evaluating non-Gaussianity has been developed to decompose deterministic signals [7]. This section briefly explains the two conventional ICA algorithms, based on FastICA and MLICA, to compare them to our proposed algorithm.

3.1 FastICA Algorithm

To determine the reconstruction matrix $\boldsymbol{W}$, the FastICA algorithm uses kurtosis, the fourth standardized moment, of the separated signals as the criterion to maximize the non-Gaussianity. In this algorithm, the update rule for $\boldsymbol{W}$ is given by [1]

$$\begin{aligned} \boldsymbol{W}_{k+1} &= \overline{\hat{\boldsymbol{x}}\left(\boldsymbol{W}_k{}^H\hat{\boldsymbol{x}}\right)^* g\left(|\,\boldsymbol{W}_k{}^H\hat{\boldsymbol{x}}\,|^2\right)} \\ &\quad \overline{-g\left(|\,\boldsymbol{W}_k{}^H\hat{\boldsymbol{x}}\,|^2\right) + |\,\boldsymbol{W}_k{}^H\hat{\boldsymbol{x}}\,|^2\, g'\left(|\,\boldsymbol{W}_k{}^H\hat{\boldsymbol{x}}\,|^2\right)}\boldsymbol{W}_k, \\ \boldsymbol{W}_{k+1} &= \boldsymbol{W}_{k+1}/\,\|\,\boldsymbol{W}_{k+1}\,\|, \end{aligned} \tag{5}$$

where k expresses the number of iterations, $\overline{\,\cdot\,}$ denotes time averaging, ^{H} denotes Hermitian transpose, g denotes any suitable non-quadratic contrast function, g' denotes a derivative of g, and * is complex conjugate. Since FastICA is based on maximizing non-Gaussianity to measure the statistical independence, it is difficult to maintain separation performance when each source signal has a highly correlated relationship.

3.2 MLICA Algorithm

Another approach is ICA based on maximum likelihood criteria (MLICA) [2], [8], [9], which uses the PDF of source signals. This algorithm updates $\boldsymbol{W}$ by maximizing the likelihood function

$$\mathcal{L}(\boldsymbol{W}) = \log p_s(\boldsymbol{W}\hat{\boldsymbol{x}}) + \log|\det \boldsymbol{W}|, \tag{6}$$

where p_s is the PDF of the source signals. This algorithm [2] yields the natural gradient updates in optimizing $\mathcal{L}(\boldsymbol{W})$. The update rule is expressed as

$$\boldsymbol{W}_{k+1} = \boldsymbol{W}_k + \mu\left(\boldsymbol{I} - \overline{\boldsymbol{\psi}(\boldsymbol{u})\boldsymbol{u}^H}\right)\boldsymbol{W}_k, \tag{7}$$

where $\boldsymbol{I}$ is the unit matrix and μ is an empirically-determined learning coefficient. $\boldsymbol{\psi}(\boldsymbol{u})$ is called the score function defined as $\boldsymbol{\psi}(\boldsymbol{u}) \equiv [\psi(u_1), \psi(u_2), ..., \psi(u_N)]^T$, with each component $\psi(u_l)$ determined by

$$\psi(u_l) = \frac{1}{2}\left(\frac{\partial \log p_s\left(u_l^{\mathrm{R}}, u_l^{\mathrm{I}}\right)}{\partial u_l^{\mathrm{R}}} + \mathrm{j}\frac{\partial \log p_s\left(u_l^{\mathrm{R}}, u_1^{\mathrm{I}}\right)}{\partial u_l^{\mathrm{I}}}\right), \tag{8}$$

where u_l^{R}, u_l^{I} are the real and imaginary part of u_l. In the conventional MLICA, the form of the PDF must typically be selected from the sub-Gaussian or super-Gaussian nature of the estimated source signals [8]. Since the MLICA algorithm requires *a priori* knowledge of the PDF of the source signals, the separation performance is severely degraded when the selected PDF is far from the actual one.

