

An Adaptive Time Delay Estimation Method Based on Canonical Correlation Analysis

정준형 상관 분석을 이용한 적응 시간 지연 추정에 관한 연구

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ABSTRACT: The localization of sources has a numerous number of applications. To estimate the position of sources, the relative delay between two or more received signals for the direct signal must be determined. Although the generalized cross-correlation method is the most popular technique, an approach based on eigenvalue decomposition (EVD) is also popular one, which utilizes an eigenvector of the minimum eigenvalue. The performance of the eigenvalue decomposition (EVD) based method degrades in the low SNR and the correlated environments, because it is difficult to select a single eigenvector for the minimum eigenvalue. In this paper, we propose a new adaptive algorithm based on Canonical Correlation Analysis (CCA) in order to extend the operation range to the lower SNR and the correlation environments. The proposed algorithm uses the eigenvector corresponding to the maximum eigenvalue in the generalized eigenvalue decomposition (GEVD). The estimated eigenvector contains all the information that we need for time delay estimation. We have performed simulations with uncorrelated and correlated noise for several SNRs, showing that the CCA based algorithm can estimate the time delays more accurately than the adaptive EVD algorithm.

Keywords: Time delay estimation, Adaptive estimation

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초 록: 음원 위치 추정은 여러 방면에서 쓰임이 있는 응용 기술이다. 음원의 위치를 추정하기 위한 기본 기법 중에는 시간 지연 추정 기법이 있다. 이 기법에선 음원의 위치를 추정하기 위해서 두 개 또는 그 이상의 수신기에 들어오는 신호 간의 상대적 시간 지연을 알아내야 한다. 시간 지연 추정 기법에는 GCC (Generalized Cross-Correlation) 대표적이지만, 최소 고유치에 대응하는 고유 벡터를 이용하는 방법도 많이 쓰인다. 이 방법은 최소 고유치에 해당하는 고유벡터를 이용한다. 최소 고유치에 대응하는 고유 벡터를 이용하는 방법은 낮은 신호 대 잡음비 환경에서나 상관도가 있는 잡음 환경에서, 최소 고유치에 해당하는 고유 벡터를 추정하는데 어려움이 있어서, 성능이 떨어진다. 본 논문에서는 정준형 상관 분석 (CCA)를 이용한 새 기법을 제안한다. 이 방법은 일반 고유치 분해 중에서 최대 고유치에 대응하는 고유벡터를 사용한다. 따라서 추정에 사용하는 고유벡터는 시간 지연 추정에 필요한 정보가 충분히 들어있다. 본 논문에서는 여러 서로 다른 신호 대 잡음비 환경 하에서 상관도가 없는 경우와 상관도가 있는 경우의 잡음에 대해 비교 모의실험을 하였고, 이 비교 실험을 통하여 얻는 데이터를 통해서 제안한 CCA 기반 알고리즘이 기존 최소 고유치에 해당하는 고유 벡터를 사용하는 시간 지연 추정법의 성능보다 더 우수하다는 것을 보인다.

핵심용어: 시간 지연 추정, 적응 신호처리

I. Introduction

Time delay estimation (TDE) between two (or more)

received signals can be used as a means for the localization of the dominant source in applications such as receiver array beam steering for suppressing reverberation in all types of communication and voice processing systems.^[1-3]

There is a trend towards the use of multiple receivers in

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research and industry; however, the use of two receivers is present in actual applications such as humanoid robotics^[2] and hearing aids.^[4]

