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Research Article

Detection and Separation of Speech Events in Meeting Recordings Using a Microphone Array

Futoshi Asano,[1] Kiyoshi Yamamoto,[1] Jun Ogata,[1] Miichi Yamada,[2] and Masami Nakamura[2]

[1] *Information Technology Research Institute, National Institute of Advanced Industrial Science and Technology, Tsukuba Central 2, 1-1-1 Umezono, Tsukuba 305-8568, Japan*
[2] *Advanced Media, Inc., 48F Sunshine 60 Building, 3-1-1 Higashi-Ikebukuro, Toshima-Ku, Tokyo 170-6048, Japan*

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When applying automatic speech recognition (ASR) to meeting recordings including spontaneous speech, the performance of ASR is greatly reduced by the overlap of speech events. In this paper, a method of separating the overlapping speech events by using an adaptive beamforming (ABF) framework is proposed. The main feature of this method is that all the information necessary for the adaptation of ABF, including microphone calibration, is obtained from meeting recordings based on the results of speech-event detection. The performance of the separation is evaluated via ASR using real meeting recordings.

1. INTRODUCTION

The analysis, structuring, and automatic transcription of meeting recordings have attracted considerable attention in recent years (e.g., [1–5]). Especially for small informal meetings, a major difficulty is that the discussion consists of spontaneous speech, and various types of unexpected speech or nonspeech events may occur. One such event is the responses by listeners such as “Uh-huh” or “I see” being inserted in short pauses in the main speech. These responses are sometimes very close to or even overlap the speech of the main speaker, and it is difficult to remove them by segmentation in the time domain. Due to the insertion of these small speech events, the performance of automatic speech recognition (ASR) is sometimes greatly reduced.

In the field of signal processing, various types of sound separation, such as blind source separation (BSS, e.g., [6]) and adaptive beamforming (ABF, e.g., [7]), have been investigated. By using these methods, signals from different sound sources located at different positions can be separated in the spatial domain, and can thus be effective for the separation of speech events that overlap in the time domain.

In most of these previous approaches, a general framework of sound separation for a general scenario, in which the target signal and interference coexist in an unknown environment, was treated. Especially, BSS utilizes (almost) no prior knowledge on the observed signal and the sources, and can thus be applied to a wide variety of applications. Due to this difficult blind scenario, however, the BSS approach has a tradeoff that requires longer adaptation (learning) time. In the meeting situation addressed in this paper, the length of the overlapping section of speech events is often very short and the data sufficient for BSS may not be obtained.

In the ABF approach, the condition assumed in the BSS scenario is somewhat relaxed, and the spatial information of the target is provided by the user while the spatial information of the interference is estimated in the adaptation process. To provide the spatial information on the target, a calibration based on measurement is usually employed. In measurement-based calibration, precise measurement must be done for every individual microphone array, and this hinders mass production. For the generalized sidelobe canceller (GSC), online self-calibration algorithms have been proposed [8–10]. Such algorithms are necessary for a general scenario in which only the mixture of target signal and interference can be observed. However, if the target signal alone can be observed, it is obvious that the calibration process can be much simpler and easier.

Also, in the estimation of the spatial information of the interference, the adaptation will be easier and more efficient when the interference alone can be observed. In a general scenario in which this “target-free” interference is not available,

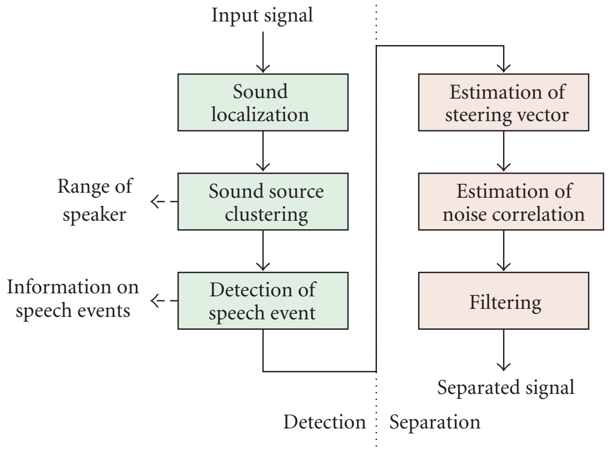

Input signal
Sound localization
Range of speaker
Sound source clustering
Information on speech events
Detection of speech event
Estimation of steering vector
Estimation of noise correlation
Filtering
Separated signal
Detection
Separation

Figure 1: Outline of the proposed method.

the class of ABF which can be used in the mixed situation such as a minimum variance (MV) beamformer or a GSC must be used. When the interference alone can be observed, on the other hand, the classical maximum-likelihood (ML) beamformer, which outperforms the other types of beamformers in this limited situation [11], can be used. In [12], an audio-visual information fusion was employed to detect the absence of the target so that the interference alone could be observed.

