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A Fast Directionally Constrained Minimization of Power Algorithm for Extracting a Speech Signal Perpendicular to a Microphone Array

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***Abstract*—** In this paper, an extended method of the directionally constrained minimization of power (DCMP) algorithm for broadband signals is proposed. The DCMP algorithm is one of the useful techniques of extracting a target signal from observed signals of a microphone array system. In the DCMP algorithm, output power of the microphone array is minimized under a constraint of constant responses to directions of arrival (DOAs) of specific signals.

In our algorithm, by limiting the directional constraint to the perpendicular direction to the sensor array system, the calculating time is reduced.

***Keywords*—**Beamformer, directionally constrained minimization of power, direction of arrival, microphone array.

I. Introduction

IN recent years, the technique of noise reduction has been demanded with the development of teleconferences, hands-free telephones, and speech recognition systems. Especially to apply such applications to the real environments, extraction of desired speech from observation signals at a microphone array, which include undesired sounds such as speech of other speakers, car noise and so on, is required. The adaptive beamformer is one of the useful methods for extracting the desired signal using a sensor array. The adaptive beamformer generates its directional pattern using the directions of arrival (DOAs) of signals, the replica of the desired signal, etc [1], [3]. The directionally constrained minimization of power (DCMP) algorithm is a method of the beamformer utilizing the DOAs of signals. In the DCMP algorithm, the output power of the sensor array is minimized under a constraint based on directional responses. However, since the DCMP algorithm is a technique for narrowband signals, it cannot be applied directly to broadband signals such as speech.

The Griffiths-Jim beamformer (GJBF) is well known as a method for broadband signals [2]. In the GJBF, the target signal is extracted by minimizing the power of array output under a liner constraint. The liner constraint is employed to avoid zero output. Generally, the GJBF consists of a fixed beamformer, a multiple-input canceller, and a blocking matrix. The fixed beamformer and the blocking matrix are practically performed by delay-and-sum and delay-and-subtract operation, respectively. Therefore, the GJBF requires a delay system to shift the phases of the microphone array inputs so that the target signal components included in the inputs are in-phase.

On the other hand it has been shown that the DCMP algorithm can be applied to broadband signals by using discrete-time Fourier transform (DTFT) [3]. However, in the DCMP algorithm for broadband signals, the computational cost is relatively heavy, since calculation of multiplications and inverse of relatively large matrices is included in this algorithm.

In this paper, we propose a fast DCMP algorithm for extracting the speech signal perpendicular to the sensor array system. In the algorithm, by limiting the directional constraint to the perpendicular direction to the sensor array system, the calculating time is effectively eliminated.

II. The Model

Let discrete-time observed signals at a K -channel sensor array be $x_k(t) \quad (k=1,2,\cdots,K)$. When $x_k(t)$ consists of $M(\le K)$ source signals, $x_k(t)$ can be modeled as

$$x_k(t)=\sum_{m=1}^{M} s_m(t-\tau_m(k)),(k=1,2,\cdots,K), \tag{1}$$

where $s_m(t) \quad (m=1,2,\cdots,M)$ is the m -th source signal incoming from the direction θ_m, and $\tau_m(k)$ donates the time delay in $s_m(t)$. In the case of the liner sensor array in which the distance between adjacent sensors is d , $\tau_m(k)$ is given by

$$\tau_m(k)=\frac{f_s(k-1)d\sin\theta_m}{c},$$
$$(k=1,2,\cdots,K;m=1,2,\cdots,M), \tag{2}$$

where f_s and c indicate the sampling frequency and velocity of signals, respectively. Fig. 1 shows an example of a K -channel liner sensor array.

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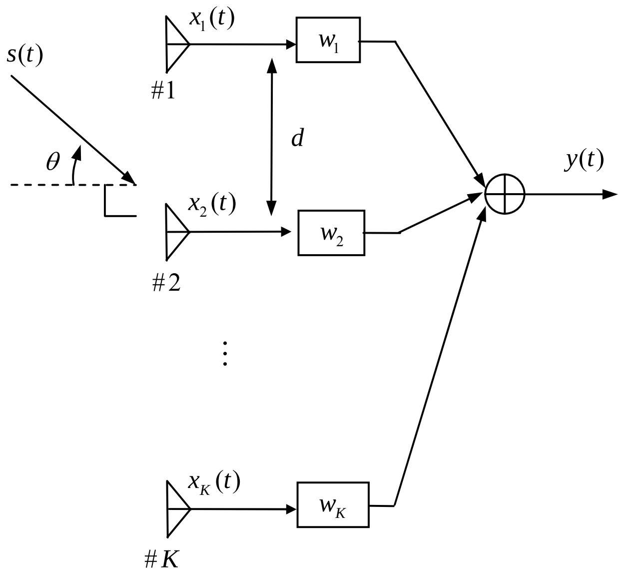

