# NOISE SUPPRESSION METHOD FOR BODY-CONDUCTED SOFT SPEECH ENHANCEMENT BASED ON EXTERNAL NOISE MONITORING

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## ABSTRACT

This paper presents a novel approach to suppressing adverse effects of external noise on body-conducted soft speech for silent speech communication in noisy environments. Nonaudible murmur (NAM) microphone as one of the body-conductive microphones is capable of detecting very soft speech. However, body-conducted soft speech easily suffers from external noise owing to its faint volume. To address this issue, the proposed method additionally uses an air-conductive microphone to detect only an external noise signal and uses the detected external noise signal to suppress its effect on the body-conducted soft speech. A semi-blind source separation technique is applied to the proposed method for estimating a linear filter to suppress the noise components without voice activity detection. Experimental results demonstrate that the proposed method yields 10 dB SNR improvements in 80 dBA noisy conditions and also yields significant improvements in sound quality of body-conducted soft speech.

***Index Terms*—** silent speech communication, nonaudible murmur microphone, noise suppression, external noise monitoring, semi-blind source separation

## 1. INTRODUCTION

Speech communication plays a principal role in our daily life as the most efficient human communication method. In recent decades, thanks to mobile phone or other devices, we have come to be able to talk with each other beyond limitations of distance and location. However, there still exist some situations where we hesitate to talk with others using those devices; e.g., we have difficulty in talking about private information in a crowd; and speaking itself would sometimes annoy others in quiet environments such as in a library.

Recently, *silent speech interfaces* [1] have attracted attention as a technology to achieve a new style of speech communication. They enable us to talk with each other without the necessity of emitting an audible acoustic signal. To detect silent speech, several sensing devices have been explored as alternatives to a usual air-conductive microphone, such as body-conductive microphones [2, 3], electromyography [4], ultrasound imaging [5], and so on.

We especially focus on nonaudible murmur (NAM) microphone [3] as one of the body-conductive microphones capable of detecting silent speech. It has been originally developed to detect an extremely soft whispered voice called NAM, which is so quiet that people around the speaker barely hear its emitted sound. **Figure 1** shows a structure of the NAM microphone and its setting position. The NAM

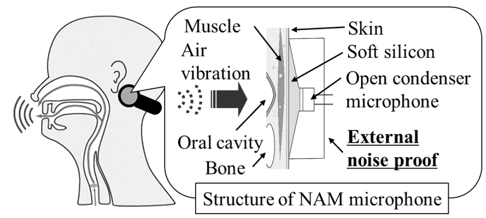


**Fig. 1**. Setting position and structure of NAM microphone.

microphone is capable of detecting various types of speech, such as NAM, a whispered voice, a soft voice, and normal speech, from this setting position through only the soft tissues of the head. It is also more robust against external noise owing to its noise-proof structure compared to the usual air-conductive microphone. Although severe degradation of speech quality is caused by essential mechanisms of body conduction [6], the body-conducted speech detected with the NAM microphone still has a great potential to be used as a communication medium if people get used to hear its special sound quality. Moreover, there are several attempts to directly address this quality-degradation issue by developing body-conducted speech enhancement techniques to convert it into air-conducted speech using a statistical voice conversion technique [7, 8].

There still remain some issues to be addressed in order to make it possible to practically use the body-conducted soft speech detected with the NAM microphone for silent speech communication. Although the previous work uses the body-conducted soft speech recorded in a sound-proof room [7], external noise usually exists in real environments. Even though the NAM microphone is robust against external noise, it cannot completely block external noise signals. Therefore, their effect on the body-conducted speech signal is not ignored. In particular, when detecting soft speech like NAM or a whispered voice, its body conducted speech signal significantly suffers from external noise because power of soft speech is too small.