In this paper, a new approach for the separation of overlapping speech events in meetings based on the ML-type ABF framework is proposed [13]. As described above, if "pure" information on the target and interference sources is available, the calibration and the adaptation process is much easier and more effective. In a usual small-sized meeting treated in this paper, there are some advantages that can be utilized in the automatic calibration and adaptation of ABF as follows:

(i) In the neighborhood of overlapping speech events, sections in which the target speaker and the competing speaker are speaking on their own are usually found (these sections are termed "single-talking" sections hereafter).

(ii) The movements of speakers are relatively small.

(iii) The processing does not have to be real-time.

Utilizing these characteristics peculiar to meeting recordings, in this paper, the ABF framework is modified so that it is suitable for the separation of speech events in a meeting recording. The basic idea is that the pure information on the target and the interference is extracted from the single-talking sections before or after the overlapping section. Regarding the automatic calibration, even if only the target source is active, the calibration cannot be accomplished by using the cross-spectrum between the microphones due to the presence of the room reverberation and background noise. In this paper, a method of automatic calibration based on the subspace approach is proposed. The effect of reducing reverberation and background noise by the subspace approach has been demonstrated in [14]. Also, a selection algorithm of an appropriate single-talking section effective for the separation of overlapping speech events is proposed. This selection algorithm is essential to the proposed method since the location information included in the overlapping section and that included in the single-talking sections may differ due to the fluctuation of the position of the speakers.

An important issue in the analysis of meetings is the automation of the analyzing process. By employing the proposed method including self-calibration of the microphone array, the signal processing component of the system is almost completely automated. The application of a beamformer to the reduction of overlapping speech in meeting recordings has already been proposed in the previous studies (e.g., [1]). However, the viewpoint of the automation of the process has not been mentioned in previous approaches.

2. OVERVIEW OF THE PROPOSED METHOD

In this paper, meetings are recorded by using a microphone array and are stored in a computer. Figure 1 shows an outline of the proposed method. In the first half of the method (left half of Figure 1), speech events are detected based on sound localization, and the speaker in each event is identified (Section 3). In the second half (right half of Figure 1), the overlapping sections of the speech events are separated based on the information regarding the detected speech events (Section 4). ASR is then applied to separated speech events for evaluation (Section 5).

3. DETECTION OF SPEECH EVENTS

3.1. Sound localization

Meeting data recorded by using a microphone array are segmented into time blocks. The spatial spectrum for each block is then estimated by the MUSIC method [15]. The MUSIC spectrum is obtained by

$$P(\theta,\omega,\bar{t}) = \frac{\mathbf{v}^H(\theta,\omega)\mathbf{v}(\theta,\omega)}{\left|\mathbf{v}^H(\theta,\omega)\mathbf{E}_n\right|^2}. \tag{1}$$

The symbols ω and $\bar{t}$ denote the indices for the frequency and the time block, respectively. The matrix $\mathbf{E}_n$ consists of the eigenvectors of the noise subspace of the spatial correlation matrix (eigenvectors corresponding to the smallest $M - N$ eigenvalues where M and N denote the number of microphones and the number of active sound sources, resp.). The spatial correlation matrix is defined as

$$\mathbf{R} = E[\mathbf{x}(\omega,t)\mathbf{x}^H(\omega,t)]. \tag{2}$$

The vector $\mathbf{x}(\omega,t) = [X_1(\omega,t),\dots,X_M(\omega,t)]^T$ is termed the input vector, where $X_m(\omega,t)$ denotes the short-term Fourier transform of the mth microphone input. The index t corresponds to each Fourier transform within a single time block.