Fig. 1 An example of a K -channel sensor array

III. Summary of the Directionally Constrained Minimization of Power Algorithm for Narrowband Signals

The DCMP algorithm is one of the techniques of the beamformer to retrieve the target signal from the observations. In the conventional DCMP algorithm, narrowband signals with the normalized center frequency $f_c (0 \le f_c \le 1)$ are considered. In the beamformer for the narrowband signals, the output of the sensor array is generated by the summations of the multiplications of observed signals and weights as

$$\begin{aligned} y(t) &= \sum_{k=1}^{K} w_k^* x_k(t) \\ &= \sum_{k=1}^{K} \boldsymbol{w}^H \boldsymbol{x}(t) \\ &= \sum_{k=1}^{K} \boldsymbol{x}^T(t) \boldsymbol{w}^*, \end{aligned} \tag{3}$$

where $y(t)$ is output of the sensor array, w_k is the weight, the superscript * donates the complex conjugate, the superscript ^{H}, and ^{T} donate Hermitian transpose and transpose of a vector or a matrix, respectively. The column vectors $\boldsymbol{x}(t)$ and $\boldsymbol{w}$ are respectively given by

$$\begin{aligned} \boldsymbol{w} &= \left[w_1, w_2, \cdots, w_K \right]^T, \\ \boldsymbol{x}(t) &= \left[x_1(t), x_2(t), \cdots, x_K(t) \right]^T. \end{aligned} \tag{4}$$

Signal extraction is carried out so that null points of the sensor array are directed to the DOAs of the undesired signals by adjusting $\boldsymbol{w}$ appropriately. The DCMP algorithm adjusts $\boldsymbol{w}$ so as to minimize the power of $y(t)$ under a constraint which is based on the DOAs of signals [5]. The purpose of employing the directionally constraint is to avoid zero output of the sensor array. The DCMP algorithm is defined by

$$\arg\min_{w} \left(P_{out} = \frac{1}{2} \boldsymbol{w}^H \boldsymbol{R}_{xx} \boldsymbol{w} \right), \tag{5}$$

subject to

$$\boldsymbol{C}^T \boldsymbol{w}^* = \boldsymbol{h}, \tag{6}$$

where

$$\begin{aligned} \boldsymbol{C} &= \left[\boldsymbol{c}_1, \boldsymbol{c}_2, \cdots, \boldsymbol{c}_N \right], \\ \boldsymbol{h} &= \left[h_1, h_2, \cdots, h_N \right]^T, \end{aligned} \tag{7}$$

and $\boldsymbol{R}_{xx}$ is an autocorrelation matrix of $\boldsymbol{x}(t)$:

$$\boldsymbol{R}_{xx} = E\left[\boldsymbol{x}(t) \boldsymbol{x}(t)^H \right], \tag{8}$$

where $E[\bullet]$ is an expectation operation. $\boldsymbol{c}_n$ and h_n are referred to as the constraint vector and the constraint response, respectively. $\boldsymbol{c}_n$ is obtained as

$$\boldsymbol{c}_n = \left[c_{1n}, c_{2n}, \cdots, c_{Kn} \right]^T, (n = 1, 2, \cdots, N), \tag{9}$$

where

$$\begin{aligned} c_{kn} &= \exp(-j 2\pi f_c \tau_{kn}), \\ \tau_{kn} &= \frac{f_c (k-1) d \sin \phi_n}{c}, \\ &(k = 1, 2, \cdots, K; n = 1, 2, \cdots, N), \end{aligned} \tag{10}$$

and ϕ_n is a constraint direction in radian. In general, h_n is set to either unity when ϕ_n is associated with the target signal, or zero when ϕ_n is corresponding to the undesired signal. The optimal weight of (5) under the constraint (6) is obtained as

$$\boldsymbol{w}_{opt} = \boldsymbol{R}_{xx}^{-1} \boldsymbol{C} (\boldsymbol{C}^H \boldsymbol{R}_{xx}^{-1} \boldsymbol{C})^{-1} \boldsymbol{h}^*. \tag{11}$$