Most TDE methods rely on relative delays between the two receivers^[5]. Although there are many effective TDE methods, the generalized cross-correlation (GCC) method, proposed by Knapp and Carter in 1976^[6], is the most popular technique for TDE. The delay estimate in this technique is obtained as the time lag maximizes the cross-correlation between filtered versions of the received signals. This method has been well studied and performs adequately^[7]. Another interesting idea was proposed in^[8] and it was further developed by Doclo and Moonen^[9]. The algorithm in^[8] estimates time delay using eigenvalue decomposition. The eigenvector that corresponds to the minimum eigenvalue of the covariance matrix of the received signals contains the impulse responses of the source and the received signals; subsequently all information necessary for time delay estimation can be derived from the eigenvector. However, it meets difficulty to select a single eigenvector for the minimum eigenvalue in the low SNR environments and correlated noise environments. This is because several small eigenvalues at roughly the same value are frequently found in the low SNR environments and correlated noise environments. In this case, the TDE performance degrades in the eigenvalue decomposition based algorithm in [8]. The algorithm in [9] improved the performance of the algorithm in [8] under the noisy environments by using an adaptive generalized eigenvalue decomposition (GEVD) algorithm. The usage of an adaptive GEVD in [9] needed to measure the pure noise signal. The GEVD introduced whitening effect to the algorithm in [8] so that it made it more better to derive a single eigenvector for the minimum eigenvalue.

Hotelling in [10] proposed a new multivariate analysis approach of Canonical Correlation Analysis (CCA). CCA was developed to measure the linear relationship of two multidimensional sets of variables. CCA has been widely used in economics, meteorology and in modern information processing fields, such as communication theory,^[11]

statistical signal processing^[12] and blind source separation.^[13]

In [10] and [14], CCA can be defined as the problem of finding two vectors, \mathbf{w}_1 and \mathbf{w}_2 , such that the variates $\mathbf{y}_1 = \mathbf{X}_1 \mathbf{w}_1$ and $\mathbf{y}_2 = \mathbf{X}_2 \mathbf{w}_2$ are maximally correlated with two multidimensional sets of variables of \mathbf{X}_1 and \mathbf{X}_2 . Typically, CCA is formulated as a generalized eigenvalue (GEV) problem.

This paper proposes a more robust TDE algorithm than the eigenvalue decomposition based algorithm of [8]. In order to derive a new TDE algorithm using the eigenvector of the maximum eigenvalue rather than the eigenvector of the minimum eigenvalue, we can apply CCA concept to the proposed algorithm, because CCA can be defined as the problem of finding two vectors, \mathbf{w}_1 and \mathbf{w}_2 , such that the variates $\mathbf{y}_1 = \mathbf{X}_1 \mathbf{w}_1$ and $\mathbf{y}_2 = \mathbf{X}_2 \mathbf{w}_2$ are maximally correlated with two multidimensional sets of variables of \mathbf{X}_1 and \mathbf{X}_2 , as it is described above. In the proposed method, the CCA method is applied to the TDE by estimating vectors to maximize the linear relationship between the two received signal sets. We show that the eigenvector contains time delay information in 3.1, and formulate an adaptive algorithm to estimate the eigenvector for the maximum eigenvalue based on CCA. In order to derive an adaptive algorithm, we utilize the adaptive GEVD formulation in [9] as a solver. The proposed algorithm has no noise whitening effect although the noise whitening is a major contribution in [9]. In the simulation, we confirm the performance of the proposed TDE algorithm by comparing it with two different algorithms such as GCC and an adaptive eigenvalue decomposition based TDE. In the simulation, we consider normal independent white Gaussian noise case and correlated noise case. From the simulation, we confirm that the proposed algorithm works better than the eigenvalue decomposition based algorithm.

II. Models for the TDE Problem

This section discusses two models often used for the TDE problem. First, the 'ideal model' is described and then is followed by the 'real model' which more accurately describes a real acoustic environment.^[8]

2.1 Ideal model

A simple and widely used signal model for the classical TDE problem is as follows. Let $x_i(k)$, $i=1, 2$, denote the i -th receiver signal, then:

$$x_i(k) = \alpha_i s(k - \tau_i) + n_i(k), \tag{1}$$

where α_i is the attenuation factor due to propagation effects, τ_i is the propagation time from the unknown source $s(k)$ to receiver i , and $n_i(k)$ is an additive noise signal at the i th receiver. It is assumed that $s(k)$, $n_1(k)$, and $n_2(k)$ are zero-mean, uncorrelated, and stationary Gaussian random processes. The relative delay between the two received signals 1 and 2 is defined as.