The vector $\mathbf{v}(\theta,\omega)$ is termed the steering vector, which consists of the transfer function of the direct path from the (virtual) sound source located at angle θ to the microphones as follows:

$$\mathbf{v}(\theta,\omega) = \left[V_1(\theta,\omega)e^{j\omega\tau_1(\theta)},\dots,V_M(\theta,\omega)e^{j\omega\tau_M(\theta)}\right]^T, \tag{3}$$

where $V_m(\theta, \omega)$ and $\tau_m(\theta)$ denote the gain and the time delay at the mth microphone. For sound localization, the set of steering vectors in the range of angles of interest (e.g., every 1 degree from 0° to 359°, 360 directions) is required. The steering vector can be calculated based on the geometric configuration of a microphone array and a (virtual) sound source. This calculated steering vector is hereafter termed the prototype steering vector (PSV) for the sake of convenience. PSV differs from the actual one due to the gain difference of the microphones, complicated acoustics such as diffraction from the array surface, and geometric errors. An alternative way of obtaining a set of steering vectors is calibration using a test signal such as a TSP (time-stretched pulse) signal [16]. While the steering vectors measured in the calibration are more precise than the PSVs, the calibration is time-consuming and is not practical for mass production. Since sound localization is less sensitive to the above-described errors than sound separation, PSVs are employed for the sound localization. In (3), the gain difference is assumed to be zero, that is, $V_1(\theta, \omega) = \cdots = V_M(\theta, \omega) = 1$, and the time difference $\tau_m(\theta)$ is calculated by the microphone array configuration.

After obtaining the spatial spectrum at each frequency, $P(\theta, \omega, \bar{t})$ is averaged over the frequencies of interest so that the spatial spectrum for the broadband signal is obtained:

$$\overline{P}(\theta, \bar{t}) = \frac{1}{N_\omega} \sum_{\omega=\omega_L}^{\omega_H} \lambda_\omega P(\theta, \omega, \bar{t}). \tag{4}$$

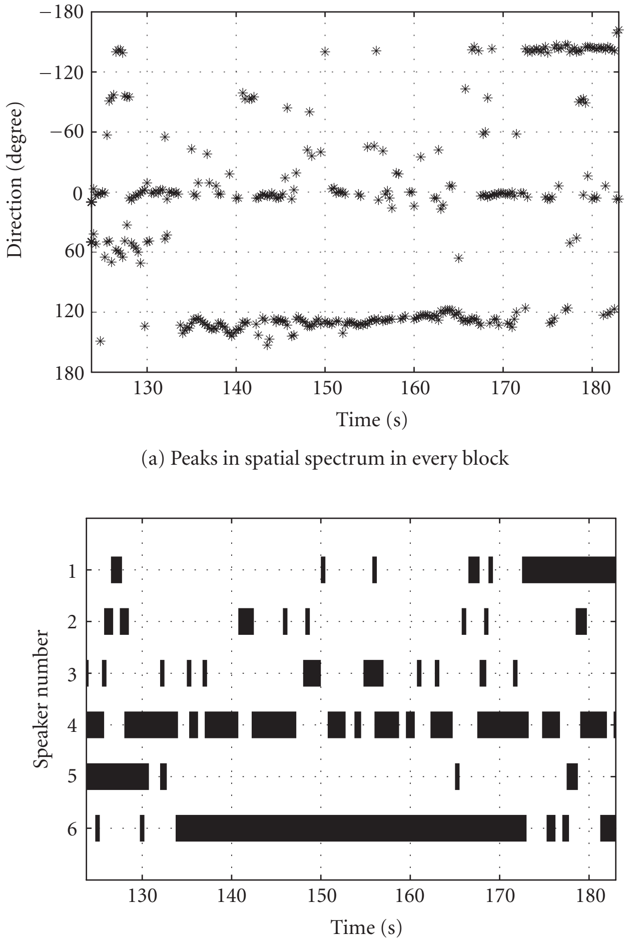
The symbols $[\omega_L, \omega_H]$ and N_ω denote the frequency range of interest and the number of frequency bins, respectively. The symbol λ_ω is the frequency weight. In this paper, the square root of the sum of the eigenvalues for the signal subspace is used as λ_ω [12]. By detecting the peaks in the spatial spectrum $\overline{P}(\theta, \bar{t})$, the location of the active sound sources (speakers) in each time block can be estimated. An example of the estimated location of the speakers in a meeting recording is shown in Figure 2(a).