In (11), $\boldsymbol{R}_{xx}$ is required. In practice, however, $\boldsymbol{R}_{xx}$ is not available since the length of $\boldsymbol{x}(t)$ is not infinite. Hence, the adaptive beamformer is used instead. The adaptive beamformer modifies $\boldsymbol{w}$ sample-by-sample using some leaning rule. For the learning rule, the least mean square (LMS) algorithm is commonly used. The LMS algorithm for the DCMP criterion is given by

$$\begin{aligned} \hat{\boldsymbol{w}}(t+1) &= \boldsymbol{P}\left[\hat{\boldsymbol{w}}(t) - \mu \boldsymbol{x}(t) y^*(t) \right] + \boldsymbol{g}, \\ \hat{\boldsymbol{w}}(0) &= \boldsymbol{g}, \end{aligned} \tag{12}$$

where

$$\begin{aligned} \boldsymbol{P} &= \boldsymbol{I} - \boldsymbol{C}(\boldsymbol{C}^H \boldsymbol{C})^{-1} \boldsymbol{C}^H, \\ \boldsymbol{g} &= \boldsymbol{C}(\boldsymbol{C}^H \boldsymbol{C})^{-1} \boldsymbol{h}^*, \end{aligned} \tag{13}$$

$\hat{\boldsymbol{w}}(t)$ is the estimate of $\boldsymbol{w}$ at the sample t, and μ is the step-size parameter. Alternatively, to estimate $\boldsymbol{R}_{xx}^{-1}$ in (11), the sample matrix inversion (SMI) algorithm can also be available. The SMI algorithm estimates $\boldsymbol{R}_{xx}^{-1}$ sample-by-sample, and then, $\boldsymbol{w}$ is calculated by (11). The SMI algorithm is described as

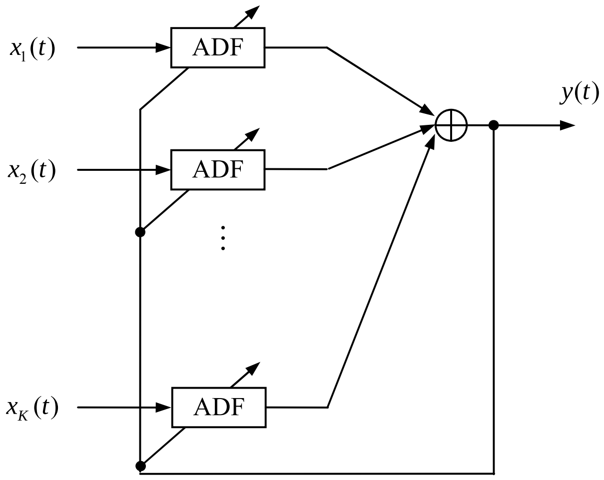

Fig. 2 A block diagram of the beamformer for broadband signals

$$\hat{\boldsymbol{R}}_{xx}^{-1}(t) = \frac{1}{\beta}\hat{\boldsymbol{R}}_{xx}^{-1}(t-1) - \frac{(1-\beta)\hat{\boldsymbol{R}}_{xx}^{-1}(t-1)\boldsymbol{x}(t)\boldsymbol{x}^H(t)\hat{\boldsymbol{R}}_{xx}^{-1}(t-1)}{\beta^2 + \beta(1-\beta)\boldsymbol{x}^H(t)\hat{\boldsymbol{R}}_{xx}^{-1}(t-1)\boldsymbol{x}(t)}, \tag{14}$$

where $\hat{\boldsymbol{R}}_{xx}^{-1}(t)$ is an estimate of $\boldsymbol{R}_{xx}^{-1}$ at the sample t, and $\beta(0<\beta<1)$ is the forgetting factor that defines importance of past samples.

