

## PAPER

# Super Resolution TOA Estimation Algorithm with Maximum Likelihood ICA Based Pre-Processing

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**SUMMARY** High-resolution time of arrival (TOA) estimation techniques have great promise for the high range resolution required in recently developed radar systems. A widely known super-resolution TOA estimation algorithm for such applications, the multiple-signal classification (MUSIC) in the frequency domain, has been proposed, which exploits an orthogonal relationship between signal and noise eigenvectors obtained by the correlation matrix of the observed transfer function. However, this method suffers severely from a degraded resolution when a number of highly correlated interference signals are mixed in the same range gate. As a solution for this problem, this paper proposes a novel TOA estimation algorithm by introducing a maximum likelihood independent component analysis (MLICA) approach, in which multiple complex sinusoidal signals are efficiently separated by the likelihood criteria determined by the probability density function (PDF) of a complex sinusoid. This MLICA schemes can decompose highly correlated interference signals, and the proposed method then incorporates the MLICA into the MUSIC method, to enhance the range resolution in richly interfered situations. The results from numerical simulations and experimental investigation demonstrate that our proposed pre-processing method can enhance TOA estimation resolution compared with that obtained by the original MUSIC, particularly for lower signal-to-noise ratios.

**key words:** maximum likelihood independent component analysis (MLICA), multiple signal classification (MUSIC), super-resolution TOA estimation, highly correlated signal separation

## 1. Introduction

A high resolution time of arrival (TOA) estimation technique is strongly required in general radar systems to obtain a sufficient range resolution. As a classical TOA estimation scheme, cross-correlation based methods [1], [2] have been widely employed. However, such algorithms barely separate the target signals within the same range gate which is strictly determined by the transmission bandwidth, and the algorithms then cannot offer the necessary resolution and accuracy in actual radar applications. To resolve the above difficulty, a super-resolution approach, the multiple-signal classification (MUSIC), based on the resolution exploiting the orthogonality between the signal and noise subspaces, has been established in recent decades [3], [4]. However, its range resolution seriously degrades when there are a number of highly correlated interference signals in the same range gate, and this property becomes more severe in lower signal

to noise (SNR) situations.

To overcome the above problem, this paper proposes a novel TOA estimation algorithm by introducing an independent component analysis (ICA) based pre-processing. The ICA scheme is one of the most useful tools for blind source separation, and requires only the statistical independence of the source signals for signal reconstruction [5], [6]. In recent years, several ICA algorithms suitable for complex signals, aimed at radar applications, have been developed and have successfully decomposed multiple deterministic signals as complex sinusoidal signals with different frequencies [7]. In addition, such algorithms are useful for TOA estimation, because TOA estimation corresponds to the separation of the multiple mixed complex sinusoidal signals in the frequency domain. Moreover, to enhance the separation performance of complex sinusoidal signals with respect to frequency resolution, we have already proposed an improved maximum-likelihood (ML) ICA algorithm [8] to specify the separation of complex sinusoidal signals with different frequencies [9]. This ICA algorithm employs *a priori* information of the probability density function (PDF) of complex sinusoidal signals, and accomplishes higher separation performance for complex sinusoidal signals in the case of less than nominal frequency resolution.

Exploiting the distinct feature of the above MLICA [9], this paper proposes a higher resolution TOA estimation method, by employing MLICA for separating highly correlated signals. Note that, to create the quasi multiple channels required in a typical ICA model, we adopt the single channel ICA (SCICA) scheme [10], which employs a frequency shift of the transfer function for increasing the number of channels. Both results from numerical simulations and experimental investigation, carried out in an anechoic chamber, verify that the proposed pre-processing incorporated into MUSIC significantly enhances the discriminating property for the number of source signals, i.e., range resolution, compared with that in the conventional MUSIC method without serious degradation in accuracy.

This paper is organized as follows. Section 2 describes the system model in radar systems and the received signal model assumed in this paper. Section 3 introduces the conventional TOA estimation method as the MUSIC algorithm for comparison of the method. Section 4 describes the basic theory of MLICA specified for the complex sinusoidal separation principle and the detailed procedure of the proposed method, including the SCICA approach. In Sect. 5, the numerical evaluations are investigated for some typical

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cases, and discussed. Finally, in Sect. 6, the experimental data validates the effectiveness of the proposed method.

## 2. System and Received Signal Model

Figure 1 shows the system model. This study assumes a mono-static radar and multiple-point scatterers. A received signal is obtained through a duplexer and A/D converter. We consider a chirp-modulated transmitted signal, and the received signal is simply expressed as

$$x(t) = \sum_{i=1}^L a_i s(t - \tau_i) + n(t), \quad (1)$$

where  $a_i$  is an amplitude,  $\tau_i$  denotes each time of arrival,  $L$  is the number of signals,  $s(t)$  denotes the transmitted signal with chirp modulation, and  $n(t)$  expresses a Gaussian white noise. We define the angular frequency transfer function  $Z(\omega)$  as:

$$Z(\omega) = \frac{X(\omega)}{S(\omega)} = \sum_{i=1}^L a_i \exp(-j\omega\tau_i) + \frac{N(\omega)}{S(\omega)} \quad (2)$$