3.2. Clustering of sound sources

By clustering the estimated location of the sound sources collected from the entire meeting, the range of each speaker is determined. For clustering, k-means is used in this paper. The number of participants is given to the system as the number of clusters. An example of the distribution of the estimated locations and the clustering is depicted in Figure 3.

3.3. Detection of speech events

From the estimated sound source locations (Figure 2(a)) and the range of speakers (Figure 3), the active speakers are identified in each block. Adjacent blocks with the same active speakers are then merged into a single speech event. The adjacent speech events with small gaps (short pauses) are also merged. An example of the detected and merged speech events is shown in Figure 2(b).



(a) Peaks in spatial spectrum in every block

(b) Detected speech events

Figure 2: An example of detected speech events.

4. SEPARATION OF SPEECH EVENTS

In this section, overlapping speech events are separated using an adaptive/nonadaptive beamformer based on the information of the detected speech events.

Some types of beamformers are described in the frequency domain as follows (e.g., [7]):

$$y(\omega, t) = \mathbf{w}^H \mathbf{x}(\omega, t), \tag{5}$$

$$\mathbf{w} = \frac{\mathbf{R}_n^{-1}\mathbf{a}}{\mathbf{a}^H \mathbf{R}_n^{-1}\mathbf{a}}. \tag{6}$$

Here, $\mathbf{x}(\omega, t)$ and $y(\omega, t)$ represent the input and output of the beamformer, respectively. Vector $\mathbf{w}$ consists of the beamformer coefficients. Steering vector $\mathbf{a}$ consists of the transfer function of the direct path from the target speaker to the microphones in the same way as (3). Matrix $\mathbf{R}_n$ is termed the noise spatial correlation matrix,

$$\mathbf{R}_n = E[\mathbf{x}_n(\omega, t)\mathbf{x}_n^H(\omega, t)], \tag{7}$$

where $\mathbf{x}_n(\omega, t)$ is the input vector corresponding to the noise sources (competing speakers).

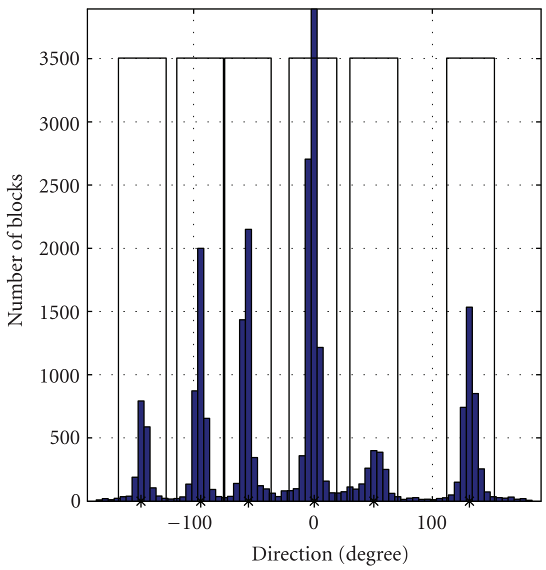


Figure 3: Distribution of the estimated active sound sources and the results of clustering.

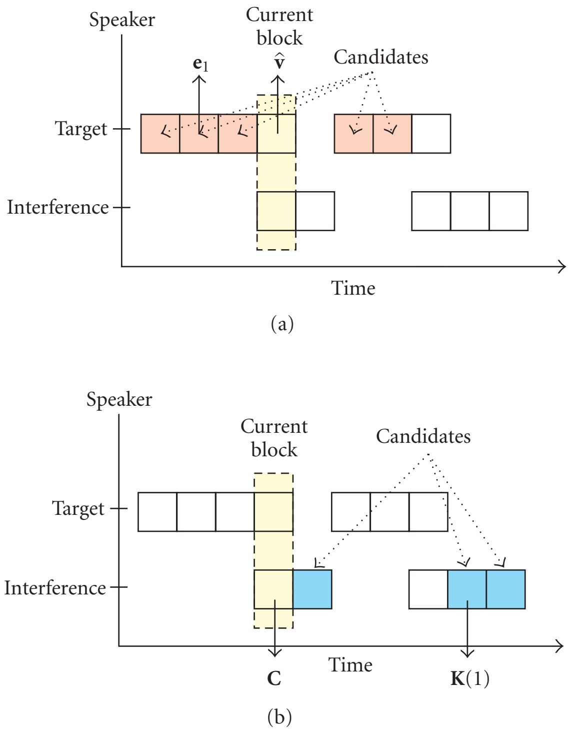


Figure 4: Estimation of (a) the steering vector and (b) the noise correlation.