4. Proposed Algorithm

To solve this problem, we incorporate the PDF of the complex sinusoidal signal into the present MLICA as *a priori* information. For common radar or communication, it is, in general, acceptable to assume that the source signal has a complex sinusoidal form [5], [6]. For example, estimating the TOA in radar systems is equivalent to estimating the frequency of the mixed complex sinusoidal signals in the frequency domain. Noting that the phase angle of a complex sinusoidal signal u_l is uniformly distributed between 0 and 2π, the PDF of a complex sinusoidal signal having amplitude 1 is given by

$$p_s(u_l) = p_r(|u_l|)p_\theta(\angle u_l) = \frac{1}{2\pi}\delta(|u_l| - 1), \tag{9}$$

where p_r is the PDF of $|u_l|$, p_θ is the PDF of phase angle $\angle u_l$, and δ denotes Dirac's delta function. To derive the score function from the above PDF in a differentiable form, this method approximates Eq. (9) with the Gaussian function by:

$$p_s(u_l) = \frac{1}{(2\pi)^{\frac{3}{2}}\sigma}\exp\left(-\frac{(|u_l| - 1)^2}{2\sigma^2}\right), \tag{10}$$

where σ satisfies $\sigma \ll 1$ to be close to Eq. (9). From Eqs. (8) and (10), the score function $\psi(u_l)$ is formulated as

$$\psi(u_l) = \frac{|u_l| - 1}{2\sigma^2}\exp(\mathrm{j}\angle u_l). \tag{11}$$

Although Eq. (10) becomes close to Eq. (9) when $\sigma \to 0$, the score function should diverge to infinity, which makes it difficult for the reconstruction matrix $\boldsymbol{W}$ to converge in Eq. (7). Then, we consider that there is an optimal value of σ in Eq. (11) when we maximize the separation performance. To attain the optimal σ, we focus on the fact that the maximum value of the likelihood function is positively correlated to the separation performance. Then, the evaluation value $\mathcal{L}(\boldsymbol{W}(\sigma))$ determined by σ is derived from Eqs. (6) and (10) as,

$$\mathcal{L}(\boldsymbol{W}(\sigma)) = T\log|\det \boldsymbol{W}(\sigma)| - \frac{1}{2\sigma^2}\sum_{k=1}^{T}\sum_{l=1}^{\hat{N}}(|u_l(k;\sigma)| - 1)^2, \tag{12}$$

where T is the number of the total data length, and $u(k;\sigma)$ and $\boldsymbol{W}(\sigma)$ denote the estimated signal at the k th time index and the reconstruction matrix, respectively, which are determined by the proposed MLICA using the score function in Eq. (11). Then, the proposed algorithm optimizes σ as

$$\sigma_{\mathrm{opt}} = \arg\max_{0<\sigma<1} \mathcal{L}(\boldsymbol{W}(\sigma)). \tag{13}$$

Finally, the reconstruction matrix is calculated as $\boldsymbol{W}_{\mathrm{opt}} = \boldsymbol{W}(\sigma_{\mathrm{opt}})$. The proposed ICA algorithm is described as follows

Step 1) Uncorrelated observed signals $\hat{\boldsymbol{x}}$ are obtained by the PCA in Eq. (2).

Step 2) For given σ, MLICA is applied with the score function in Eq. (11) to obtain $\boldsymbol{W}(\sigma)$.

Step 3) $\mathcal{L}(\boldsymbol{W}(\sigma))$ is evaluated, and if $\mathcal{L}(\boldsymbol{W}(\sigma))$ is maximized, the procedure is over. Otherwise, σ is updated and Step 2) is repeated.

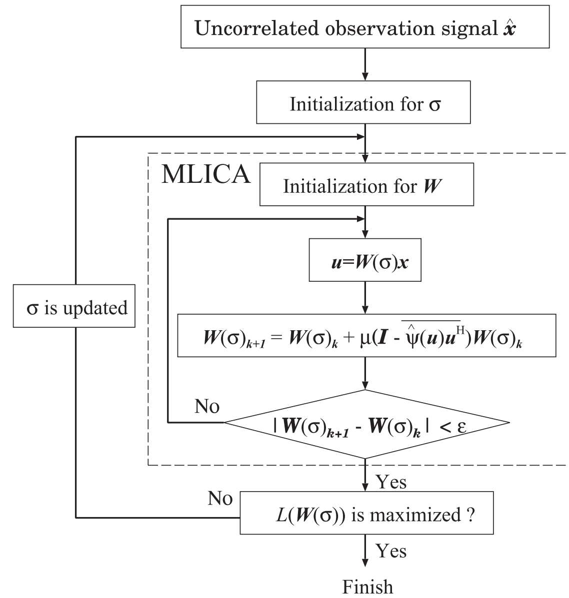

Fig. 2 Flowchart of the proposed ICA algorithm.