where  $X(\omega)$ ,  $S(\omega)$  and  $N(\omega)$  are the Fourier transforms of  $x(t)$ ,  $s(t)$  and  $n(t)$ . The discrete form in Eq. (2) is expressed as

$$Z(n\Delta\omega) = \frac{X(n\Delta\omega)}{S(n\Delta\omega)} = \sum_{i=1}^L a_i \exp(-jn\Delta\omega\tau_i) + \frac{N(n\Delta\omega)}{S(n\Delta\omega)}, \quad (n = 1, 2, \dots, \Omega), \quad (3)$$

where  $\Omega$  is the total number of angular frequency points and  $\Delta\omega$  denotes the sampling interval of the angular frequency. Here, the vector format of the above transfer function is defined as,

$$\tilde{\mathbf{Z}} = [Z(\Delta\omega), Z(2\Delta\omega), \dots, Z(\Omega\Delta\omega)] = \tilde{\mathbf{A}}\tilde{\mathbf{H}} + \tilde{\mathbf{N}}, \quad (4)$$

where

$$\tilde{\mathbf{A}} = [a_1, a_2, \dots, a_L], \quad (5)$$

$$\tilde{\mathbf{H}} = [\tilde{\mathbf{h}}(\tau_1), \tilde{\mathbf{h}}(\tau_2), \dots, \tilde{\mathbf{h}}(\tau_L)]^T, \quad (6)$$

$$\tilde{\mathbf{h}}(\tau_i) = [\exp(-j\Delta\omega\tau_i), \exp(-j2\Delta\omega\tau_i), \dots, \exp(-j\Omega\Delta\omega\tau_i)]^T, \quad (7)$$

$$\tilde{\mathbf{N}} = \left[ \frac{N(\Delta\omega)}{S(\Delta\omega)}, \frac{N(2\Delta\omega)}{S(2\Delta\omega)}, \dots, \frac{N(\Omega\Delta\omega)}{S(\Omega\Delta\omega)} \right], \quad (8)$$

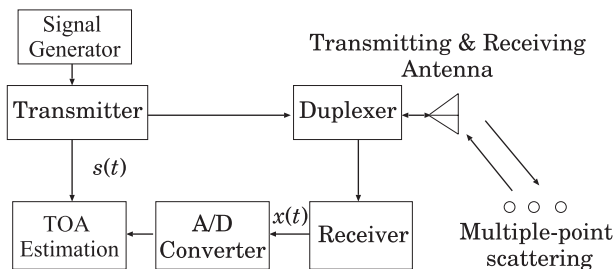


Fig. 1 System model.

and the superscript  $T$  denotes the transpose operation.

## 3. Conventional Method

Several TOA estimation algorithms for radar systems have already been proposed. This section briefly explains one of the most efficient TOA estimation methods known as MUSIC [3], [4], for comparison with the proposed method. MUSIC has been known as the super-resolution TOA techniques, which positively employs eigenvectors determined by the noise subspace decomposed from the correlation matrix of the observed transfer function  $Z(\omega)$ . To suppress a negative effect from the correlated interference signals, frequency averaging is adopted in calculating the correlation matrix as:

$$\bar{\mathbf{R}} = \sum_{n=1}^{\Omega-M+1} \alpha_n \mathbf{Z}_n \mathbf{Z}_n^H, \quad (9)$$

where  $^H$  denotes the Hermitian transpose,  $\mathbf{Z}_n = [Z(n\Delta\omega), \dots, Z((n+M-1)\Delta\omega)]^T$ ,  $M(< \Omega)$  denotes the dimension of the subspace in the frequency domain, and  $\alpha_n = 1/(\Omega - M + 1)$ , for simplicity. The output in time domain of the conventional MUSIC is expressed as:

$$y_{\text{music}}(t) = \frac{\mathbf{b}^H(t)\mathbf{b}(t)}{\mathbf{b}^H(t)\mathbf{E}_n\mathbf{E}_n^H\mathbf{b}(t)}, \quad (10)$$

where  $\mathbf{b}(t) = [\exp(-j\Delta\omega t), \dots, \exp(-jM\Delta\omega t)]^T$  is called a steering vector,  $\mathbf{E}_n = [\mathbf{e}_{n,\hat{L}+1}, \dots, \mathbf{e}_{n,\Omega-M-\hat{L}+1}]$  is defined, where  $\mathbf{e}_{n,i}$ , ( $i = \hat{L} + 1, \dots, \Omega - M - \hat{L} + 1$ ) corresponds to the noise eigenvectors, and  $\hat{L}$  is the estimated number of signals. The desired TOAs are obtained from the local maxima of  $y_{\text{music}}(t)$ . Although frequency averaging is applied to suppress resolution degradation due to the coherent interference signals as in Eq. (3), it still suffers from the degradation of range resolution, when the number of correlated signals increases or their time interval becomes closer.

## 4. Proposed Method

As a solution to the problem, this paper newly introduces a ICA-based pre-processing for super-resolution TOA estimation. First, for clarity, we briefly explain a basic ICA model. Second, the maximum likelihood ICA (MLICA) algorithm in specifying the separation of complex sinusoidal signals [9] is introduced. Third, the SCICA scheme is presented to generate the quasi-multiple channels in the mono-static radar model. Finally, the actual procedure of this method is summarized.