To address this issue, several enhancement methods additionally using the air-conducted noisy speech signal detected with the usual air-conductive microphone have been proposed. For example, the direct filtering method [9] and the statistical enhancement method [10] have been proposed although these methods actually deal with speech enhancement with a bone-conductive microphone under heavy noisy conditions. Inspired by these methods, a body-conducted soft speech enhancement method additionally using air-conducted soft speech detected under noisy conditions has been proposed and its effectiveness has been reported in [11]. On the other hand, it has also been reported that adaptation of the statistical enhancement model to each external noise condition is essential. However, it is not straightforward to accurately adapt the model to arbi-

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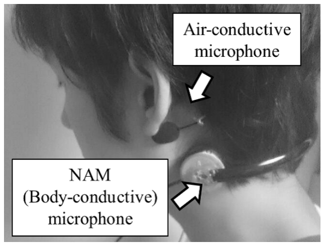



**Fig. 2**. Setting position of body- and air-conductive microphones.

trary noisy conditions, and consequently model adaptation performance is usually limited. Therefore, it is worthwhile to develop a front-end noise suppression technique robust against any external noisy conditions for reducing the external noise components as much as possible.

In this paper, we propose a noise suppression method for the body-conducted soft speech based on external noise monitoring using the air-conductive microphone. Because power of emitted soft speech such as NAM is too small, it is possible to detect only an external noise signal by setting the air-conductive microphone to a place not close to the speaker's mouth, e.g., a place just close to the setting position of the NAM microphone. The proposed method effectively uses the air-conducted external noise signal to suppress its components detected with the NAM microphone, which is called the body-conducted external noise signal in this paper. A semi-blind source separation technique [12] is used to estimate a linear filter to suppress the body-conducted external noise signals without voice activity detection. Several experimental evaluations are conducted, demonstrating that the proposed method is capable of significantly suppressing the body-conducted external noise signals to enhance the body conducted soft speech and the semi-blind source separation technique is more effective compared to other alternative techniques.

## 2. EXTERNAL NOISE MONITORING USING AIR-CONDUCTIVE MIROPHONE

NAM is an extremely soft whispered voice and it is relatively difficult to be detected with the usual air-conductive microphone in particular under noisy conditions because of its faint volume. Considering this property of NAM, the proposed method uses the air-conductive microphone to detect only the external noise signal, and then uses the detected signal to suppress the body-conducted external noise signal. It is expected that a proper setting position of the air-conductive microphone will be 1) far away from the speaker's mouth in order to reduce components of the emitted NAM signal detected with the air-conductive microphone as much as possible and 2) close to the setting position of the NAM microphone in order to detect the air-conducted external noise signal of which acoustic characteristics are similar to those of the body-conducted external noise signal detected with the NAM microphone. Thus in this paper we set the air-conductive microphone as shown in **Fig. 2**.

As a preliminary experiment, we recorded some types of external noise signals with the NAM microphone and the air-conductive microphone, and also separately recorded the NAM signal with both microphones. Then, the signal-to-noise ratio (SNR) of the NAM signal detected with each microphone was calculated. **Table 1** shows results. We can see that SNR of the body-conducted NAM is much higher than that of the air-conducted NAM thanks to the noise-proof structure of the NAM microphone but it starts to significantly decrease when the sound pressure level of external noise is higher than

**Table 1**. SNR of NAM detected with each of air- and body-conductive microphones under several noisy conditions

| Noise | SNR (air) [dB] | SNR (body) [dB] |
|---|---|---|
| office 50 dBA | -12.7 | 12.7 |
| crowd 60 dBA | -17.1 | 10.1 |
| booth 70 dBA | -27.4 | 5.5 |
| station 80 dBA | -36.9 | -2.8 |

60 dBA. Namely, it is expected that the noise suppression process is not necessary up to 60 dBA of the sound pressure level of external noise but it is essential under more than 60 dBA noisy conditions. We can also see that the SNR of the air-conducted NAM signal is very low under more than 60 dBA noisy conditions (i.e., booth 70 dBA and station 80 dBA). Therefore, in such noisy conditions, the signal detected with the air-conductive microphone will be well approximated by only the external noise signals without including the emitted NAM signal. Please note that this preliminary experiment ignores the Lombard reflex [13] that is also observed in NAM [14]; i.e., as the external noise level is higher, power of the emitted NAM is usually larger. Therefore, actual SNR is expected to be higher than shown in **Table 1** in particular under 70 dBA and 80 dBA noisy conditions.