IV. Review of the Directionally Constrained Minimization of Power Algorithm for Broadband Signals

Fig. 2 shows the block diagram of the DCMP for broadband signals [3]. To extend the DCMP algorithm to broadband signals such as speech signals, let the broadband signals be composed of a number of narrowband signals as follows:

$$x(t) = \sum_f x(f;t), \tag{15}$$

where $x(f;t)$ is the narrowband signal at the normalized center frequency f. From (15), it is clear that the directional constraint should be taken into account at each frequency. Hence, (6) is rewritten as

$$\boldsymbol{C}^T(f)\boldsymbol{w}^*(f) = \boldsymbol{h}(f), \tag{16}$$

where $\boldsymbol{C}(f)$, $\boldsymbol{w}(f)$, and $\boldsymbol{h}(f)$ are the constraint matrix, the weight vector, and the constraint response vector at the frequency f, respectively. Since (16) is a constraint in the frequency domain, the DCMP criterion can be extended to broadband signals by transforming into the time domain.

Consider the n-th constraint. The n-th constraint at the frequency f is given by

$$\boldsymbol{c}_n^T(f)\boldsymbol{w}^*(f) = \sum_{k=1}^{K} c_{kn}(f)w_k^*(f) = h_n(f). \tag{17}$$

Each term of (17) can be regarded as the multiplication of two spectra. Thus, the time-domain constraint is expressed by applying the inverse discrete-time Fourier transform (IDTFT). The IDTFT of (17) is written by

$$\begin{aligned}\sum_{k=1}^{K}\tilde{c}_{kn}(t) * \tilde{w}_k^*(t) &= \sum_{k=1}^{K}\sum_{p=-\infty}^{\infty}\tilde{c}_{kn}(t-p)\tilde{w}_k^*(p)\\ &= \sum_{k=1}^{K}\sum_{p=0}^{P}\tilde{c}_{kn}(t-p)\tilde{w}_k^*(p)\\ &= \sum_{k=1}^{K}\tilde{\boldsymbol{c}}_{kn}(t)\tilde{\boldsymbol{w}}_k^*\\ &= \tilde{h}_n(t),\end{aligned} \tag{18}$$

where $\tilde{c}_{kn}(t)$, $\tilde{w}_k(t)$, and $\tilde{h}_n(t)$ are the IDTFT of $c_{kn}(f)$, $w_k(f)$, and $h_n(f)$, respectively, and $*$ donates the convolution operation. $\tilde{\boldsymbol{c}}_{kn}(t)$ and $\tilde{\boldsymbol{w}}_k$ are respectively obtained as

$$\begin{aligned}\tilde{\boldsymbol{c}}_{kn}(t) &= \left[\tilde{c}_{kn}(t), \tilde{c}_{kn}(t-1), \cdots, \tilde{c}_{kn}(t-P)\right]^T,\\ \tilde{\boldsymbol{w}}_k &= \left[\tilde{w}_k(0), \tilde{w}_k(1), \cdots, \tilde{w}_k(P)\right]^T.\end{aligned} \tag{19}$$

Note that the convolution operation is truncated to $0 \le p \le P$ in (18). Since $c_{kn}(f)$ is given by (10), $\tilde{c}_{kn}(t)$ is identical with the impulse response of a time delay system in which the filter input is delayed for τ_{kn} samples. Therefore, $\tilde{c}_{kn}(t)$ is expressed as in the form

$$\tilde{c}_{kn}(t) = \frac{1}{\pi(t-\tau_0-\tau_{kn})}\sin(\pi(t-\tau_0-\tau_{kn})), \tag{20}$$

where $\tau_0 = P/2$ is a constant delay in order to shift the current input to the center of the filter. Note that $\tilde{c}_{kn}(t) = 1$ when $t-\tau_0-\tau_{kn} = 0$ in (20). $\tilde{h}_n$ is given by

$$\tilde{h}_n(t) = \begin{cases} h_n, (t=0) \\ 0, (t \ne 0)\end{cases}, \tag{21}$$

since h_n is constant for any f in the frequency domain. Hence the directional constraint for broadband signals is expressed as

$$\tilde{\boldsymbol{C}}^T\tilde{\boldsymbol{W}}^* = \tilde{\boldsymbol{H}}, \tag{22}$$