In the next sections, a method of obtaining the information required for constructing the beamformer coefficient vector $\mathbf{w}$, namely, $\mathbf{a}$ and $\mathbf{R}_n$, is proposed.

4.1. Estimation of steering vector a (calibration)

As described above, the steering vector for the target speaker, $\mathbf{a}$, is required for updating (6). In this and the subsequent sections, the indices ω and t are omitted for the sake of simplicity. As described in Section 3.1, a PSV for the target, $\hat{\mathbf{v}}$, that is selected in the sound localization process, is a rough approximation of the actual steering vector, and thus cannot be used for speech event separation (see the results of the experiment described in Section 5). In this subsection, therefore, the steering vector for the target is estimated from the data of meeting recordings.

For the sake of convenience, the time block in which the overlapping speech events are to be separated is termed the “current block.” In the neighborhood of the current block, the time blocks in which the target alone is speaking (single-talking blocks) are expected to be found, as shown in Figure 4(a). The steering vector for the target can be estimated using the data in these blocks. Single-talking blocks can be easily found by using the speech-event information obtained in Section 3.

Once a single-talking block is found, an estimate of the target steering vector can be obtained as the eigenvector of the spatial correlation matrix corresponding to the largest eigenvalue. This can be easily understood from the subspace structure of the spatial correlation matrix as follows (e.g., [7]). Figure 5 shows the relation of the steering vectors and the eigenvectors of the spatial correlation matrix. This example shows the case of $N = 2$ (number of sound sources) and $M = 3$ (number of microphones). It is assumed that the input signal $\mathbf{x}$ is modeled as

$$\mathbf{x} = \mathbf{A}\mathbf{s} + \mathbf{n}, \tag{8}$$

where matrix $\mathbf{A}$ consists of the steering vectors as $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2]$ and vector $\mathbf{s}$ consists of the source spectrum as $\mathbf{s} = [S_1(\omega, t), S_2(\omega, t)]^T$. Vector $\mathbf{n}$ represents the background noise. It is known that the eigenvectors corresponding to the largest N eigenvalues become the basis of the signal subspace spanned by the steering vectors $\{\mathbf{a}_1, \ldots, \mathbf{a}_N\}$. In this example, eigenvectors $\mathbf{e}_1$ and $\mathbf{e}_2$ become the basis of the signal subspace spanned by steering vectors $\mathbf{a}_1$ and $\mathbf{a}_2$. From this, it is obvious that when a speaker is speaking on his/her own ($N = 1$), the dimension of the signal subspace becomes one and the direction of eigenvector $\mathbf{e}_1$ matches that of steering vector $\mathbf{a}_1$. Therefore, the steering vector can be estimated by finding a single-talking block for the target and extracting the eigenvector corresponding to the largest eigenvalue.

Since there will be multiple single-talking blocks in the neighborhood of the current block, as shown in Figure 4(a), the most appropriate steering vector must be chosen from the set of the estimated steering vectors. This set of the estimates is denoted as $\mathbf{\Psi} = [\mathbf{e}_1(1), \ldots, \mathbf{e}_1(L)]$, and is termed candidates. The symbol L denotes the number of candidates. In this paper, the optimal steering vector is chosen so that it is closest to the PSV for the target, $\hat{\mathbf{v}}$, that is chosen in the localization process as follows:

$$\hat{\mathbf{a}} = \arg\max_{\mathbf{e}_1 \in \mathbf{\Psi}} \frac{\hat{\mathbf{v}}^H \mathbf{e}_1}{\hat{\mathbf{v}}^H \hat{\mathbf{v}}}. \tag{9}$$

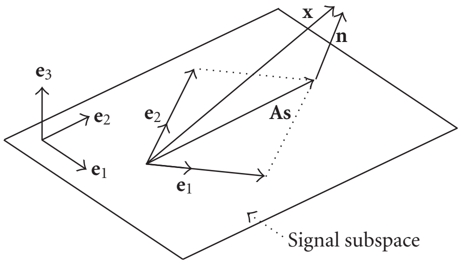


FIGURE 5: Relation of steering vectors and eigenvectors.

Since small movements of the speaker are expected during the meeting, the steering vector whose corresponding location is the closest to that of the target in the current block is expected to be selected by using (9).