Figure 2 presents the flowchart of the proposed ICA algorithm. The threshold ϵ is empirically determined in this process.

5. Performance Evaluation in Numerical Simulation

This section investigates the separation performance of the conventional and proposed algorithms in numerical simulations. To evaluate the separation performance quantitatively, we introduce the separation performance (SEP) index

$$\mathrm{SEP} = \frac{1}{\hat{N}}\sum_{i=1}^{\hat{N}}\frac{\max_j\left(|\hat{P}_{ij}|^2\right)}{\sum_{j=1}^{\hat{N}}|\hat{P}_{ij}|^2 - \max_j\left(|\hat{P}_{ij}|^2\right)}, \tag{14}$$

where $\hat{\boldsymbol{P}} = \boldsymbol{WMB}$ is a $\hat{N}\times\hat{N}$ complex matrix, and $\hat{P}_{ij}$ denotes the element of $\hat{\boldsymbol{P}}$ at the i th row and the j th column. SEP becomes infinity when the ICA completely decomposes the observed signals into the source signal. SEP also means the ratio of the desired-signal power to the undesired-signal power for each channel. Here, the trust-region algorithm [11] is used to solve the optimizing problem in our proposed algorithm. This algorithm guarantees global convergence and local super convergence, which is based on the idea of calculating the trial step size by checking if the next value belong to the trust region.

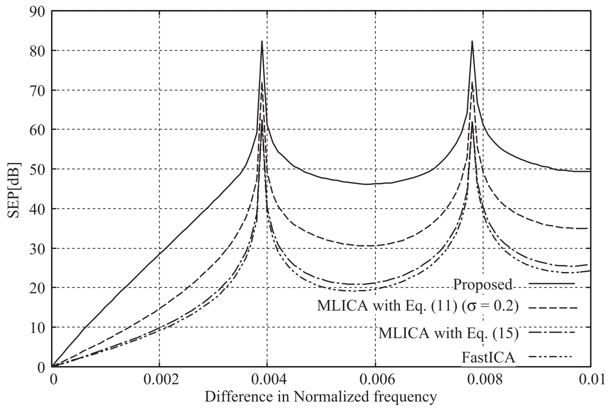

Fig. 3 Separation performance with each algorithm versus normalized frequency difference in noiseless environment, where 100 different mixing cases are averaged.

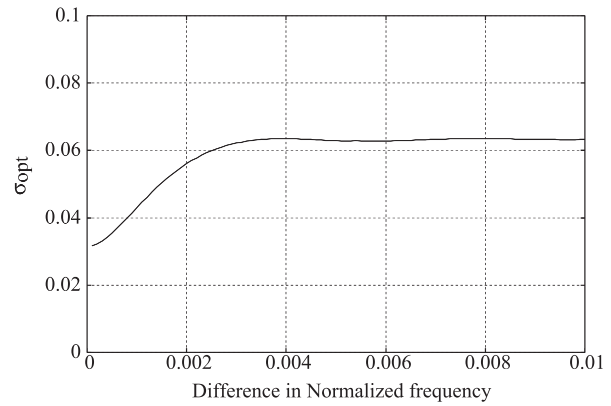

Fig. 4 Optimized σ in the proposed method versus normalized frequency difference.

5.1 Separation Performance for $N = 2$

First, we assume a noiseless environment. Two complex sinusoidal signals $\boldsymbol{s} = [s_1(t), s_2(t)]$ with different frequencies are created, and observed signal $\boldsymbol{x}$ is generated using a proper mixing matrix $\boldsymbol{B}$ in Eq. (1). Here, the conventional MLICA uses the score function with the following sub-Gaussian function

$$\psi(u_l) = \frac{1}{2}\left(\tanh(u_l{}^{\mathrm{R}}) - u_l{}^{\mathrm{R}} + \mathrm{j}\left(\tanh(u_l{}^{\mathrm{I}}) - u_l{}^{\mathrm{I}}\right)\right). \quad (15)$$