where

$$\begin{aligned}\tilde{\boldsymbol{C}} &= \begin{bmatrix}\tilde{\boldsymbol{C}}_{11} & \cdots & \tilde{\boldsymbol{C}}_{1N}\\ \vdots & \ddots & \vdots\\ \tilde{\boldsymbol{C}}_{K1} & \cdots & \tilde{\boldsymbol{C}}_{KN}\end{bmatrix},\\ \tilde{\boldsymbol{C}}_{kn} &= \left[\tilde{\boldsymbol{c}}_{kn}(-Q), \cdots, \tilde{\boldsymbol{c}}_{kn}(Q)\right],\\ \tilde{\boldsymbol{W}} &= \left[\tilde{\boldsymbol{w}}_1^T, \cdots, \tilde{\boldsymbol{w}}_K^T\right]^T,\\ \tilde{\boldsymbol{H}} &= \left[\tilde{\boldsymbol{h}}_1^T, \cdots, \tilde{\boldsymbol{h}}_N^T\right]^T,\\ \tilde{\boldsymbol{h}}_n &= \left[\tilde{h}_n(-Q), \cdots, \tilde{h}_n(Q)\right]^T.\end{aligned} \tag{23}$$

TABLE I
COMPARISON OF THE NUMBER OF MULTIPLICATIONS OF CONVENTIONAL AND PROPOSED METHOD

	$\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}}$	$\tilde{\boldsymbol{C}}^H\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}}$
Conventional Method	$(P+1)^3K^2$	$(P+1)^4K^2$
Proposed Method	0	0

P and K indicate the length of the filter and the number of the microphones, respectively.

TABLE II
COMPARISON OF CALCULATING TIME

P	Method	Calculating time	NRR
30	Proposed	13.00[s]	18.05[dB]
	Conventional	18.14[s]	
62	Proposed	53.79[s]	16.12[dB]
	Conventional	94.94[s]	
126	Proposed	270.05[s]	13.28[dB]
	Conventional	608.52[s]	

s :second, dB : decibel

Q indicates the maximum value of the delay or the preceding which can be represented in $\tilde{\boldsymbol{c}}_{kn}(t)$.

In addition, in (18), $\tilde{\boldsymbol{w}}_k$ is considered as the FIR filter at the k-th channel. Therefore, the output of the sensor array is written by

$$y(t) = \sum_{k=1}^{K} \tilde{\boldsymbol{w}}_k^H \tilde{\boldsymbol{x}}_k(t) = \tilde{\boldsymbol{W}}^H \tilde{\boldsymbol{X}}(t), \quad (24)$$

where

$$\tilde{\boldsymbol{x}}_k(t) = \left[x_k(t), x_k(t-1), \cdots, x_k(t-P)\right]^T,$$
$$\tilde{\boldsymbol{X}}(t) = \left[\tilde{\boldsymbol{x}}_1^T(t), \tilde{\boldsymbol{x}}_2^T(t), \cdots, \tilde{\boldsymbol{x}}_K^T(t)\right]^T. \quad (25)$$

Consequently, the DCMP algorithm for broadband signals is defined by

$$\arg\min_{\tilde{\boldsymbol{W}}}\left(P_{out} = \frac{1}{2}\tilde{\boldsymbol{W}}^H \tilde{\boldsymbol{R}}_{XX}\tilde{\boldsymbol{W}}\right), \quad (26)$$

where

$$\tilde{\boldsymbol{R}}_{XX} = E\left[\tilde{\boldsymbol{X}}(t)\tilde{\boldsymbol{X}}^H(t)\right]. \quad (27)$$

The optimum solution of (26) under the constraint (22) is obtained as

$$\tilde{\boldsymbol{W}}_{opt} = \tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}}(\tilde{\boldsymbol{C}}^H\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}})^{-1}\tilde{\boldsymbol{H}}^*. \quad (28)$$

Since the structure of (28) is analogous to (11), the adaptive learning algorithms (12)-(14) are available.

V. PROPOSED METHOD

In the previous section, the DCMP algorithm for broadband signals has been reviewed. The algorithm is available for any constraint directions. Since the size of matrices formed in the algorithm is relatively large, however, the calculation cost is heavy. In this section, in order to eliminate the computational task, the constraint direction is limited to perpendicular to the sensor array system, i.e., $\phi_n = 0$.