The procedure for estimating the steering vector can be summarized as follows.

(1) Find single-talking blocks based on the speech event information.
(2) Calculate the correlation matrix $\mathbf{R} = E[\mathbf{x}\mathbf{x}^H]$.
(3) Perform eigenvalue decomposition on $\mathbf{R}$ and extract the eigenvector $\mathbf{e}_1$ corresponding to the largest eigenvalue.
(4) Select the optimum steering vector using (9).

4.2. Estimation of the noise spatial correlation $\mathbf{R}_n$

Since $\mathbf{x}_n(\omega, t)$ cannot be observed separately in the current block, the ideal noise correlation $\mathbf{R}_n$ is also not available. In a manner similar to the estimation of the steering vector, the noise correlation is estimated from the neighborhood of the current block. First, the blocks in which the overlapping speaker (noise source) is speaking and the target speaker is not speaking are found based on the information of the speech events as depicted in Figure 4(b). The set of the spatial correlations calculated in these blocks is denoted as $\Phi = [\mathbf{K}(1), \ldots, \mathbf{K}(L)]$. When the noise correlation selected from these candidates has spatial characteristics close to those of the noise in the current block, the beamformer becomes an approximation of the maximum-likelihood (ML) adaptive beamformer.

In addition to the set of the candidates Φ, two other noise correlation candidates are taken into account to enhance the performance of the separation and the speech enhancement. The first one is the identity matrix $\mathbf{I}$, which is the theoretical noise correlation when the noise is spatially white. A beamformer using $\mathbf{I}$ is termed a delay-and-sum (DS) beamformer. Even when the target speaker is speaking on his/her own, there is room reverberation that reduces the performance of ASR. By applying this beamformer in the single-talking blocks, the effect of speech enhancement is expected.

Another candidate is the correlation calculated in the current block. This correlation is denoted as $\mathbf{C}$, and the beamformer using $\mathbf{C}$ is termed a minimum variance (MV) beamformer. The correlation $\mathbf{C}$ differs from the ideal noise correlation $\mathbf{R}_n$ since not only the noise but also the target signal is included in $\mathbf{C}$. When the level of the target is comparable to or larger than that of the noise, the MV beamformer causes significant distortion of the target signal. On the other hand, when the noise is dominant in the current block, $\mathbf{R}_n \simeq \mathbf{C}$, and the noise is effectively reduced since the characteristics of noise used in the beamformer perfectly match those of the current block. The characteristics of these three types of beamformers are summarized in Table 1.

For selecting the noise correlation from the candidates described above, a criterion similar to that used in the MV beamformer, that is, the output power of the beamformer in the current block, is used as follows:

$$\hat{\mathbf{R}}_n = \arg \min_{\mathbf{R}_n \in \Phi, \mathbf{I}, \mathbf{C}} \mathbf{w}^H \mathbf{C} \mathbf{w}, \tag{10}$$

$$\text{where } \mathbf{w} = \frac{\mathbf{R}_n^{-1} \hat{\mathbf{a}}}{\hat{\mathbf{a}}^H \mathbf{R}_n^{-1} \hat{\mathbf{a}}}. \tag{11}$$

In (10), $\mathbf{w}^H \mathbf{C} \mathbf{w}$ represents the output power of the beamformer. As a steering vector in the beamformer coefficient vector $\mathbf{w}$, the one selected in the previous subsection, $\hat{\mathbf{a}}$, is used. Since only the output power is taken into account in (10), $\mathbf{C}$ is selected in most cases and a distortion is imposed on the target signal. Therefore, $\mathbf{C}$ is included as a candidate only when the target signal is absent (short pauses in speech events).

The procedure for estimating the noise correlation can be summarized as follows.

(1) Find time blocks in which the target is absent and the noise is present.
(2) Calculate the correlation in the above time blocks and form the candidates $\Phi = [\mathbf{K}(1), \ldots, \mathbf{K}(L)]$ (ML).
(3) Add $\mathbf{I}$ to the candidates (DS).
(4) Add $\mathbf{C}$ to the candidates only when the target is absent in the current block (MV).
(5) Select the noise correlation from among the candidates using (10).