$$\tau_{12} = \tau_1 - \tau_2. \tag{2}$$

2.2 Real model

In a real acoustic environment we must consider the reverberation of the room; therefore, the ideal model no longer holds. A more complicated but more complete model for received signals $x_i(k)$, $i=1, 2$, can be expressed as follows:

$$x_i(k) = g_i * s(k) + n_i(k), \tag{3}$$

where $*$ denotes convolution and g_i is the channel impulse response between the source $s(k)$ and the i th receiver. Moreover, $n_1(k)$ and $n_2(k)$ might be correlated which is the case when the noise is directional, e.g., from a ceiling fan or an overhead projector. This case is a very challenging problem that requires an accurate determination of the two impulse responses between the source and the two receivers.

III. The Proposed Method

3.1 TDE based on Canonical Correlation Analysis

In this work, transformation is performed on a sequence

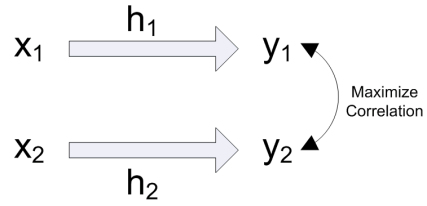


Fig. 1. Concept of CCA.

of features during speaking spurts.

Let $\mathbf{X}_1, \mathbf{X}_2$ be two known full-rank data matrices of size $M \times N$ and $M \times N$, respectively. In Fig. 1, CCA can be defined as an approach to solve the problem of finding two vectors: \mathbf{h}_1 of size $N \times 1$ and \mathbf{h}_2 of size $N \times 1$, such that the variates $\mathbf{y}_1 = \mathbf{X}_1 \mathbf{h}_1$ and $\mathbf{y}_2 = \mathbf{X}_2 \mathbf{h}_2$ are maximally correlated, i.e. ^[13],

$$\arg \max_{\mathbf{h}_1, \mathbf{h}_2} \rho = \frac{\mathbf{y}_1^T \mathbf{y}_2}{\|\mathbf{y}_1\| \|\mathbf{y}_2\|} = \frac{\mathbf{h}_1^T \mathbf{R}_{12} \mathbf{h}_2}{\sqrt{\mathbf{h}_1^T \mathbf{R}_{11} \mathbf{h}_1 \mathbf{h}_2^T \mathbf{R}_{22} \mathbf{h}_2}}, \tag{4}$$

where $\mathbf{R}_{ij} = \mathbf{X}_i^T \mathbf{X}_j$ is an estimate of the correlation matrix.

The aforementioned CCA concept can be utilized to the time delay estimation between two different receiving sensors. Assuming \mathbf{x}_1 and \mathbf{x}_2 are the received signal vectors in the receiving sensors in the size of $N \times 1$, \mathbf{h}_2 means the mapping channel between \mathbf{x}_2 and \mathbf{y}_2 , and \mathbf{h}_1 means the channel between \mathbf{x}_1 and \mathbf{y}_1 . The mapping channel \mathbf{h}_1 and \mathbf{h}_2 maximize the correlation between \mathbf{y}_1 and \mathbf{y}_2 with delays, D_1 and D_2 . The mapping channels operate as follows.

$$\begin{aligned} y_1(k) &= h_1 * x_1(k) = \alpha_1 s(k - \tau_1 - D_1) + n_1(k - D_1), \\ y_2(k) &= h_2 * x_2(k) = \alpha_2 s(k - \tau_2 - D_2) + n_2(k - D_2). \end{aligned} \tag{5}$$

When the correlation between $y_1(k)$ and $y_2(k)$ becomes maximum, the relationship between the delays in the received signals and the delays in the mapping channels satisfies as follows.

$$\tau_1 + D_1 = \tau_2 + D_2. \tag{6}$$

$$\tau_{12} = \tau_1 - \tau_2 = D_2 - D_1. \tag{7}$$

Therefore, the difference between the peaks of \mathbf{h}_1 and \mathbf{h}_2 , becomes the relative time delay between \mathbf{x}_1 and \mathbf{x}_2 as (2).