By limiting the constraint direction to perpendicular to the sensor array, the number of the directional constraints is fixed to $N = 1$. Hence, the constraint matrix $\tilde{\boldsymbol{C}}$ is formed as

$$\tilde{\boldsymbol{C}} = \begin{bmatrix} \tilde{\boldsymbol{C}}_{11} \\ \vdots \\ \tilde{\boldsymbol{C}}_{K1} \end{bmatrix},$$
$$\tilde{\boldsymbol{C}}_{k1} = \left[\tilde{\boldsymbol{c}}_{k1}(-Q), \cdots, \tilde{\boldsymbol{c}}_{k1}(Q)\right]. \quad (29)$$

In addition, the direction for the constraint is limited to $\phi = 0$. Therefore, $\tau_{kn} = 0$ for any k. Consequently, (20) is rewritten by

$$\tilde{c}_{k1}(t) = \frac{1}{\pi(t-\tau_0)}\sin(\pi(t-\tau_0)). \quad (30)$$

Note that $\tilde{c}_{kn}(t) = 1$ when $t - \tau_0 = 0$ in (30). Therefore, $\tilde{\boldsymbol{c}}_{k1}$ is given by

$$\begin{aligned}
&\vdots \\
\tilde{\boldsymbol{c}}_{k1}(\tau_0 - 2) &= \left[0, 0, \cdots, 0, 0, 0, \cdots, 0, 0\right]^T \\
\tilde{\boldsymbol{c}}_{k1}(\tau_0 - 1) &= \left[0, 0, \cdots, 0, 0, 0, \cdots, 0, 0\right]^T \\
\tilde{\boldsymbol{c}}_{k1}(\tau_0) &= \left[1, 0, \cdots, 0, 0, 0, \cdots, 0, 0\right]^T \\
\tilde{\boldsymbol{c}}_{k1}(\tau_0 + 1) &= \left[0, 1, \cdots, 0, 0, 0, \cdots, 0, 0\right]^T \\
&\vdots \quad \ddots \\
\tilde{\boldsymbol{c}}_{k1}(\tau_0 + P/2) &= \left[0, 0, \cdots, 0, 1, 0, \cdots, 0, 0\right]^T \\
\tilde{\boldsymbol{c}}_{k1}(\tau_0 + P/2 + 1) &= \left[0, 0, \cdots, 0, 0, 1, \cdots, 0, 0\right]^T \\
&\vdots \quad \ddots \\
\tilde{\boldsymbol{c}}_{k1}(\tau_0 + P - 1) &= \left[0, 0, \cdots, 0, 0, 0, \cdots, 1, 0\right]^T \\
\tilde{\boldsymbol{c}}_{k1}(\tau_0 + P) &= \left[0, 0, \cdots, 0, 0, 0, \cdots, 0, 1\right]^T \\
\tilde{\boldsymbol{c}}_{k1}(\tau_0 + P + 1) &= \left[0, 0, \cdots, 0, 0, 0, \cdots, 0, 0\right]^T \\
\tilde{\boldsymbol{c}}_{k1}(\tau_0 + P + 2) &= \left[0, 0, \cdots, 0, 0, 0, \cdots, 0, 0\right]^T \\
&\vdots
\end{aligned}, \quad (31)$$

Obviously, $\tilde{\boldsymbol{c}}_{k1}(t) = \boldsymbol{0}$ when $t < \tau_0$ or $t > \tau_0 + P$, where $\boldsymbol{0}$ is a $(P+1)\times 1$ column vector of which all the elements are zero.

Hence, by using $\tilde{c}_{k1}(t)$ when $\tau_0 \le t \le \tau_0 + P$, which have nonzero element, constraint matrix can be constructed. As a result, $\tilde{\boldsymbol{C}}_{k1}$ can be obtained as

$$\tilde{\boldsymbol{C}}_{k1} = \begin{bmatrix} 1 & & \boldsymbol{0} \\ & \ddots & \\ \boldsymbol{0} & & 1 \end{bmatrix} = \boldsymbol{I}, \tag{32}$$

where $\boldsymbol{I}$ is a $(P\times1)\times(P\times1)$ unit matrix. Therefore, $\tilde{\boldsymbol{C}}$ is formed by using unit matrices:

$$\tilde{\boldsymbol{C}} = \begin{bmatrix} \boldsymbol{I} \\ \vdots \\ \boldsymbol{I} \end{bmatrix}. \tag{33}$$