4.3. Filtering

Using the estimated steering vector $\hat{\mathbf{a}}$ and the noise correlation $\hat{\mathbf{R}}_n$, the beamformer coefficient vector $\mathbf{w}$ is updated in every block using (6). The microphone array inputs are then filtered by the updated coefficient vector using (5). In actual filtering, the beamformer coefficient vector $\mathbf{w}$ is inverse-Fourier-transformed into the time domain, and (5) is conducted in the time domain.

5. EXPERIMENT

5.1. Condition

The meeting recorded and analyzed was a “group interview,” such as that used for Japanese market research. The language used was Japanese. In such a meeting, a professional interviewer asks questions regarding a product and has a discussion with interviewees. The number of interviewees in the recorded meeting was five. The interviewer was female while all the interviewees were male (university students).

The meeting was recorded in an ordinary meeting room with a reverberation time of approximately 0.5 second. The length of the meeting was 104 minutes. Fifty nine percent of the time blocks were classified as the overlapping blocks. (The detected overlapping blocks differ from the actual blocks with overlapping speech since the presence of any sound other than target speech was detected as an overlap.)

Figure 6 shows the input device used for the recording, which consists of a microphone array and a camera array (PointGray Research, Ladybug-2). The microphone array is circular in shape with a diameter of 15 cm and consists of eight omnidirectional microphones (Sony, ECM-C115). The sampling frequency was 16 kHz. The distance between the microphone array and the participants was 1.0–1.5 m.

In the analysis and separation, the length of the time block was 0.5 second with an overlap of 0.25 second with the succeeding block. The length of the Fourier transform was 512 points (32 milliseconds). The processing time for the detection and separation for a single session (104 minutes) was approximately 5.5 hours (processed by a PC with Xeon 2.8 GHz). In the overlapping sections, only the signals from the two speakers with the largest and the second largest powers were separated and recognized, regardless of the actual number of active sound sources for the sake of convenience.

In the ASR used for evaluation, an HMM-based recognizer was used. For the initial acoustic model, a tied-state triphone (1500 states) was trained on about 60 hours of speech from our meeting corpus. For the language model (LM) in the recognizer, both an open language model and a closed language model trained with the transcription of this meeting by a human listener were used. Although the use of the closed LM was not practical in terms of the application, it was employed to focus on the acoustic aspect of the speech-event separation. For the open LM, a 14 K-word trigram was trained on a general spontaneous speech corpus (3.41 MB in text size) plus those of eight group interview sessions (432 Kb). For the closed LM, on the other hand, a 1.4 K-word trigram was trained from data in a single group interview session used in the evaluation (55 kB). The topic of the group interview in the evaluation was about cellular phones while those of the group interviews in the open LM were various but covered the cellular phone (the data used for the closed LM and that for the open LM did not overlap). The speech events with a duration of more than 5 seconds (367 speech events) were subjected to ASR for the evaluation.

5.2. Results

Table 2 shows the results of evaluation using ASR. In the columns labeled "without AM adaptation," the output of one of the microphones and the separated output are compared. In the case of "before separation," the microphone closest to the speaker was selected from among the eight microphones based on the localization results. In the comparison between "before separation" and "after separation," the word-accuracy score was improved by approximately 19% in the closed LM and 12% in the open LM.

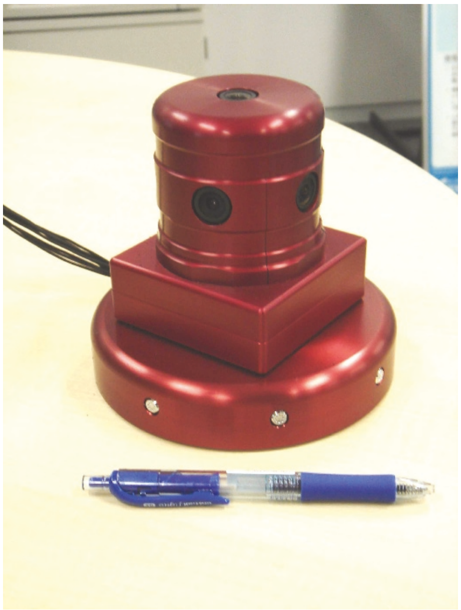


Figure 6: Input device used for the recording.