### 4.1 Basic Model of ICA

It is a well-known fact that ICA requires only the statistical independence of source signals for separation and no *a priori* information of desired signals, where uncertainty in the scale and permutation shifts are allowed [5]. The basic ICA model assumes array antennas for receiving signals, where

the number of antennas is denoted by  $K$ . This model also assumes that the observed signals are expressed as a linear mixture of the source signals. Then, the observed signals  $\mathbf{Z}'$  are given by:

$$\mathbf{Z}' = \mathbf{A}'\mathbf{S}' + \mathbf{n}, \quad (11)$$

where  $\mathbf{Z}' = [Z'_1, Z'_2, \dots, Z'_{K'}]^T$ ,  $\mathbf{S}' = [S'_1, S'_2, \dots, S'_{L'}]^T$ ,  $\mathbf{A}'$  is called a mixing matrix, and  $\mathbf{n} = [n_1, n_2, \dots, n_{K'}]^T$  denotes the white Gaussian noise. We assume that  $K' \geq L'$ . ICA reconstructs source signals as  $\mathbf{Y}$  using a reconstruction matrix  $\mathbf{W}$  as

$$\mathbf{Y}' = \mathbf{W}'\mathbf{Z}'. \quad (12)$$

$\mathbf{W}'$  is determined by some bases, such as a non-Gaussianity [6] or a likelihood criteria [8]. In the case of a complete decomposition of the observed signals, the following equation should be satisfied:

$$\mathbf{W}'\mathbf{A}' = \mathbf{P}\mathbf{C}, \quad (13)$$

where  $\mathbf{P}$  is a permutation matrix and  $\mathbf{C}$  denotes a diagonal matrix.

#### 4.2 MLICA Specifying Sinusoidal Signal Separation

While the typical ICA deals with statistical signals, it has been theoretically verified that ICA successfully decomposes the multiple deterministic signals as complex sinusoidal waves with different frequencies [7]. This paper is based on the fact that the TOA estimation is equivalent to the frequency estimation of the mixed complex signals in the frequency domain as in Eq. (3). Several ICA algorithms suitable for this type of separation have been developed on the basis of maximizing the non-Gaussianity [6] or likelihood criteria [8]. Furthermore, we have already proposed an improved MLICA algorithm in specifying the separation of complex sinusoidal signals using *a priori* information of the PDF of complex sinusoidal signals [9].

Thus, in this paper, we introduce this MLICA algorithm [9] as the pre-processing for super-resolution TOA algorithm by decomposing highly correlated signals. We briefly explain the method [9] as follows. In the typical MLICA, the reconstruction matrix  $\mathbf{W}$  is updated to maximize the likelihood function [8]:

$$\mathbf{W}_{k+1} = \mathbf{W}_k + \mu \left( \mathbf{I} - \overline{\psi(\mathbf{Y})\mathbf{Y}^H} \right) \mathbf{W}_k, \quad (14)$$

where  $k$  expresses the number of iterations,  $\overline{\phantom{x}}$  denotes time averaging,  $\mathbf{I}$  is the unit matrix and  $\mu$  is a learning coefficient. Here,  $\psi(\mathbf{Y}) = [\psi(Y_1), \psi(Y_2), \dots, \psi(Y_N)]^T$  is defined, with each component  $\psi(Y_i)$  is a score function, which can be calculated from the derivative of the source signal's PDF. In this case, the PDF of the source signal (a complex sinusoidal signal) is analytically given, but is expressed as a super function with Dirac's delta function [9], i.e. an undifferentiable form. The PDF is then approximated by a Gaussian function, and its score function is derived as:

$$\psi(Y_i) = \frac{|Y_i| - A}{2\sigma^2} \exp(j\angle Y_i), \quad (15)$$

where  $A$  is the amplitude of the complex sinusoidal signal,  $\angle$  denotes the argument of the complex value and  $\sigma$  is selected so that  $\sigma \ll 1$ . Naturally, the separation performance of this ICA algorithm strongly depends on the value of  $\sigma$ . To attain the optimal value of  $\sigma$ , this method recursively assesses the likelihood function obtained from the reconstruction signals. The detail derivation of the PDF and score function, and the procedure of  $\sigma$  optimization are described in [9].

#### 4.3 SCICA for Generation of Quasi Multiple Channels

As described in 4.1, as well as in the above ICA [9], the typical ICA model requires multiple channels for the separation of multiple sources. However, our system model assumes that the observed signal is received in only a single channel. As a solution for this, SCICA [10] is adopted in this paper, which creates quasi multiple channels employing a frequency shift of the transfer function  $Z(\omega)$ . The shifted transfer function is expressed as:

$$\mathbf{Z} = [\mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_K]^T = \mathbf{A}\mathbf{H} + \mathbf{N}, \quad (16)$$

$$\mathbf{Z}_n = [Z(n\Delta\omega), Z((n+1)\Delta\omega), \dots, Z((n+\Omega-K)\Delta\omega)]^T \\ (n = 1, 2, \dots, K), \quad (17)$$

where  $K$  denotes the number of quasi-multiple channels:

$$\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_K]^T, \quad (18)$$

$$\mathbf{a}_n = \tilde{\mathbf{A}} \text{diag} [\exp(-j(n-1)\Delta\omega\tau_1), \exp(-j(n-1)\Delta\omega\tau_2), \\ \dots, \exp(-j(n-1)\Delta\omega\tau_L)], \quad (19)$$