Problem (4) can be formulated as the following constrained optimization problem.^[13]

$$\begin{aligned} \arg \max_{\mathbf{h}_1, \mathbf{h}_2} & \mathbf{h}_1^T \mathbf{R}_{12} \mathbf{h}_2, \\ \text{s.t.} & \mathbf{h}_1^T \mathbf{R}_{11} \mathbf{h}_1 = \mathbf{h}_2^T \mathbf{R}_{22} \mathbf{h}_2 = 1. \end{aligned} \quad (8)$$

The solution of (8) is given by the eigenvector corresponding to the largest eigenvalue of the following generalized eigenvalue problem.^[14-15]

$$\begin{bmatrix} \mathbf{0} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{0} \end{bmatrix} \mathbf{v} = \rho \begin{bmatrix} \mathbf{R}_{11} & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{22} \end{bmatrix} \mathbf{v}, \quad (9)$$

$$\mathbf{A} \mathbf{v} = \rho \mathbf{B} \mathbf{v}, \quad (10)$$

where ρ is the maximum correlation between the two sets of variables and $\mathbf{v}^T = [\mathbf{h}_1 \quad \mathbf{h}_2]^T$ is the eigenvector. Adding $\begin{bmatrix} \mathbf{R}_{11} & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{22} \end{bmatrix}$ to both sides in (9), we can modify (9) as follows:

$$\begin{bmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{R}_{22} \end{bmatrix} \mathbf{v} = \lambda' \begin{bmatrix} \mathbf{R}_{11} & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{22} \end{bmatrix} \mathbf{v}. \quad (11)$$

In (11), the eigenvalue will be obtained as $[\rho_1 + 1 \quad \rho_2 + 1 \quad \dots \quad 1]$,^[16] where ρ_1 is the maximum correlation coefficient. Even though \mathbf{x}_1 and \mathbf{x}_2 are noisy, the additive noise effect to the correlation coefficient is negligible because the additive noise is mutually uncorrelated white noise. The maximum eigenvalue is less affected by the additive noise; therefore, the estimated eigenvector of the maximum eigenvalue is more robust against the additive noise in the proposed algorithm. This makes the proposed algorithm superior to the adaptive eigenvalue decomposition based method that uses the eigenvector of the minimum eigenvalue.

The mapping channels, \mathbf{h}_1 and \mathbf{h}_2 , are derived from the eigenvector, \mathbf{v} , corresponding the largest eigenvalue. Alternatively, the eigenvector corresponding to the largest

eigenvalue in (10) can be obtained as the eigenvector corresponding to the smallest eigenvalue of the following equation;

$$\mathbf{B} \mathbf{v} = \lambda \mathbf{A} \mathbf{v}. \quad (12)$$

$$\begin{bmatrix} \mathbf{R}_{11} & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{22} \end{bmatrix} \mathbf{v} = \lambda \begin{bmatrix} \mathbf{0} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{0} \end{bmatrix} \mathbf{v}. \quad (13)$$

Adding $\begin{bmatrix} \mathbf{0} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{0} \end{bmatrix}$ to both sides in (13), we can modify (13) as follows:

$$\begin{bmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{R}_{22} \end{bmatrix} \mathbf{v} = \lambda' \begin{bmatrix} \mathbf{0} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{0} \end{bmatrix} \mathbf{v}. \quad (14)$$

(14) can be developed to much easier adaptive formulation. We will show it in the following subsection.

3.2 Adaptive GEVD algorithm for CCA based TDE

For the solution procedures on the GEVD, in (14), it is also possible to derive stochastic gradient algorithms that iteratively estimate the generalized eigenvector that corresponds to the smallest generalized eigenvalue of \mathbf{B} and \mathbf{A} .