The reason for this selection is that the PDF of the complex sinusoidal signal is comparatively close to the sub-Gaussian distribution as in Eq. (15). Figure 3 shows the SEP for the frequency difference between the two sinusoidal signals, which is normalized by the inverse of data length $T = 256$ and number of antenna $L = 2$, where the two-dot chain line is FastICA, the chain line is MLICA with Eq. (15), the broken line is MLICA with Eq. (11) ($\sigma = 0.2$ is fixed), and the solid line is the proposed algorithm. $\mu = 0.001$, $\epsilon = 10^{-6}$, and each amplitude of signals is set to 1. For the statistical evaluation, we investigate 100 different mixing matrices $\boldsymbol{B}$, where $\boldsymbol{B} = \begin{bmatrix} \mathrm{e}^{\mathrm{j}\theta_\alpha} & \mathrm{e}^{\mathrm{j}\theta_\beta} \\ \mathrm{e}^{\mathrm{j}\theta_\gamma} & \mathrm{e}^{\mathrm{j}\theta_\delta} \end{bmatrix}$ and each parameter of $(\theta_\alpha, \theta_\beta, \theta_\gamma, \theta_\delta)$ is independently changed according to the uniform distribution in $[0, 2\pi]$. The SEP for each frequency difference is averaged with 100 cases. Figure 3 shows that our algorithm achieves a remarkably higher separation performance compared to the conventional ICA algorithm in all frequency differences, because *a priori* knowledge of the PDF offers a more accurate solution for ICA optimization. Note that this algorithm attains a sufficient SEP when Δf, the normalized frequency difference of source signals, is smaller than the nominal frequency resolution with $f_s = 1/T$. This verifies the super-resolution property of our algorithm. Furthermore, Fig. 4 shows the optimized σ in the proposed method versus normalized frequency difference. The figure shows that the optimized σ significantly depends on the frequency difference, particularly in the case of $\Delta f < f_s$.

Here, we investigate the frequency resolution for each algorithm. In this case, the frequency resolution is defined as the minimum frequency difference, which holds SEP ≥ 20 dB. As shown in Fig. 3, each frequency resolution with FastICA is $0.84 f_s$, MLICA with Eq. (15) is $0.82 f_s$, MLICA with Eq. (11) ($\sigma = 0.2$ is fixed) is $0.66 f_s$, and the proposed algorithm is $0.36 f_s$. This comparison shows that our algorithm obtains the highest frequency resolution among all the algorithms, and accomplishes super-resolution signal decomposition. In addition, Fig. 5 shows the real part of the observed signal and separated signal waveforms for each algorithm when the difference in the frequency difference is $\Delta f = 0.5 f_s$, where the time is normalized by the data length $N = 256$. The SEP with FastICA is 8.9 dB, MLICA with Eq. (15) is 9.6 dB, MLICA with Eq. (11) ($\sigma = 0.2$ is fixed) is 14.3 dB, and our algorithm is 28.0 dB. As shown in this figure, the reconstructed signals waveform with FastICA, MLICA with Eq. (15) and MLICA with Eq. (11) ($\sigma = 0.2$ is fixed) are imperfectly separated. However, our algorithm using the optimized σ successfully separates the two original signals.

Moreover, white Gaussian noise is added to the observed signals. Here, the signal-to-noise ratio (SNR) is defined as the ratio of the signal power to the average noise power in the time domain. Figure 6 shows the SEP against the SNR for each algorithm when the difference in the normalized frequency is $\Delta f = 0.7 f_s$ and each amplitude of source signal is set to 1. Here, we investigate 500 patterns of white Gaussian noises, where the mixing matrix $\boldsymbol{B}$ is fixed. This figure shows that the proposed algorithm obtains more separation performance for all SNR values and significantly exceeds all conventional algorithms in terms of SEP evaluation.

