

ACOUSTIC BLIND SOURCE SEPARATION BASED ON THE PARTICLE VELOCITY VECTOR MEASUREMENT

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Abstract: This paper presents an autonomous directivity microphone system based on the newly proposed blind source separation method. The blind source separation principally uses no a priori knowledge about parameters of convolution, filtering and mixing. In the simplest case of the blind source separation problems, observed mixed signals are linear combinations of unknown mutually statistically independent, zeromean source signals. The blind signal separation algorithm utilizes the linearity among the four signals: (1) the sound pressure, (2)x, (3)y, and (4)z-directional particle velocities, all of which are governed by the wave equation and the equation of motion. The proposed method, therefore, has an ability to simplify the convolution blind source separation problems into the instantaneous blind source separation over the particle velocity vector space. Several acoustical experiments are performed with the particle velocity microphone (Microflown) successfully instead of sound pressure microphones.

INTRODUCTION

Blind source separation (BSS) based on the independent component analysis (ICA) plays an important role in many kind of areas. The mission of BSS is to reconstruct the single transmitted signal from the observed data. In acoustical signal processing and related areas, the observed signal consists of an unknown source signal mixed with itself and different time delays. Fourier transform techniques, therefore, are used for replacing convolutions with products in the frequency domain, although, several problems: indeterminacy of permutation and sign exist in ICA. In order to avoid the preceding problems, the proposed BSS algorithm utilizing the fact that the observed particle velocity vector can be denoted as the linear combination of sound pressures



FIGURE 1: Geometry of the three independent incident plane waves and the observation point

which are excited by each sound source. Consequently, the BSS based on the particle velocity measurement makes the convolution blind source separation problems into the simplest instantaneous mixture problems.

This paper is organized as follows: the second section presents the particle velocity blind source separation algorithm, the third section evaluates the proposed velocimetry via acoustical experiment with Microflown system.

PROBLEM FORMULATION

Overlaps of three plane waves

Assuming that three band-limited plane waves propagates in the three lineally independent directions respectively as shown in Fig.1, it can be found that the acoustic wave fields are denoted at (x, y, z) as follows:

$$f_i(x, y, z, t) = w_i(t + \frac{1}{v}(x\sin\theta_i\cos\phi_i + y\sin\theta_i\sin\phi_i + z\cos\theta_i)), \qquad (1)$$

where $i = 1, 2, 3,$

where v denotes the phase velocity of the airborne sound. Here, $w_i(t)$ denotes the band-limited source signal:

$$w_i(t) = \int_{-\omega_i}^{\omega_i} A_i(\omega) e^{j\omega t} \mathrm{d}\omega, \qquad (2)$$

where ω_i denotes the bandwidth of the each source signal. Angles, ϕ_i and θ_i denote the each propagating direction:

$$\boldsymbol{p}_i = (-\sin\theta_i \cos\phi_i - \sin\theta_i \sin\phi_i - \cos\theta_i)^T$$
(3)

At the origin, x = y = z = 0, the temporal gradient can be obtained as:

$$f_{it}(0,0,0,t) = \frac{\partial}{\partial t} f_i(x,y,z,t) \Big|_{x=y=z=0} = \dot{w}_i(t).$$
(4)

Here, $\dot{w}_i(t)$ is the time-differential of $w_i(t)$ denoted as:

$$\dot{w}_i(t) = \int_{-\omega_i}^{\omega_i} j\omega A_i(\omega) e^{j\omega t} \mathrm{d}\omega$$
(5)

Orthogonal triplet of spatial gradients are derived as follows:

$$f_{ix}(0,0,0,t) = \frac{\partial}{\partial x} f_i(x,y,z,t) \Big|_{x=y=z=0} = \frac{\sin \theta_i \cos \phi_i}{v} \dot{w}_i(t)$$
(6)

$$f_{iy}(0,0,0,t) = \frac{\partial}{\partial y} f_i(x,y,z,t) \Big|_{x=y=z=0} = \frac{\sin \theta_i \sin \phi_i}{v} \dot{w}_i(t)$$
(7)

$$f_{iz}(0,0,0,t) = \frac{\partial}{\partial z} f_i(x,y,z,t) \Big|_{x=y=z=0} = \frac{\cos\theta_i}{v} \dot{w}_i(t)$$
(8)