Instead of updating the full GEVD of \mathbf{B} and \mathbf{A} ^[17] and then deriving generalized eigenvector that corresponds to the smallest generalized eigenvalue, it is possible to iteratively estimate this generalized eigenvector by minimizing the cost function $\mathbf{v}^T \mathbf{B} \mathbf{v}$ subject to the constraint $\mathbf{v}^T \mathbf{A} \mathbf{v} = 1$,

where $\mathbf{B} = \begin{bmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{R}_{22} \end{bmatrix} = E \left\{ \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix}^T \right\} = E \{ \mathbf{x}_B \mathbf{x}_B^T \}$ and

$\mathbf{A} = \begin{bmatrix} \mathbf{0} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{0} \end{bmatrix}$. This problem can be solved by minimizing the mean square value of the error signal $e(k)$,

$$e(k) = \frac{\mathbf{v}^T(k) \mathbf{x}_B(k)}{\sqrt{\mathbf{v}^T(k) \mathbf{A} \mathbf{v}(k)}}, \quad (15)$$

Table 1. Summary of the proposed algorithm.

<p>Initialize $\mathbf{v}(0), \tilde{\mathbf{v}}(1), \mathbf{R}_{12}(0), \mathbf{R}_{21}(0)$.</p> <p>Do $k = 1 \dots$</p> <p>$\mathbf{x}_B(k) = \begin{bmatrix} \mathbf{x}_1(k) \\ \mathbf{x}_2(k) \end{bmatrix}$.</p> <p>$\mathbf{R}_{12}(k) = \mathbf{R}_{12}(k-1) + \mathbf{x}_1(k)\mathbf{x}_2^T(k)$.</p> <p>$\mathbf{R}_{21}(k) = \mathbf{R}_{21}(k-1) + \mathbf{x}_2(k)\mathbf{x}_1^T(k)$.</p> <p>$\mathbf{A}\mathbf{v}(k) = \begin{bmatrix} \mathbf{0} & \mathbf{R}_{12}(k) \\ \mathbf{R}_{21}(k) & \mathbf{0} \end{bmatrix} \mathbf{v}(k)$ or $\mathbf{A}\mathbf{v}(k) = \begin{bmatrix} \varepsilon \mathbf{I} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \varepsilon \mathbf{I} \end{bmatrix} \mathbf{v}(k)$, where ε is arbitrary small value.</p> <p>$\tilde{\mathbf{v}}(k+1) = \mathbf{v}(k) - \frac{\mu e(k)}{\mathbf{x}_1^T \mathbf{x}_1 + \mathbf{x}_2^T \mathbf{x}_2 + \delta} (\mathbf{x}_B(k) - e(k)\mathbf{A}\mathbf{v}(k))$, where $e(k) = \mathbf{v}^T(k)\mathbf{x}_B(k)$.</p> <p>$\mathbf{v}(k+1) = \frac{\tilde{\mathbf{v}}(k+1)}{\sqrt{\tilde{\mathbf{v}}^T(k+1)\tilde{\mathbf{v}}(k+1)}}$.</p> <p>Derive $\mathbf{h}_1(k)$ and $\mathbf{h}_2(k)$ from $\mathbf{v}(k+1)$.</p> <p>Find the time delay from the difference between the peak positions in $\mathbf{h}_1(k)$ and $\mathbf{h}_2(k)$.</p> <p>End</p> <p>By utilizing shift-structured input data $\mathbf{x}_i(k) = [x(k) \ x(k-1) \ \dots \ x(k-N+1)]$, the lower-right block of $\mathbf{R}_y(k)$ can be obtained by copying the upper-left block of $\mathbf{R}_y(k-1)$. The only $\mathbf{R}_y(k)$ part of the matrix that should be directly updated is the first row and first column.</p>

where $\mathbf{v}^T = [\mathbf{h}_1 \ \mathbf{h}_2]^T$.