5.2 Separation Performance for $N \geq 2$

To show the relevance of our algorithm, this section investigates the situation for $N \geq 2$. Figures 7 and 8 show the SEP against the number of source signals for a noiseless

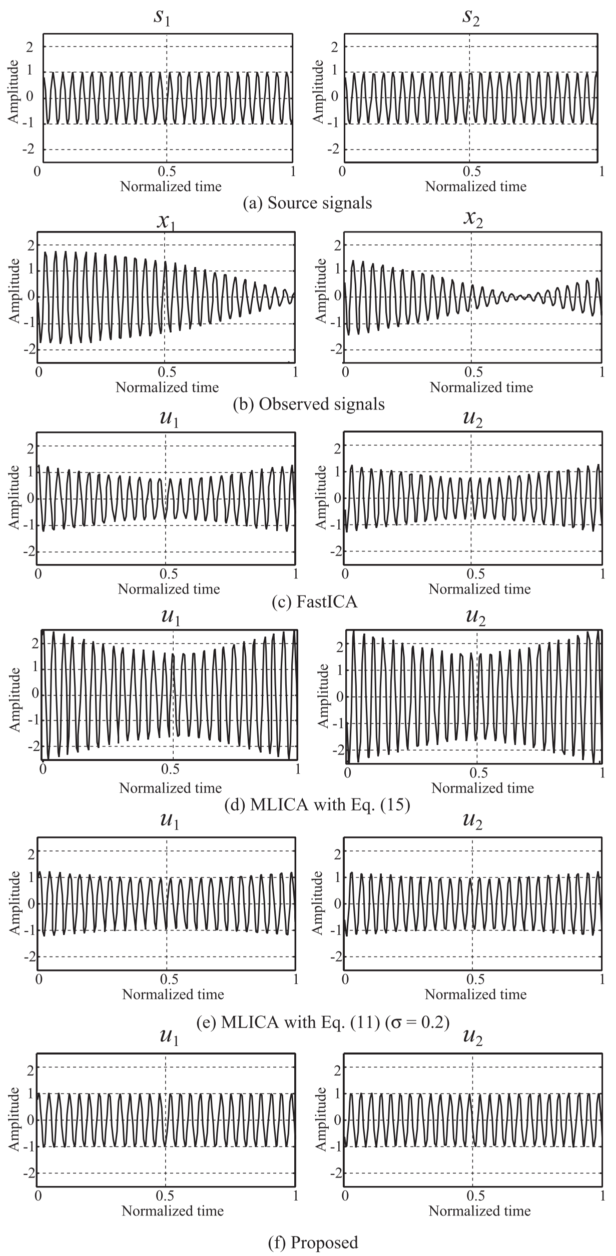

Fig. 5 Real part of waveform. (a) Source signal waveforms (b) Observed signal waveforms and separated signals with (c) FastICA (d) MLICA with Eq. (15) (e) MLICA with Eq. (11) ($\sigma = 0.2$) (f) Proposed algorithm, where $\Delta f = 0.5f_s$.

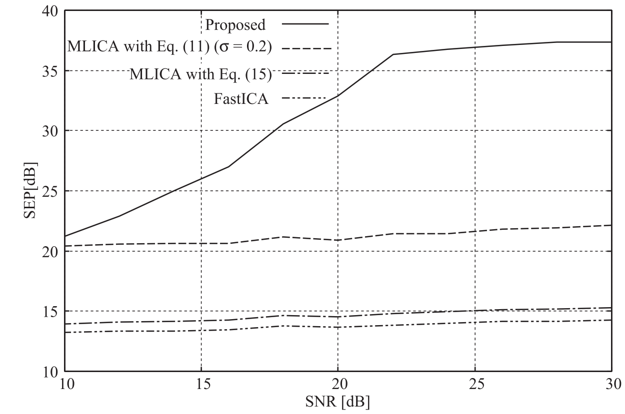

Fig. 6 Separation performance against the SNR for each algorithm, where mixing matrix is fixed.

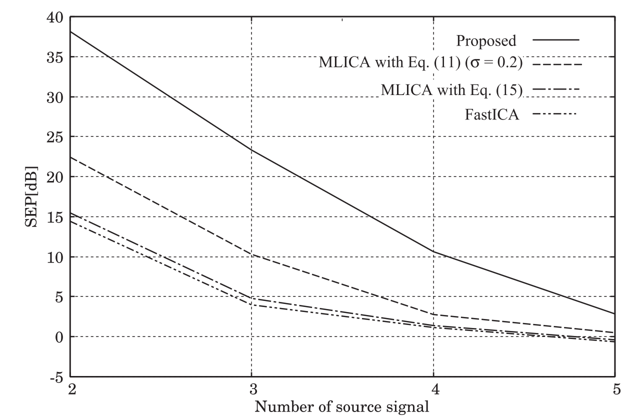

Fig. 7 Separation performance with each algorithm versus number of source signal in noiseless environment, where 100 different mixing cases are averaged.