In the columns of "with AM adaptation," unsupervised adaptation was conducted on the acoustic model (AM) of ASR. For the adaptation, MLLR (maximum-likelihood linear regression) + MAP (maximum a posteriori) [17, 18] were used. For the case of "entire data," data of all 367 speech events were used for the adaptation. For the case of "each participant," the speech event data were classified into each participant, and the six AMs were individually trained using the data for each participant. Compared with the case of without AM adaptation, the score was further improved by approximately 4%. By employing the individual adaptation, a slight improvement (1%) was observed compared with the adaptation using all the data.

As described in Section 4.2, one of the three types of beamformers, that is, DS, ML, and MV, was selected in each frequency bin at each time block independently by selecting the noise spatial correlation from $\{\mathbf{K}(1),\dots,\mathbf{K}(L)\}$(ML), $\mathbf{I}$(DS), and $\mathbf{C}$(MV). Table 1 shows the ratio of the selected beamformer algorithms, namely,

$$\text{Ratio} = \frac{\text{Number of times of ML/DS/MV being selected}}{\text{Number of total processed blocks} \times \text{Number of frequency bins}}. \tag{12}$$

Figure 7 shows a comparison of the beamformer algorithms. The proposed method in which the beamformer is selected from among the all three types is denoted as "DS + ML+MV." On the other hand, "DS+ML" denotes the case in which the beamformer is limited to DS and ML. Comparing "DS + ML + MV" with "DS + ML," only a slight difference was found, though "DS + ML + MV" sometimes yielded a better noise reduction performance in the noise-dominant blocks according to the informal listening tests. Comparing the adaptive+nonadaptive beamformer (DS + ML + MV or

Table 1: Selected beamformer algorithm and its characteristics.

	DS	ML	MV
Ratio (%)	38.90	51.64	9.46
Signal distortion	Small	Small*	Large
Noise reduction	Small	Large*	Large
Effective against	Omnidirectional noise such as reverberation	Directional noise such as speech from a competing speaker	Directional and dominant noise such as sound of cough

*Theoretically, the ML beamformer shows small signal distortion and large noise reduction. However, for the practical case with approximation as used in this paper, the performance of the ML beamformer is in between that of the DS and MV beamformers.

Table 2: Evaluation using ASR (word accuracy (%)). AM: acoustic model; LM: language model.

	Without AM adaptation		With AM adaptation	
LM	Before separation	After separation	Entire data	Each participant
Closed	51.09	70.35	74.42	75.69
Open	23.41	35.69	39.52	41.41

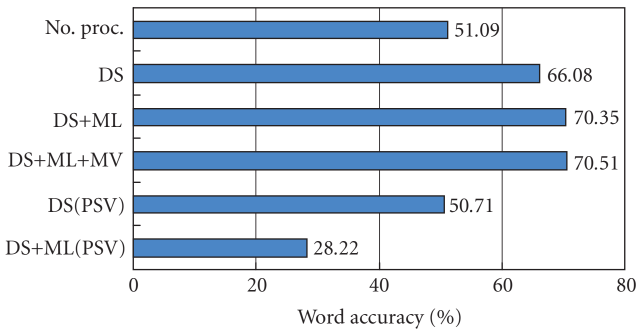


Figure 7: Word accuracy for different beamformer combinations.

DS + ML) with the nonadaptive beamformer (DS), improvement of approximately 5% was found for the adaptive + non-adaptive beamformer. In the cases of “DS(PSV)” and “DS + ML(PSV),” PSVs were used instead of the estimated steering vectors. In PSV, only geometric information on the microphone array was used to obtain the steering vectors. From these, the effect of estimating the steering vector proposed in this paper can be seen.

6. CONCLUSION

In this paper, a method of separating overlapping speech events in a meeting recording was proposed and evaluated via ASR. This method utilizes the characteristics peculiar to meeting recordings and the information on the speech events detected prior to the separation. Three types of adaptive/nonadaptive beamforming are fused so that the processing is effective with both overlapping speech events and room reverberation. As a result of evaluation experiments using ASR, the combination of “DS + ML” or “DS + ML + MV” was found to show an improvement of around 12% (open LM) and 19% (closed LM) in word accuracy compared with the single-microphone recording.

As a future work, a method of preparing a language model in ASR appropriate for each topic of a meeting should be investigated. Use of visual information is another interesting topic to be investigated in the future. In this paper, the seats of the meeting participants were assumed to be fixed. In an informal meeting, participants may move to other positions, or a new person may begin participating halfway through the meeting. These dynamic changes can possibly be solved by using visual information as well as acoustic information.

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