The iterative procedure can be done using a gradient-descent LMS procedure in [9] and [18],

$$\mathbf{v}(k+1) = \mathbf{v}(k) - \mu e(k) \frac{\partial e(k)}{\partial \mathbf{v}(k)}, \quad (16)$$

with μ the step size of the adaptive algorithm. The gradient of $e(k)$ now is equal to (17).

$$\frac{\partial e(k)}{\partial \mathbf{v}(k)} = \frac{1}{\sqrt{\mathbf{v}^T(k)\mathbf{A}\mathbf{v}(k)}} \left(\mathbf{x}_B(k) - e(k) \frac{\mathbf{A}\mathbf{v}(k)}{\sqrt{\mathbf{v}^T(k)\mathbf{A}\mathbf{v}(k)}} \right). \quad (17)$$

Substituting (17) and the constraint, $\mathbf{v}^T \mathbf{A} \mathbf{v} = 1$, into (16) gives (18).

$$\tilde{\mathbf{v}}(k+1) = \mathbf{v}(k) - \mu e(k) (\mathbf{x}_B(k) - e(k)\mathbf{A}\mathbf{v}(k)), \quad (18)$$

where $e(k) = \mathbf{v}^T(k)\mathbf{x}_B(k)$. In order to avoid round-off error propagation, we normalize the updated vector, $\tilde{\mathbf{v}}(k+1)$, as (19).

$$\mathbf{v}(k+1) = \frac{\tilde{\mathbf{v}}(k+1)}{\sqrt{\tilde{\mathbf{v}}^T(k+1)\tilde{\mathbf{v}}(k+1)}}. \quad (19)$$

For better convergence, we can utilize the normalized LMS approach with (18) as (20) [18].

$$\begin{aligned} \tilde{\mathbf{v}}(k+1) \\ = \mathbf{v}(k) - \frac{\mu e(k)}{\mathbf{x}_1^T \mathbf{x}_1 + \mathbf{x}_2^T \mathbf{x}_2 + \delta} (\mathbf{x}_B(k) - e(k)\mathbf{A}\mathbf{v}(k)). \end{aligned} \quad (20)$$

In each iteration, we can derive the estimation value of the time delay from the difference between two peak value positions in $\mathbf{h}_1(k+1)$ and $\mathbf{h}_2(k+1)$ in $\mathbf{v}^T(k+1) = [\mathbf{h}_1(k+1) \ \mathbf{h}_2(k+1)]^T$. The expected TDE can be computed as the difference between the two peak value positions in $\mathbf{h}_1(k+1)$ and $\mathbf{h}_2(k+1)$. We also try to improve the numerical stability by adding a small value to the diagonal of matrix \mathbf{A} . Table 1 summarizes the proposed algorithm.

IV. Simulation and Comparison

We began with generating two signals. In most practical

applications, the desired source signals of interest are correlated. The source signal $x_1(k)$ was generated by passing a first order AR process, viz., $s_0(k) = 0.7s_0(k-1) + w(k)$, where $w(k)$ is a white Gaussian process.^[19] Assuming the signals propagated in the free space, the second signal $x_2(k)$ is the time-delayed version of $x_1(k) = s_0(k)$ with delay $D=10$, i.e. $x_2(k) = x_1(k-10)$. Then, the two signals $x_1(k)$ and $x_2(k)$ are contaminated by two real white Gaussian noises $n_1(k)$ and $n_2(k)$, respectively. We check to ensure that the two noise sequences are mutually uncorrelated. In this simulation, we set the channel dimension of \mathbf{h}_1 and \mathbf{h}_2 to 100 and the data matrix $\mathbf{X}_1, \mathbf{X}_2$ is reduced to data vector $\mathbf{x}_1, \mathbf{x}_2$ of 100×1 , respectively, because the proposed algorithm estimates the channel \mathbf{h}_1 and \mathbf{h}_2 recursively instead of batch processing.

The signal sequences were scaled to obtain the desired SNR and added to the noise sequences as in (1) to form the sensor outputs $x_1(k)$ and $x_2(k)$. SNRs of approximately from 20 dB to -10 dB were considered, where $SNR = \frac{\sigma_s^2}{\sigma_n^2}$.