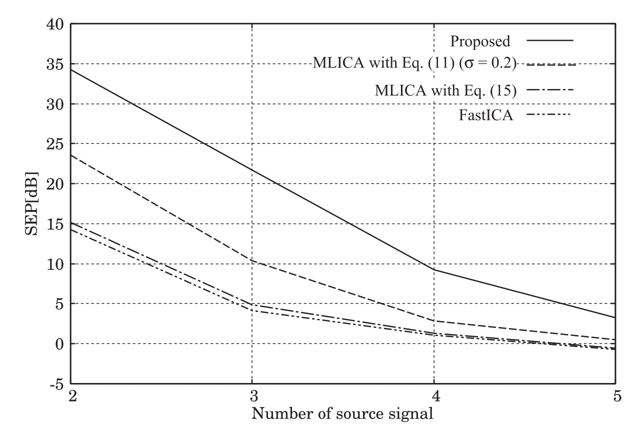

Fig. 8 Separation performance with each algorithm versus number of source signal in SNR=20 dB, where mixing matrix is fixed.

and noisy situation at SNR = 20 dB, respectively. Here, the number of antenna is $L = 6$, and the adjacent frequency difference between source signals is set to $\Delta f = 0.7f_s$ and each amplitude of source signal is 1. Here, the 500 patterns of white Gaussian noises are tested in Fig. 8, where the mixing matrix $\boldsymbol{B}$ is fixed at the each number of signals. The number of source signals is determined by extracting the distinct singular value in PCA processing. These figures confirm that our algorithm achieves the highest separation performance for any number of signals compared to the other algorithms. However, this figure shows that separation performance of all ICA algorithms becomes lower when the number of source signals is increased. As a discussion for this result, Table 1 shows multiple correlation coefficients between the source signals at each number of source signals. This table shows that the multiple correlation coefficient in-

Table 1 Multiple correlation coefficients between source signals at each number of signals.

Number of source signals	s_1	s_2	s_3	s_4	s_5
2	0.37	0.37	-	-	-
3	0.53	0.59	0.53	-	-
4	0.64	0.74	0.74	0.64	-
5	0.72	0.84	0.86	0.84	0.72

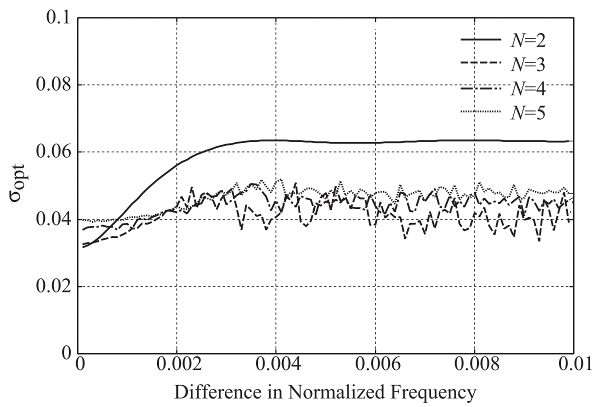

Fig. 9 Optimized σ in the proposed method versus normalized frequency difference for each number of signals in noiseless environment.

creases when the number of source signals increase. The SEPs for all the algorithms are seriously degraded in these highly correlated situations.

Finally, Fig. 9 shows the optimized σ in the proposed method versus adjacent frequency difference between source signals when changing the number of signals N in the noiseless case. Here, the number of antenna is fixed as $L = 6$, and 100 different mixing matrices $\boldsymbol{B}$ are investigated. This figure shows that the optimized σ significantly depends on the frequency difference and number of source signals. Note that there are some fluctuations in the case of $N = 3, 4$ and 5, because each multiple correlation coefficient is different and the optimized *sigma* is not uniquely determined.