$$\mathbf{H} = [\mathbf{h}(\tau_1), \mathbf{h}(\tau_2), \dots, \mathbf{h}(\tau_L)]^T, \quad (20)$$

$$\mathbf{h}(\tau_i) = [\exp(-j\Delta\omega\tau_i), \exp(-j2\Delta\omega\tau_i), \\ \dots, \exp(-j(\Omega-K+1)\Delta\omega\tau_i)]^T, \quad (21)$$

and  $\mathbf{N}$  corresponds to a transfer function of noise. For pre-processing of the general ICA, principal component analysis (PCA) is adopted, which decomposes the observed signals into the uncorrelated signals using singular value (SV) decomposition of  $\mathbf{Z}$ . The uncorrelated signals after PCA  $\mathbf{Z}^P$  are formulated as:

$$\mathbf{Z}^P = \mathbf{M}\mathbf{Z}, \quad (22)$$

where  $\mathbf{M}$  is  $\hat{L} \times K$  matrix and  $\hat{L}$  is the number of signals, which is estimated from the number of SVs, having pre-dominant values compared with other SVs.

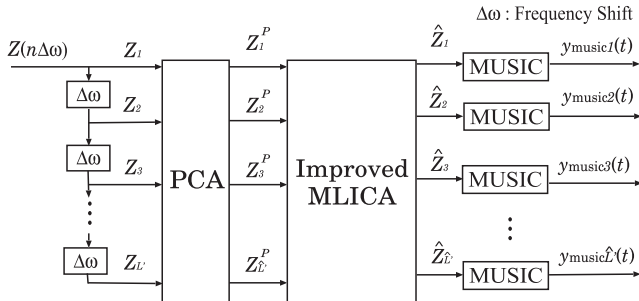
The reconstruction signal  $\mathbf{Y}$  through ICA is then formulated as:

$$\mathbf{Y} = \mathbf{W}\mathbf{Z}^P. \quad (23)$$

In this paper,  $\mathbf{W}$  is determined by the method [9] described in Sect. 4.2.

#### 4.4 Procedure for the Proposed Method

The actual procedure of this algorithm is described as follows:



**Fig. 2** Block diagram of the proposed method.

Step 1) Frequency transfer function  $Z(n\Delta\omega)$  is obtained in Eq. (3).

Step 2) Quasi multiple channels  $\mathbf{Z}$  are created by the SCICA method, in Eqs. (16) and (17).

Step 3) Uncorrelated signals  $\mathbf{Z}^P$  are obtained using the PCA in Eq. (22).

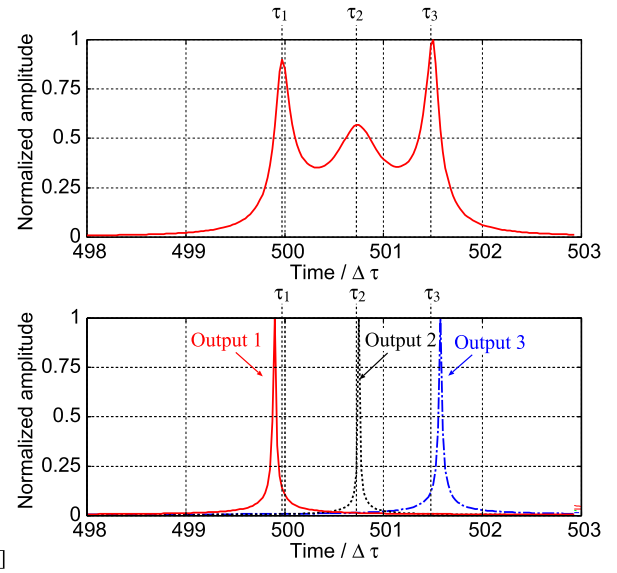
Step 4) Reconstruction matrix  $\mathbf{W}$  is determined using the method [9].

Step 5) MUSIC is applied to each channel of the reconstruction signal  $\mathbf{Y}$ , and each TOA is determined as the time when the output of MUSIC becomes maximum.

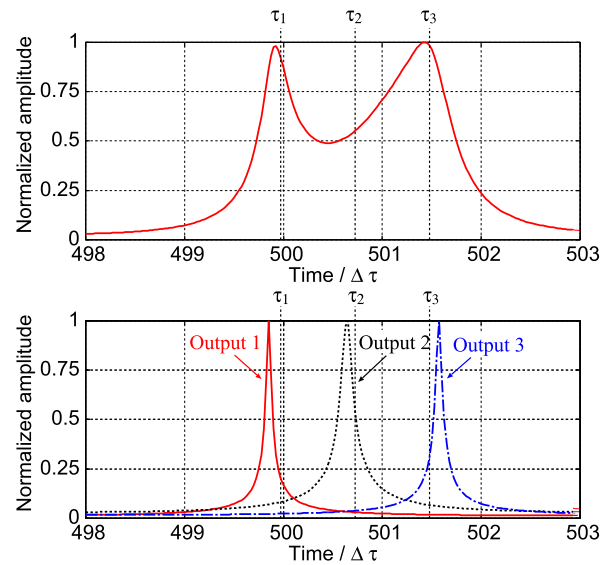
With the proposed pre-processing and MUSIC methods combined for simplicity, our method as described in the preceding has the potential to enhance TOA resolution in other TOA estimation methods such as Fourier or Capon methods because highly correlated signals are substantially decomposed by our MLICA algorithm. Figure 2 is a block diagram of the proposed method. The main advantage of this algorithm is that highly correlated signals are decomposed by the MLICA [9] in each channel of  $\mathbf{Y}$  and the range resolution of MUSIC is thus enhanced.