Considering these results, we assume the following mixing process in the proposed method:

$$x_1(t) = s_1(t) + a(t) * s_2(t) \quad (1)$$

$$x_2(t) \approx s_2(t) \quad (2)$$

where $x_1(t)$ is an observed signal detected with the NAM microphone, $x_2(t)$ is an observed signal detected with the air-conductive microphone, $s_1(t)$ is a clean body-conducted NAM signal, $s_2(t)$ is an air-conducted external noise signal, and $a(t)$ is a transfer function to compensate acoustic differences between the external noise signal detected with the air-conductive microphone and that detected with the body-conductive microphone. In the proposed noise suppression method, the clean body-conducted NAM signal $s_1(t)$ is extracted from the observed signals $x_1(t)$ and $x_2(t)$ by estimating the transfer function $a(t)$. This problem is equivalent to a classical acoustic echo cancellation (AEC) problem [15], i.e., the observed signal $x_2(t)$ is regarded as a reference signal and the transfer function $a(t)$ is regarded as an echo path. Therefore, typical AEC methods such as the Least Mean Square (LMS) algorithm [16] and the Recursive Least Squares (RLS) algorithm [16] can be used in the proposed method.

## 3. NOISE SUPPRESSION METHOD BASED ON SEMI-BLIND SOURCE SEPARATION

The typical AEC methods are originally designed to cancel only far-end echo, and they don't work well when both the far-end and near-end speakers utter simultaneously. This situation is well known as double-talk. Therefore, double-talk detection is usually needed to remove the corresponding data segments including near-end speaker's voices from the observation data used for estimating the echo path. The same problem occurs in the proposed method, i.e., the situation where NAM is uttered is regarded as double-talk. Therefore, it is necessary to perform voice activity detection (VAD) of NAM and to remove the detected voice activity segments from the observation data to estimate the transfer function $a(t)$.

In this paper, we apply a semi-blind source separation (semi-BSS) technique to the proposed method in order to achieve double-talk free noise suppression. Let us assume an observed signal vector

$\boldsymbol{x}(\omega,\tau) = [x_1(\omega,\tau), x_2(\omega,\tau)]^\top$ consisting of the observed signals and a source signal vector $\boldsymbol{s}(\omega,\tau) = [s_1(\omega,\tau), s_2(\omega,\tau)]^\top$ consisting of the clean body-conducted NAM signal $s_1(\omega,\tau)$ and the air-conducted external noise signal $s_2(\omega,\tau)$, where $\omega$ is frequency bin index, $\tau$ is time frame index, and $^\top$ is vector transpose. Because the observed signals are modeled as convolutive mixtures in the time domain as shown in Eqs. (1) and (2), the observed signal vector $\boldsymbol{x}(\omega,\tau)$ is modeled as instantaneous mixture in the frequency domain as follows:

$$\boldsymbol{x}(\omega,\tau) = \boldsymbol{A}(\omega)\boldsymbol{s}(\omega,\tau) \tag{3}$$

where $\boldsymbol{A}(\omega)$ is a $(2 \times 2)$ mixing matrix, which is assumed to be time-invariant in this paper. BSS is a technique to automatically find a $(2 \times 2)$ un-mixing matrix $\boldsymbol{W}(\omega)$ that can separate the source signals from the observation signals as follows:

$$\boldsymbol{y}(\omega,\tau) = \boldsymbol{W}(\omega)\boldsymbol{x}(\omega,\tau) \tag{4}$$