Instantaneous mixture

Based on the above equations (4),...,(8), the orthogonal spatial gradients of the observed signal, f(x, y, z, t), at the origin can be denoted respectively as:

$$\frac{\partial}{\partial x}f(x,y,z,t)\Big|_{x=y=z=0} = \sum_{i=1}^{3} f_{ix}(0,0,0,t) = \sum_{i=1}^{3} \frac{\sin\theta_i \cos\phi_i}{v} \dot{w}_i(t), \quad (9)$$

$$\frac{\partial}{\partial y}f(x,y,z,t)\Big|_{x=y=z=0} = \sum_{i=1}^{3} f_{iy}(0,0,0,t) = \sum_{i=1}^{3} \frac{\sin\theta_i \sin\phi_i}{v} \dot{w}_i(t), \quad (10)$$

$$\frac{\partial}{\partial z}f(x,y,z,t)\Big|_{x=y=z=0} = \sum_{i=1}^{3} f_{iz}(0,0,0,t) = \sum_{i=1}^{3} \frac{\cos\theta_i}{v} \dot{w}_i(t).$$
(11)

Therefore, the orthogonal spatial gradients of the observed signal can be denoted as the instantaneous mixture of the source signals as:

$$\nabla f(x, y, z, t) \Big|_{x=y=z=0} = A \begin{pmatrix} \dot{w}_1(t) \\ \dot{w}_2(t) \\ \dot{w}_3(t) \end{pmatrix},$$
(12)

where, the mixing matrix A can be defined as:

$$A = \begin{pmatrix} \boldsymbol{p}_1 & \boldsymbol{p}_2 & \boldsymbol{p}_3 \end{pmatrix} \tag{13}$$

Whereas, based on the wave equation of the airborne sound, particle velocity vector v(x, y, z, t) and the spatial gradients of the sound pressure f(x, y, z, t) satisfy the following equation:

$$\rho \frac{\partial \boldsymbol{v}(x, y, z, t)}{\partial t} = -\nabla f(x, y, z, t), \tag{14}$$

where ρ is the density of the air. Therefore, (12) can be denoted as:

$$\rho \frac{\partial \boldsymbol{v}(x, y, z, t)}{\partial t} \Big|_{x=y=z=0} = A \begin{pmatrix} \dot{w}_1(t) \\ \dot{w}_2(t) \\ \dot{w}_3(t) \end{pmatrix}.$$
(15)

After the integration of the above equation for time, the following instantaneous mixture can be obtained:

$$\boldsymbol{v}(0,0,0,t) = \frac{1}{\rho} A \begin{pmatrix} w_1(t) \\ w_2(t) \\ w_3(t) \end{pmatrix}.$$
 (16)

Blind Signal Separation

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The Blind Source Separation estimates the mixing matrix A and independent source signals $w_{i=1,2,3}(t)$ with three steps shown as Fig.2, from the observed particle velocity vector is broken down as:

$$\begin{pmatrix} v_x(t) \\ v_y(t) \\ v_z(t) \end{pmatrix} = \boldsymbol{v}(0, 0, 0, t).$$
(17)

[step1] The normalized orthogonal triplet of the particle velocities, $u_1(t)$, $u_2(t)$, and $u_3(t)$ can be obtained as:

$$\begin{pmatrix} u_1(t) \\ u_2(t) \\ u_3(t) \end{pmatrix} = B \begin{pmatrix} v_x(t) \\ v_y(t) \\ v_z(t) \end{pmatrix}.$$
(18)

[step2] The normalized independent triplet of the particle velocities are obtained by homothetic transformations with $C(\alpha)$

$$\begin{pmatrix} u_1^{[\boldsymbol{\alpha}]}(t)\\ u_2^{[\boldsymbol{\alpha}]}(t)\\ u_3^{[\boldsymbol{\alpha}]}(t) \end{pmatrix} = C(\boldsymbol{\alpha}) \begin{pmatrix} u_1(t)\\ u_2(t)\\ u_3(t) \end{pmatrix},$$
(19)

[step3] For the sake of the optimum separation, [step2] is iterated with the steepest decent method in order to minimize the Kullback-Leibler divergence: $I(u_1^{[\alpha]}, u_2^{[\alpha]}, u_3^{[\alpha]})$.