## 5. Performance Evaluation in Numerical Simulations

This section describes the performance evaluations of each method in numerical simulations. At first, the case of  $L = 3$  is investigated. The upper and lower sides in Figs. 3 and 4 show the outputs of the conventional and the proposed methods for the cases of  $\text{SNR} = 30$  dB and 20 dB. The actual TOAs are set as  $\tau_1 = 499.975\Delta\tau$ ,  $\tau_2 = \tau_1 + 0.75\Delta\tau$  and  $\tau_3 = \tau_2 + 0.75\Delta\tau$ , where  $\Delta\tau$  denotes the time resolution determined by the frequency band width of the transmitted signal. The amplitude of each signal is set to 1. White Gaussian noise is added to the observed signals, and the SNR is defined as the ratio of the peak signal power to the average noise power in the time domain. Here, the number of frequency averaging  $M$  is set to  $\Omega/2$  in the conventional method, and  $(\Omega - K)/2$  in the proposed method, where  $\Omega = 819$  and the number of the quasi multiple channel  $K$  is empirically determined as 250. Figure 3, for the case of a 30 dB SNR, demonstrates that both methods can



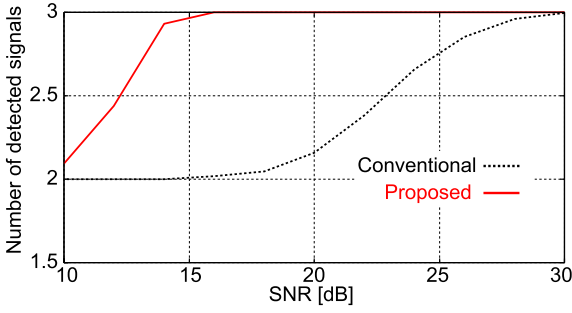
**Fig. 3** Outputs of the conventional (upper) and the proposed methods (lower) at  $\text{SNR}=30$  dB.



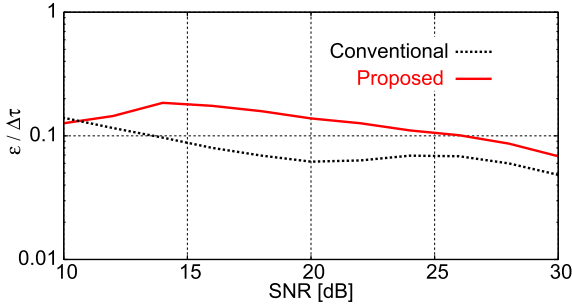
**Fig. 4** Outputs of the conventional (upper) and the proposed methods (lower) at  $\text{SNR}=20$  dB.

produce significant peaks around all actual TOAs. By contrast, in the upper side of Fig. 4 for  $\text{SNR}=20$  dB, the conventional method cannot obtain the actual TOA around  $t = \tau_2$ , that is, it suffers from insufficient range resolution. This is because uniform frequency averaging is not enough to suppress coherent interference signals and noisy components. Conversely, the proposed method produces three local peaks around the actual TOA as shown in the lower side of Fig. 4; that is, higher range resolution is achieved. This is because the proposed method can suppress the coherent signal in MLICA processing, specifying the sinusoidal wave separation.

Next, the quantitative analysis for each method is in-



**Fig. 5** Estimated number of signals against the SNR for each method at  $L = 3$ .

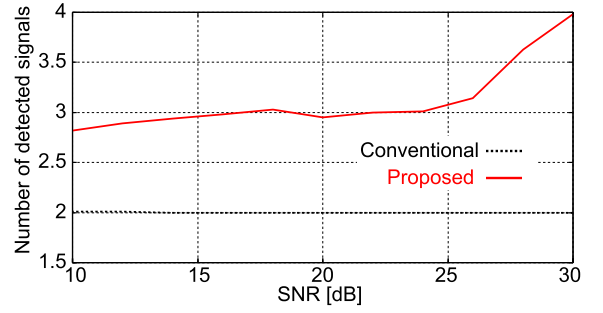


**Fig. 6** TOA errors against the SNR for each method at  $L = 3$ .

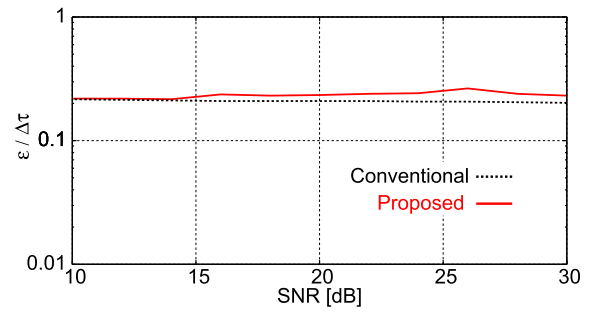
vestigated. The TOA accuracy  $\epsilon$  is defined as