where $\boldsymbol{y}(\omega,\tau) = [y_1(\omega,\tau), y_2(\omega,\tau)]^\top$ is the separated signal vector. Independent component analysis (ICA) [17] is often used to estimate the un-mixing matrix. In the proposed method, one of the two source signals (i.e., $s_2(\omega,\tau)$) is known by the external noise monitoring as shown in Eq. (2). Therefore, we can formulate the proposed method using semi-BSS rather than BSS. Some elements of the un-mixing matrix $\boldsymbol{W}$ can be explicitly given as follows:

$$\boldsymbol{W}(\omega) = \begin{bmatrix} w_{11}(\omega) & w_{12}(\omega) \\ 0 & 1 \end{bmatrix}. \tag{5}$$

Therefore, it is necessary to estimate only a part of the un-mixing matrix, an un-mixing vector $\boldsymbol{w} = [w_{11}(\omega), w_{12}(\omega)]$. In this paper, we use ICA based on natural gradient [18] to estimate the un-mixing vector. The un-mixing vector is iteratively updated as follows:

$$\Delta\boldsymbol{w} = \eta\{\boldsymbol{w}(\omega) - \langle\varphi(y_1(\omega,\tau))\boldsymbol{y}(\omega,\tau)^{\mathrm{H}}\rangle_\tau \boldsymbol{W}(\omega)\} \tag{6}$$

$$\boldsymbol{w}(\omega) \leftarrow \boldsymbol{w}(\omega) + \Delta\boldsymbol{w} \tag{7}$$

where $^{\mathrm{H}}$ is Hermitian transpose, $\eta$ is a step-size parameter, $\langle\cdot\rangle_\tau$ is a time average operator, and $\varphi(y_1(\omega,\tau))$ is a nonlinear function like a polar function given by

$$\varphi(y_1(\omega,\tau)) = \tanh(|y_1(\omega,\tau)|)\exp(j\arg(y_1(\omega,\tau))). \tag{8}$$

To handle scaling indeterminacy in ICA, a projection back method [19] is also applied. Consequently, the estimated clean body-conducted NAM signal is given by

$$y_1(\omega,\tau) = x_1(\omega,\tau) + \frac{w_{12}(\omega)}{w_{11}(\omega)} x_2(\omega,\tau). \tag{9}$$

## 4. EXPERIMENTAL EVALUATIONS

### 4.1. Experimental conditions

We simultaneously recorded clean body- and air-conducted NAM signals with the NAM microphone and the air-conductive microphone, respectively in a sound-proof room. The setting position of these microphones was the same as shown in **Fig. 2**. We also recorded body- and air-conducted signals of the following 3 kinds of noise using the same microphone settings by presenting them from a loud speaker in the sound-proof room.

- **crowd60dB**: 60 dBA crowd noise
- **booth70dB**: 70 dBA booth noise
- **station80dB**: 80 dBA station noise

The sound pressure levels of the individual noises were measured by a sound level meter placed at around the speaker's head. The noise signals recorded with the NAM microphone and the air-conductive microphone were superimposed on the clean body- and air-conducted NAM signals. The resulting signals were effectively used in objective evaluations because some distortion measures between the processed body-conducted NAM signal and the clean body-conducted NAM signal could be calculated as evaluation metrics. On the other hand, the Lombard reflex was ignored in these simulated signals as mentioned in **Section 2**. Therefore, we also recorded the noisy NAM signals with both the NAM microphone and the air-conductive microphone while presenting the noise signals. The recorded signals more accurately simulated the noisy NAM signals detected in real conditions including the Lombard reflex although the distortion measures could no longer be calculated. Therefore, they were used in a subjective evaluation.

Fifty sentences in a phoneme balanced sentence set were uttered in NAM. The sampling frequency was set to 16 kHz. The window length of STFT was set to 64 ms and the shift length was set to 32 ms. For the semi-BSS, the step-size parameter $\eta$ was set to 0.01. The number of iterations was varied from 5 to 200.