ACOUSTICAL EXPERIMENTS

We have implemented and tested the proposed particle velocity blind source separation algorithm with the Proof-Of-Concept (POC) model.



FIGURE 2: Sketch of the signal flow of BSS based on the particle velocity measurement, $w_{i(=1,2,3)}$: source signals, $v_{i(=1,2,3)}$: observed particle velocities, $u_{i(=1,2,3)}$: prewhitened signals, $u_{i(=1,2,3)}(\alpha)$: separated signals, A: mixing matrix, B: whitening matrix, $C(\alpha)$: rotation matrix for α .



FIGURE 3: POC model and experimental setup:(1)geometrical setup and block diagram, and (2)sensor head of POC model.

experimental setup

Figure 3(1) geometrical setup and block diagram of the POC model, and (2) shows the sensor head of the particle-velocity microphone. Table 1 shows the specifications of source signals which are two female voices.

Blind source separation

The original source sounds are recoded female voices shown in the Fig.4(1)and (2). The observed particle velocities in the Dickerson's of x-axis and y-axis are plotted in (3) and (4) respectively. The estimated sound pressures of original sound sources are shown in Fig.4(5) and (5) respectively. Fig.5 (1) shows the convergence plots of the estimated directions of the original sources No.1 and No.2. Signal to interference ration (SIR) are plotted in (2).

	$w_1(t)$	$w_2(t)$
source	female voice, "NHK Stereo Broadcasting- Opening narration" recoded in 1954	female voice, "National Stereo Hall-Opening narration" recorded in 1961
length	10s	
sampling resolution	16bit, 44.1kHz	
mean	$m_1 = 0.0$	$m_2 = 0.0$
standard deviation	$\sigma_1 = 3698$	$\sigma_2 = 3838$
moments		
the 3rd	-2.75×10^{10}	1.10×10^{10}
the 4th	$7.28e \cdot 10^{20}$	5.91×10^{20}
the 5th	-7.34×10^{18}	1.64×10^{18}
mutual information	0.048bit	

TABLE 1: Specifications of source signals

Discussion

The SIR plots show that the proposed particle velocity blind source separation method has an ability to separate the original sound sources from the orthogonal pair of observed particle velocities.

For the statistical stability, the blind source separation process is started 1sec after the signal arrival. From the results, the separation process converged in almost 1sec (cf. Fig.4(5),(6)).

The convergence error is considered to be caused by the unsteady airflow in the experimental environment.

Concluding Remarks

This paper proposes the particle velocity blind source separation method to be independent of source-locations, and presents simple digital signal processing algorithm characterizing the wave field where incident three plane waves overlap each other.

For detecting the directions of arrivals, the analysis of the linear dependency among the sound pressure, the orthogonal triplet of the particle velocity is used. The 2dimensional acoustical experiments realized by the POC-model, were conducted with following conclusions and remarks:

- 1. the particle velocity measurement has an ability to simplify the convolution blind source separation problems into the instantaneous blind source separation over the spatio-temporal gradient space,
- 2. the directions of wave propagation can be determined with the proposed blind source separation.



FIGURE 4: Original sound signals:(1)No.1, (2) No.2. Observed particle velocities in the directions of (3)x-axis and (4) y-axis. Separated sound signals: (5)No.1, (6)No.2



FIGURE 5: Convergence plots of the estimated directions of the original sound waves: No.1 and No.2, and (2)curves of SIR1 and 2.

3. three sources can be discriminated autonomously even when they are slightly moving.

Acknowledgment

This paper was supported by Grant-in-Aid for Scientific Research(KAKENHI 17560375) from JSPS and MEXT of the Japanese Government.

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