$$\epsilon = \sqrt{\frac{1}{\hat{L}} \sum_{i=1}^{\hat{L}} \min_{\tau_1 - 5\Delta\tau \leq t \leq \tau_3 + 5\Delta\tau} (\tau_i - \hat{\tau}_j)^2}, \quad (24)$$

where  $\hat{\tau}_j$  denotes the estimated TOA and  $\hat{L}$  is the estimated number of signals given in this case. Here, to eliminate an outlier of TOA estimation, the range of the TOA is narrowed down to  $\tau_1 - 5\Delta\tau \leq t \leq \tau_3 + 5\Delta\tau$ , which can be easily discriminated by the inverse Fourier transform of the observed signal. Figure 5 shows SNR versus the number of estimated signals in each method, which can be detected in the searching TOA range in Eq. (24). Figure 6 indicating the TOA accuracy illustrates the SNR versus  $\epsilon$  in each method. The number of random seeds is 500 for each SNR, and each evaluation value is averaged. Figure 5 assessing the TOA resolution indicates that the proposed method correctly detects the number of signals even in lower SNR situations, where the conventional MUSIC misses the detection, even if the number of signals  $L$  is given. This is because our proposed method suppresses Gaussian white noise and highly correlated signals through decorrelation processing employing PCA and MLICA, which is not used in the conventional MUSIC. However, as shown in Fig. 6, the TOA accuracy obtained by the proposed method is slightly degraded from that obtained by the conventional method. The cause for this small degradation is presumed to stem from a phase error in each observation signal caused by noisy components that might be slightly enhanced by the SCICA processing. This is because the SCICA creates quasi-multiple channels by a data shift operation where noisy components from each



**Fig. 7** Estimated number of signals against the SNR for each method at  $L = 4$ .



**Fig. 8** TOA errors against the SNR for each method at  $L = 4$ .

channel have a certain level of correlation. Each separated signal after PCA and MLICA then possibly includes a certain amount of noisy component, that slightly degrades the accuracy for frequency estimation in the frequency domain, and hence the TOA accuracy in the time domain. Our next step would be to clarify the above cause in more detail so that TOA accuracy can be enhanced. In addition,  $\epsilon$  only assesses TOA accuracy and is independent of the evaluation for the number of estimated signals, namely, the TOA resolution. Thus, the possibility remains that, if the number of estimated signals is correctly estimated,  $\epsilon$  would not be necessarily improved, as indicated by Figs. 5 and 6.

Furthermore, we investigated the situations for more signals. Figures 7 and 8 present the estimated number of signals and the TOA errors versus SNR in the case of  $L = 4$ , where the adjacent interval of the TOA is set to  $0.75\Delta$ . These results show that in the case of more signals, the proposed method significantly enhance the discriminating property for the number of signals without accuracy degradation. This is because in the case of a larger number of signals, multiple correlated coefficients among signals become higher, and the interference effect due to multiple correlated signals is more dominant in determining TOA accuracy.

## 6. Performance Evaluation in an Experiment

This section presents a performance example using experimental data. Figures 9 and 10 show the experimental appearance and geometry. The 3 dB beam width of the horn antenna is 27 degrees, and the interval between the transmitting and receiving antennas is 48 mm. Three metallic

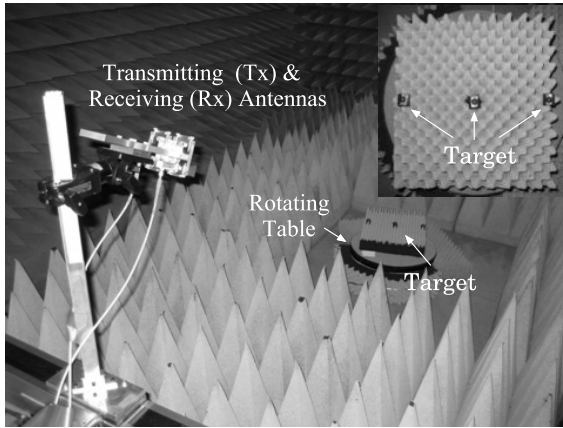


Fig. 9 Experimental appearance.