6. Conclusion

In this paper, we proposed a new ICA algorithm in specifying the separation of complex sinusoidal signals with different frequencies. The FastICA algorithm, using only the statistical independence among source signals, results in separation performance degradation, particularly when the frequency difference is below a nominal frequency resolution. In addition, the conventional MLICA algorithm needs to select the PDF from the typical candidates, and its separation performance is severely lowered when the PDF is wrongly estimated. To solve this problem with an existing ICA algorithm, we newly introduced an MLICA algorithm in which the score function is modified to suit the complex sinusoidal signal, where the PDF of the amplitude of the complex sinusoidal signal is approximated as a Gaussian function with a small standard deviation. Moreover, to attain maximum separation performance, this method optimizes the standard deviation of the PDF to suppress the numerical divergence in calculating the MLICA reconstruction matrix. Numerical simulations verified that the separation performance of the proposed algorithm is remarkably enhanced when the frequency difference of source signals is lower than the nominal frequency resolution. Furthermore, we confirmed the significant advantage of our algorithm even for a noisy case and a higher number of source signals. One result shows that the proposed algorithm has a super-resolution property for decomposing separation for a complex sinusoidal signal, and is most suitable for actual radar applications such as TOA estimation and clutter rejection.

Acknowledgment

The authors are grateful to Dr. Hirata and Dr. Amishima of Information Technology R&D Center, Mitsubishi Electric Corporation for their fruitful discussions.

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Appendix: Derivation of Eq. (11)

Equation (10) can be written as

$$p_s(u_l^{\mathrm{R}}, u_l^{\mathrm{I}}) = \frac{1}{(2\pi)^{\frac{3}{2}}\sigma} \exp\left(-\frac{\left(\sqrt{{u_l^{\mathrm{R}}}^2 + {u_l^{\mathrm{I}}}^2} - 1\right)^2}{2\sigma^2}\right). \quad (\mathrm{A}\cdot 1)$$

Then, with Eqs. (8) and (A· 1), the score function $\psi(u_l)$ is formulated as

$$\begin{aligned}\psi(u_l) &= \frac{1}{2}\left(\frac{\partial \log p_s\left(u_l^{\mathrm{R}}, u_l^{\mathrm{I}}\right)}{\partial u_l^{\mathrm{R}}} + \mathrm{j}\frac{\partial \log p_s\left(u_l^{\mathrm{R}}, u_1^{\mathrm{I}}\right)}{\partial u_l^{\mathrm{I}}}\right) \\ &= -\frac{\left(\sqrt{{u_l^{\mathrm{R}}}^2 + {u_l^{\mathrm{I}}}^2} - 1\right)\left(u_l^{\mathrm{R}} + \mathrm{j}u_l^{\mathrm{I}}\right)}{2\sigma^2\sqrt{{u_l^{\mathrm{R}}}^2 + {u_l^{\mathrm{I}}}^2}} \\ &= \frac{|u_l| - 1}{2\sigma^2}\exp(\mathrm{j}\angle u_l). \quad (\mathrm{A}\cdot 2)\end{aligned}$$

Tetsuhiro Okano received his B.E. degree in Electronic Engineering, and his M.M. degree in Mechanical Engineering and Intelligent Systems from University of Electro-Communications in 2010 and 2012, respectively. He joined Hokkaido Electric Power Co., Inc. in 2012.

Shouhei Kidera received his B.E. degree in Electrical and Electronic Engineering from Kyoto University in 2003 and M.I. and Ph.D. degrees in Informatics from Kyoto University in 2005 and 2007, respectively. He is an assistant professor in Graduate School of Informatics and Engineering, University of Electro-Communications, Japan. His current research interest is in advanced signal processing for the near field radar, UWB radar. He is a member of the Institute of Electrical and Electronics Engineering (IEEE) and the Institute of Electrical Engineering of Japan (IEEJ).

Tetsuo Kirimoto received the B.S. and M.S. and Ph.D. degrees in Communication Engineering from Osaka University in 1976, 1978 and 1995, respectively. During 1978–2003 he stayed in Mitsubishi Electric Corp. to study radar signal processing. From 1982 to 1983, he stayed as a visiting scientist at the Remote Sensing Laboratory of the University of Kansas. From 2003 to 2007, he joined the University of Kitakyushu as a Professor. Since 2007, he has been with the University of Electro-Communications, where he is a Professor at the Graduate School of Informatics and Engineering. His current study interests include digital signal processing and its application to various sensor systems. Prof. Kirimoto is a senior member of IEEE and a member of SICE (The Society of Instrument and Control Engineers) of Japan.