To investigate the effectiveness of the proposed method using noise suppression based on the external noise monitoring, the following 7 methods were evaluated.

- **unprocessed**: no noise suppression
- **upper bound**: upper bound of time-invariant linear filter in the proposed method
- **LS w/ VAD**: least squares (LS) with ideal VAD in the proposed method
- **NLMS w/ VAD**: AEC based on the normalized LMS [20] with ideal VAD in the proposed method
- **APA w/ VAD**: AEC based on the affine projection algorithm (APA) [21] with ideal VAD in the proposed method
- **RLS w/ VAD**: AEC based on the RLS with ideal VAD in the proposed method
- **semi-BSS**: the semi-BSS with no VAD in the proposed method

In **upper bound**, we used the transfer function estimated by the LS algorithm using the recorded noise signals detected with the NAM microphone and the air-conductive microphone before their superimposition on the clean NAM signals. In **LS w/ VAD** and the AEC algorithms (i.e., **NLMS w/ VAD**, **APA w/ VAD**, and **RLS w/ VAD**), we performed double-talk detection based on ideal VAD results, which were determined by applying VAD to a clean air-conducted NAM signal with high SNR recorded with another air-conductive microphone set to a place just close to the speaker's mouth. **LS w/ VAD** uses the batch-type filter estimation process while the AEC algorithms use the adaptive filter estimation process. On the other hand, in **semi-BSS**, the filter estimation process was performed in completely unsupervised manner without VAD.

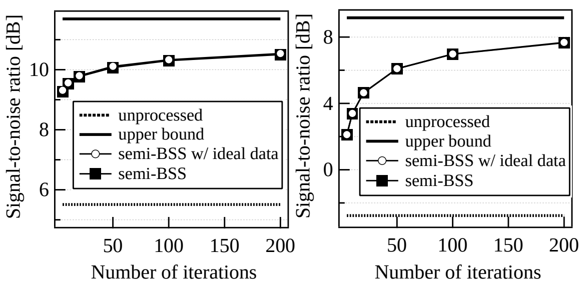
### 4.2. Objective evaluations

Noise suppression performance was evaluated using SNR and mel-cepstral distortion (MCD) calculated using the $1^{\mathrm{st}}$ through $24^{\mathrm{th}}$ mel-cepstral coefficients between the estimated body-conducted NAM signals and the clean body-conducted NAM signals.

First, we evaluated the SNR improvements yielded by **semi-BSS**. We also investigated whether or not the assumption used in

**Table 2**. Parameter settings for individual AEC algorihtnms

| |
|---|
| NLMS |
| Filter length: 64 ms<br>Step size: 0.01(60dBA), 0.05(70dBA), 0.5(80dBA) |
| APA |
| Filter length: 64 ms<br>Step size: 0.01(60dBA), 0.05(70dBA), 0.25(80dBA)<br>Number of constrains: 2 |
| RLS |
| Filter length: 16 ms<br>Forgetting factor: 0.999(80dBA), 1(60dBA, 70dBA) |




(a) booth70dB (b) station80dB

**Fig. 3**. Improvement in SNR yielded by semi-BSS-based noise suppression.

the proposed method (shown in Eq. (2)) holds. **Figure 3** shows the improvement in SNR yielded by **semi-BSS**. SNR is significantly improved even after only five iterations compared to **unprocessed**. More iterations make SNR improvements close to that by **upper bound**. Moreover, in **Fig.** 3, **ideal data** indicates results of using the air-conducted signals including only external noise signals with no superimposition (i.e., simulated data when $x_2(t)$ is completely equivalent to $s_2(t)$ in Eq. (2)). We can see that there is almost no difference between **semi-BSS** and **semi-BSS w/ ideal data**. This reveals that the assumption in Eq. (2) actually holds in the proposed external noise monitoring method.