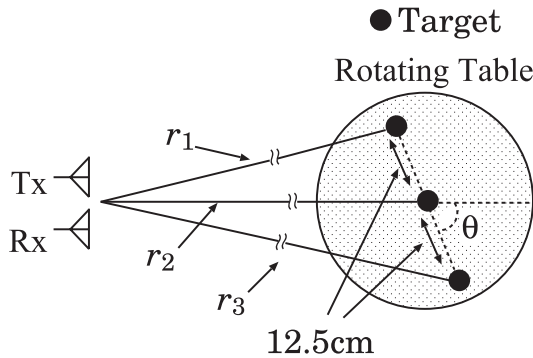


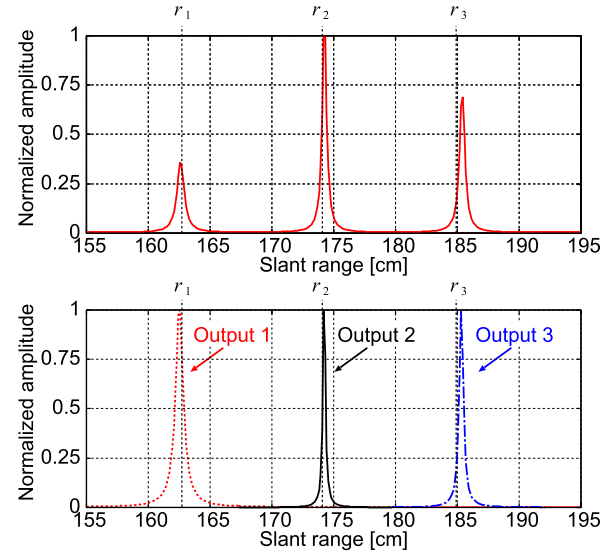
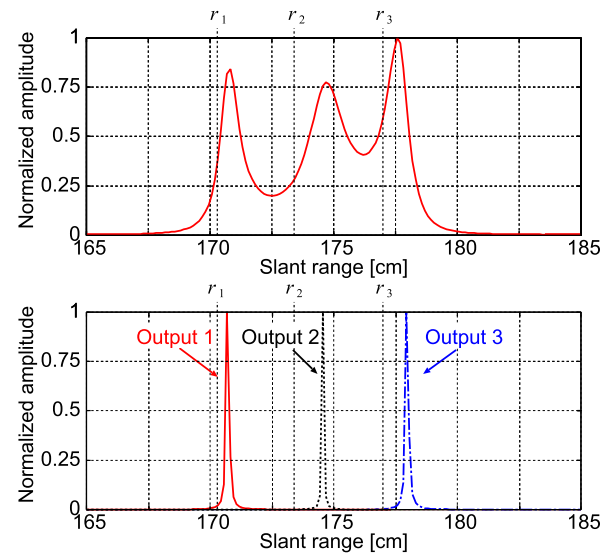
Fig. 10 Experimental geometry.

Table 1 Experimental parameters.

|                                   |         |
|-----------------------------------|---------|
| Center frequency                  | 34 GHz  |
| Frequency bandwidth               | 6 GHz   |
| Slant range resolution $\Delta r$ | 2.5 cm  |
| Frequency step-size               | 7.5 MHz |
| Number of frequency steps         | 801     |

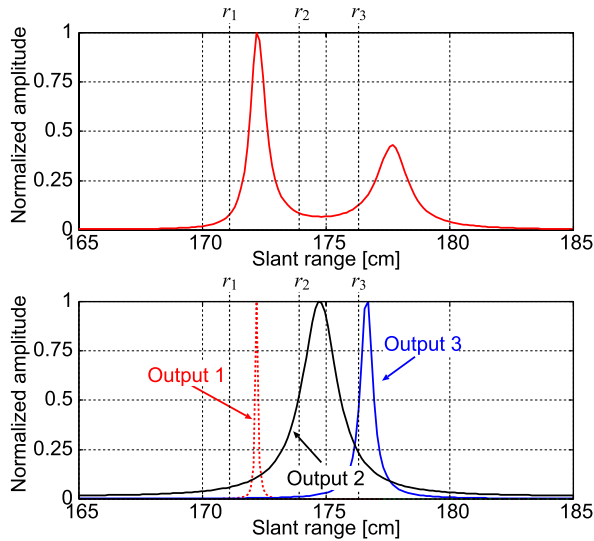
spheres with 10 mm diameter are used as targets, arranged on the rotation table. The interval of the TOA can be continuously adjusted by controlling the angle  $\theta$  of the rotating table at a fixed target alignment. In transmitting and receiving, a vector network analyzer is used, where the frequency range is set from 31 GHz to 37 GHz with 7.5 MHz sampling. Table 1 shows the parameters for the experimental setup.

First, we show an easily resolvable case as a reference. The lower and upper sides of Fig. 11 show the outputs of the conventional and the proposed methods at  $\theta = 0^\circ$ , where the SNR is 35.3 dB. Here, the TOA is converted to the slant range using the speed of light in air, for clarity, and they are set to  $r_1 = 162.7$  cm,  $r_2 = r_1 + 4.6\Delta r$  and  $r_3 = r_2 + 4.3\Delta r$ , where  $\Delta r = 2.5$  cm is the slant range resolution determined by the frequency bandwidth. In addition, the actual slant ranges  $r_1$ ,  $r_2$  and  $r_3$  are calibrated from the local peaks of the MUSIC, where a transmitting bandwidth is set to 14 GHz, which is enough to accurately resolve each signal into clearly separated cases. Figure 11 shows that conven-

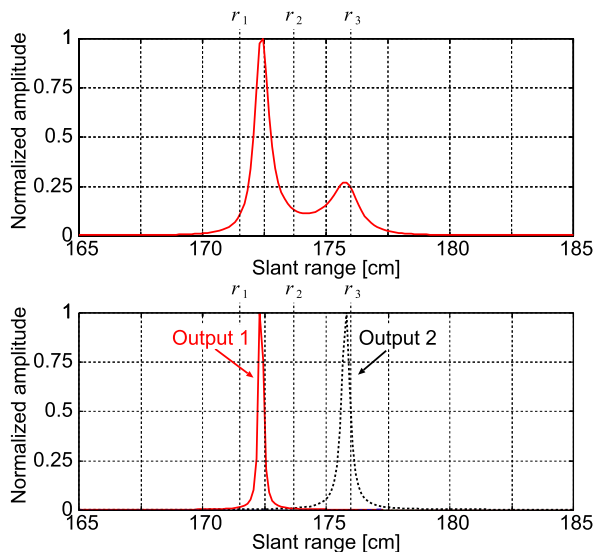
Fig. 11 Outputs of the conventional (upper) and the proposed methods (lower) when  $|r_1 - r_2| = 4.6\Delta r$  and  $|r_2 - r_3| = 4.3\Delta r$ .Fig. 12 Outputs of the conventional (upper) and the proposed methods (lower) when  $|r_1 - r_2| = 1.24\Delta r$  and  $|r_2 - r_3| = 1.44\Delta r$ .

tional MUSIC and the proposed method both produce significant peaks around all the actual slant ranges.