The sequences $x_1(k)$ and $x_2(k)$ were processed using the traditional GCC,^[6] adaptive eigenvalue decomposition based method^[8] and the proposed method. We compared the mean squared delay errors (MSDE) for the performance comparison. All the results provided were averages of 1000 independent trials. Fig. 2 shows the MSDE of the three algorithms and compares them with Cramér-Rao lower bound (CRLB).^[13] When $SNR \geq 0$ dB, the proposed method and the adaptive eigenvalue decomposition

method are better than the GCC. When $SNR < -3$ dB, the performance of the adaptive eigenvalue decomposition method suddenly deteriorates; however, the proposed method still provides good performance. When SNR drops down to -10 dB, all of the TDE algorithms begin to deteriorate. Especially, as an eigenvector based method, the proposed method is more robust against noise than the adaptive eigenvalue decomposition based method. The better performance is because the proposed algorithm estimates the time delay by the eigenvector of the maximum eigenvalue.

In the second experiment, the case of the correlate noises was considered. This case frequently happens when the noise is directional such as from a ceiling fan or an overhead projector. We generated correlated noise as i.e. $n_1(k) = n_2(k-5)$, where $n_2(k)$ is real white Gaussian noise. We also compared the MSDE for the performance comparison by 1000 independent trials. SNRs from 20 dB to 0 dB were considered, because all the algorithms failed below 0 dB. Fig. 3 shows the MSDE of the three algorithms: When $SNR \geq 3$ dB, the proposed estimator outperforms the GCC. When $SNR \leq 10$ dB, the proposed estimator is parallel with the adaptive eigenvalue decomposition method. When $SNR > 10$ dB, the proposed method performs superior to the adaptive eigenvalue decomposition based method. From these results, we can conclude that the proposed method is a good time delay estimator.

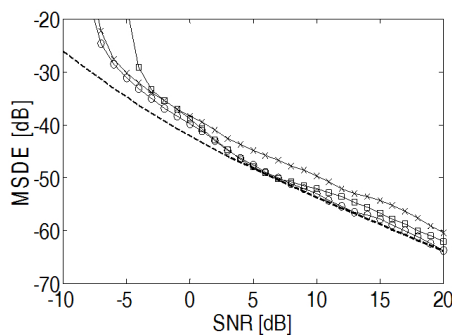


Fig. 2. MSDE comparison in the uncorrelated additive noise environments (-o-: proposed algorithm. -x-: GCC in [6], -□-: adaptive eigenvalue decomposition method in [8], dashed line: CRLB).

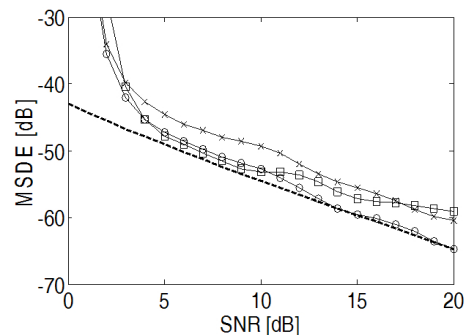


Fig. 3. MSDE comparison in the correlated additive noise environments (-o-: proposed algorithm. -x-: GCC in [6], -□-: adaptive eigenvalue decomposition method in [8], dashed line: CRLB).

V. Conclusion

This paper proposed a new approach to time delay estimation. The method derives the time delay parameter from the eigenvector for the maximum eigenvalue estimated by canonical correlation analysis of the receiver signals. In comparison with other methods, the proposed algorithm is more robust in reverberation environments as well as in uncorrelated noise environments and correlated noise environments.

In further research, we will study the performance comparison between the proposed algorithm and the algorithm in [9]. We think that it is worthwhile to compare the two algorithms in the following aspects:

- Two algorithms use an adaptive GEVD formulation.
- The proposed algorithm uses an eigenvector for a maximum eigenvalue.
- The algorithm in [9] uses an eigenvector for a minimum eigenvalue.
- The proposed algorithm needs no noise whitening.
- The algorithm in [9] needs noise whitening so that it should measure the pure noise signal.

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