By using (33), the calculation task is reduced. Consider the inverse of the autocorrelation matrix of $x(t)$, $\tilde{\boldsymbol{R}}_{XX}^{-1}$. By introducing a number of small matrices $\tilde{\boldsymbol{U}}_{ij}$, $\tilde{\boldsymbol{R}}_{XX}^{-1}$ can be expressed as

$$\tilde{\boldsymbol{R}}_{XX}^{-1} = \begin{bmatrix} \tilde{\boldsymbol{U}}_{11} & \cdots & \tilde{\boldsymbol{U}}_{1K} \\ \vdots & \ddots & \vdots \\ \boldsymbol{U}_{K1} & \cdots & \tilde{\boldsymbol{U}}_{KK} \end{bmatrix}, \tag{34}$$

where $\tilde{\boldsymbol{U}}_{ij}$ is a $(P+1)\times(P+1)$ square matrix. From (34), $\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}}$ and $\tilde{\boldsymbol{C}}^H\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}}$ in (28) are respectively given by

$$\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}} = \begin{bmatrix} \tilde{\boldsymbol{U}}_{11} & \cdots & \tilde{\boldsymbol{U}}_{1K} \\ \vdots & \ddots & \vdots \\ \boldsymbol{U}_{K1} & \cdots & \tilde{\boldsymbol{U}}_{KK} \end{bmatrix} \begin{bmatrix} \boldsymbol{I} \\ \vdots \\ \boldsymbol{I} \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^{K} \tilde{\boldsymbol{U}}_{1j} \\ \vdots \\ \sum_{j=1}^{K} \tilde{\boldsymbol{U}}_{Ij} \end{bmatrix},$$

$$\tilde{\boldsymbol{C}}^H\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}} = \begin{bmatrix} \boldsymbol{I} & \cdots & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \tilde{\boldsymbol{U}}_{11} & \cdots & \tilde{\boldsymbol{U}}_{1K} \\ \vdots & \ddots & \vdots \\ \boldsymbol{U}_{K1} & \cdots & \tilde{\boldsymbol{U}}_{KK} \end{bmatrix} \begin{bmatrix} \boldsymbol{I} \\ \vdots \\ \boldsymbol{I} \end{bmatrix} = \left[\sum_{i=1}^{K} \sum_{j=1}^{K} \tilde{\boldsymbol{U}}_{ij} \right]. \tag{35}$$

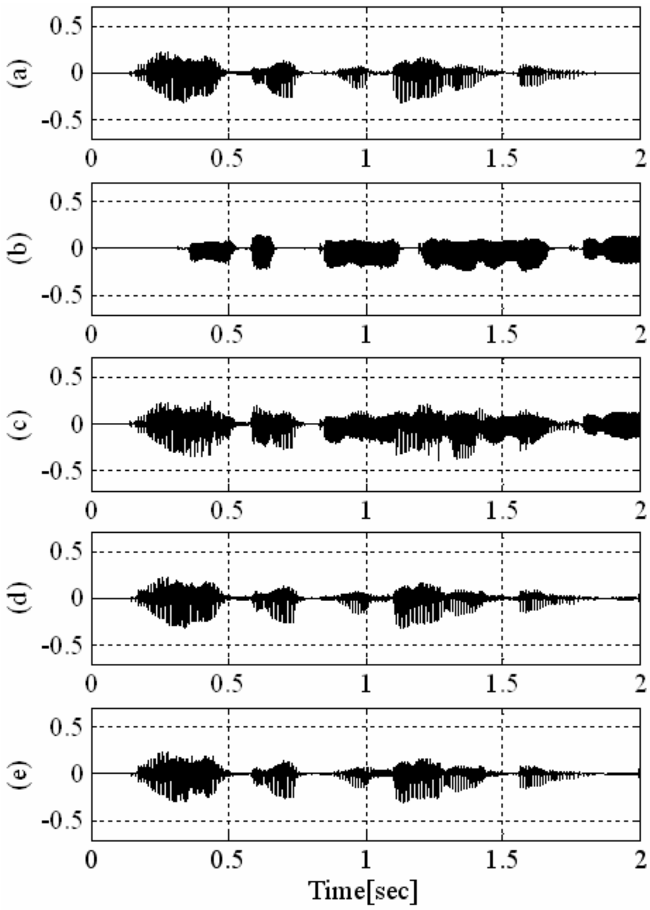

Fig. 3 Waveforms: (a) Original Speech 1 ($\theta_1 = 0$ [degree]), (b) Original Speech 2 ($\theta_2 = 27.99$ [degree]), (c) Mixture at Channel 1, (d) Array Output by the Optimum Solution, and (e) Array Output by the SMI Algorithm