Next, the lower and upper sides of Fig. 12 show the same views as in Fig. 11 at  $\theta = 73^\circ$ , where  $r_1 = 170.3$  cm,  $r_2 = r_1 + 1.24\Delta r$  and  $r_3 = r_2 + 1.44\Delta r$ . i.e., the more interfered case, and the SNR is around 35 dB. The actual ranges are calculated from those obtained at  $\theta = 0^\circ$  considering the rotation angle  $\theta$  and the spatial relationship between the antenna locations and the center of the rotation table. This result demonstrates that both methods can still separate the three signals without serious degradation in accuracy. This is because the uniform frequency averaging and MLICA process in each method still suppress coherent interference signals. On the contrary, the lower and upper side of Fig. 13

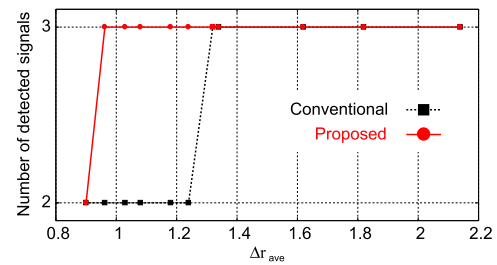


**Fig. 13** Outputs of the conventional (upper) and the proposed methods (lower) when  $|r_1 - r_2| = 1.1\Delta r$  and  $|r_2 - r_3| = 0.96\Delta r$ .



**Fig. 14** Outputs of the conventional (upper) and the proposed methods (lower) when  $|r_1 - r_2| = 0.88\Delta r$  and  $|r_2 - r_3| = 0.92\Delta r$ .

show the outputs of each method at  $\theta = 77^\circ$ , where the actual slant ranges are set to  $r_1 = 171.1$  cm,  $r_2 = r_1 + 1.1\Delta r$  and  $r_3 = r_2 + 0.96\Delta r$ , and the SNR is at the same level as in the previous case. This figure shows that while a slant range resolution provided by the conventional MUSIC algorithm degrades, our proposed method can obtain three local peaks in the vicinity of the actual slant range. This result proves that the MLICA process in the proposed method is still efficient in decomposing highly correlated signals. The upper and lower sides of Fig. 14 show the outputs of each method, at  $\theta = 80^\circ$ , where  $r_1 = 171.5$  cm,  $r_2 = r_1 + 0.88\Delta r$  and  $r_3 = r_2 + 0.92\Delta r$ , where the SNR is also around 35 dB. In this case, both methods cannot provide the actual number of signals, which is considered to be a performance limitation of the proposed method. Finally, Fig. 15 shows the detected



**Fig. 15** Detected number of signals versus  $\Delta r_{\text{ave}} = |r_1 - r_3|/2$  at  $L = 3$  in the experiment.

number of signals versus the average interval for range defined as  $\Delta r_{\text{ave}} = |r_1 - r_3|/2$  for each method. As seen in this figure, the effective range for enhancing the range resolution by the proposed method is  $0.9\Delta r \leq \Delta r_{\text{ave}} \leq 1.3\Delta r$  in this instance. Here, the apparent resolution of both methods are degraded compared with that obtained in the numerical simulations, because the frequency characteristics of the transmitting and receiving horn antennas can narrow the actual bandwidth, even if the vector network analyzer provides the signal with a non-frequency dependency.

## 7. Conclusion

This paper proposed a novel approach for super resolution TOA estimation, introducing an improved MLICA algorithm for decomposing highly correlated signals. First, it has been confirmed that the conventional MUSIC cannot offer sufficient range resolution in situations of severe interference or strong noises. To mitigate this limitation, the extended MLICA algorithm for specifying the separation of complex sinusoidal signals was introduced as the pre-processing of MUSIC. The distinct advantage of our proposed method is that highly correlated interference signals or strong noisy components are effectively decomposed by the PCA and the specified MLICA processing. The results obtained from numerical simulations and experimental investigations verified that the range resolution of the proposed method, were superior to those obtained by the conventional MUSIC, particularly in lower SNR or richly interfered situations, while maintaining range accuracy. In closing, that the proposed approach, namely, MLICA based pre-processing, can be incorporated into not only the MUSIC method but also other useful TOA estimation schemes, such as Fourier or Capon methods, because highly correlated signal decomposition is a common and significant issue for each of these methods warranting an efficient TOA resolution.

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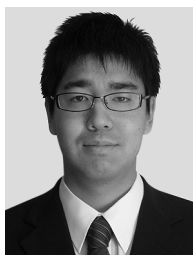
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