Then, we evaluated performance of individual noise suppression algorithms. The number of iterations in **semi-BSS** was set to 200. For the individual AEC algorithms, their parameters were optimized (except for the number of constrains in **APA**) so that SNR was maximized. The optimized parameter settings are shown in **Table** 2. **Figures 4** and **5** show SNR and MCD of the body-conducted NAM signals estimated by each method, respectively. We can see that SNR and MCD are significantly improved by the proposed method using any noise suppression algorithm. Especially, semi-BSS yields significantly large improvements in both SNR and MCD under 80 dBA noisy conditions even though no VAD is needed.

### 4.3. Subjective evaluation

We conducted an opinion test on sound quality using a 5-point opinion scale, such as 1: very bad, 2: bad, 3: fair, 4: good, and 5: excellent. We evaluated the clean body-conducted NAM signals, the unprocessed noisy body-conducted NAM signals, and the body-conducted NAM signals estimated by semi-BSS. The number of listeners was 10. Each listener evaluated 18 samples for each method.

**Figure** 6 shows the result. The sound quality of estimated body-conducted NAM signals is significantly improved by the proposed method under 70 dBA both and 80 dBA station noisy conditions. It is interesting that the result under 70 dBA noisy condition is similar to that under 80 dBA noisy condition. This is because several acoustic changes are caused by the effect of Lombard reflex and the NAM signal itself tends to be more intelligible as the external noise level increases. Therefore, the Lombard reflex doesn't cause any adverse effects in the proposed method and it is actually helpful for improving quality of the estimated NAM signal.

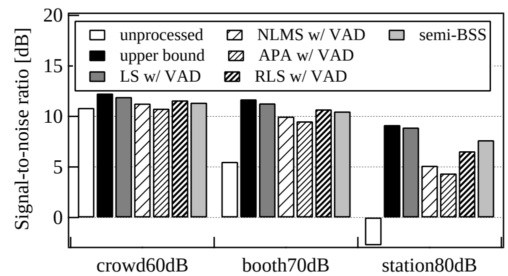



**Fig. 4**. SNR of body-conducted NAM.

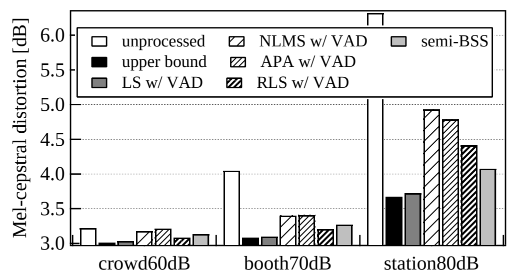



**Fig. 5**. Mel-cepstral distortion of body-conducted NAM.

## 5. CONCLUSIONS

This paper has presented a noise suppression method for the body-conducted soft speech based on external noise monitoring using the air-conductive microphone. We have shown that only an external noise signal can be detected with the air-conductive microphone by setting it to a place far away from the speaker's mouth and the detected signal can be effectively used to estimate a linear filter to suppress the external noise components observed in the body-conducted signals. We have also applied a semi-blind source separation technique to the proposed method to make it possible to estimate the linear filter without voice activity detection. Experimental results have demonstrated that the proposed method yields significant improvements in both estimation accuracy and sound quality of body-conducted soft speech.

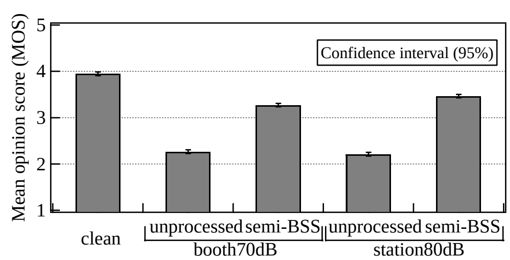



**Fig. 6**. Result of subjective evaluation on speech quality of body-conducted NAM.

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