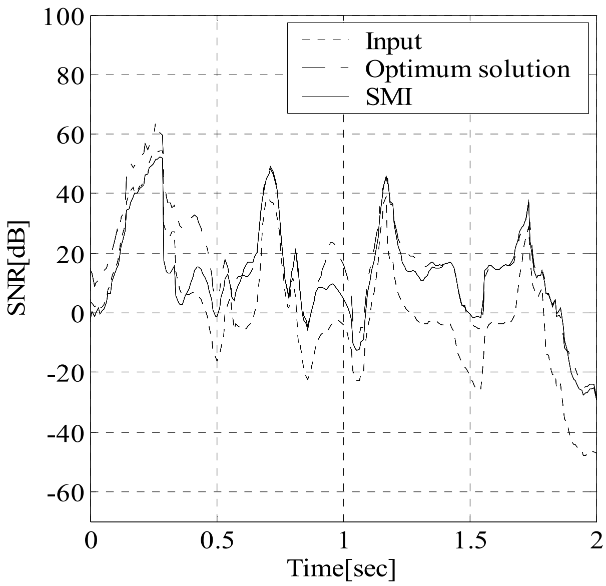

Fig. 4 Comparison in terms of SNR

Hence, the multiplication in $\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}}$ and $\tilde{\boldsymbol{C}}^H\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}}$ are implemented by only addition of small matrices $\tilde{\boldsymbol{U}}_{ij}$.

Table I shows the comparison of the number of the times of multiplications in the conventional and proposed methods. As shown in table I, it is seen that the proposed method dose not require multiplications for calculating $\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}}$ and $\tilde{\boldsymbol{C}}^H\tilde{\boldsymbol{R}}_{XX}^{-1}\tilde{\boldsymbol{C}}$.

VI. Simulation

In this simulation, two speech signals were used as the source signals and these were observed at two-channel microphone array, i.e., $K = M = 2$. The speech signals were sampled at 8 [kHz]. The speech signal uttered by a male was used as a desired signal $s_1(t)$, and a speech signal uttered by a female was used as an undesired signal $s_2(t)$. The length of both $s_1(t)$ and $s_2(t)$ were 2 [s]. The incoming directions of $s_1(t)$ and $s_2(t)$ were $\theta_1 = 0$ [degree] and $\theta_2 = 27.99$ [degree], respectively. d and c were assumed to be $d = 0.18$ [m] and $c = 338$ [m/s], respectively. The parameters for the directional constraint were set to $N = 1$, $\phi_1 = \theta_1 = 0$ and $h_1 = 1$. In the adaptive beamformer, the SMI algorithm was used as the learning rule with $\beta = 0.9997$. P was varied as $P = 30$, 62, and 126. In order to confirm the validity, the objective measurements in terms of the instantaneous SNR, calculating time, and the noise reduction rate (NRR) were considered. The instantaneous SNR and NRR are respectively defined by

$$SNR(t) = 10\log_{10}\frac{\sum_{l=0}^{L-1}\left|s(t+l-\tau_0)\right|^2}{\sum_{l=0}^{L-1}\left|s(t+l-\tau_0)-y(t+l)\right|^2}, \tag{36}$$

and

$$NRR = SNR_{out} - SNR_{in}. \tag{37}$$

SNR_{in} and SNR_{out} are respectively obtained as follows:

$$SNR_{out} = 10\log_{10}\frac{\left|s(t-\tau_0)\right|^2}{\left|y(t)-s(t-\tau_0)\right|^2},$$

$$SNR_{in} = 10\log_{10}\frac{\sum_{t=0}^{N-1}\left|s(t)\right|^2}{\sum_{t=0}^{N-1}\left|x(t)-s(t)\right|^2}, \tag{38}$$

where $s(t)$, $y(t)$, and $x(t)$ are the target, retrieved, and observed signals, respectively, N is the length of the signals, and τ_0 is a constant delay in (30). In this simulation, L was set to 256.

Fig. 3, Fig. 4, and Table II show the simulation results. As shown in Fig. 3 (d) and (e), the proposed method extracts the target signal from observed signals effectively. Furthermore, as shown in Table II, the calculating time is reduced.

VII. Conclusion

We have proposed a fast algorithm based on the DCMP criterion for extracting the speech signals perpendicular to the sensor array system. Our approach reduces calculation time by limiting the directional constraint to perpendicular to the sensor array system.

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