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The real and imaginary part-based GSC beamformer's improvement

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ABSTRACT

The use of microphone array (MA) has been more popular in numerous types of speech applications, due to its convenience of high spatial diversity, high noise suppression and flexible incorporation with other different signal processing methods for concerning the pattern at certain sound locations while suppressing the surrounding noise environment. MA beamformer also installed into teleconference systems, smart home, voice-controlled equipment, virtual assistant, surveillance device to recover the useful speech component and remove background noise. Generalized sidelobe canceller (GSC) beamformer is an efficient solution for exacting the desired speaker with high directivity index. However, in a realistic recording situation, the different microphone sensitivities, the inaccurate estimation of steering vector, the displacement of MA's configuration, the movement of talker during conversation, the existence of unwanted competitive speaker, the presence of undetermined noise sources, the complicated annoying environment, the different start recorded time between two microphones, the error of sampling rate cause degradation of GSC beamformer's evaluation in an adverse environment. In this paper, the authors presented using the real and imaginary part of cross power spectral densities to achieve effective gain function for enhancing the speech quality of GSC beamformer's output signal. The experimental simulations showed the advantage of the suggested technique in reducing speech distortion to 8.1 dB and improving the overall speech quality in the terms of signal-to-noise ratio from 7.8 to 8.9 dB.

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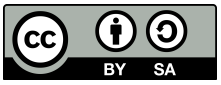

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1. INTRODUCTION

There is a growing market for teleconference systems, surveillance devices, voice-controlled equipment, smartphone and mobile device, cochlear implant, hearing aids. The captured microphone signals are commonly corrupted by the complex environment, ambient noise or reverberation. Consequently, the speech quality or speech intelligibility usually degrades. The traditional single-channel approach often properly works on a stationary environment and uses a spectral subtraction method for removing the background noise and extracting the desired target speech. However, in a rapidly changing scenario, this method causes the speech distortion and residual noise. In recent decades, microphone array (MA) beamforming is widely integrated into various types of speech applications, due to its effectiveness of suppressing background noise while at-

tempting the frequency response at specified direction of sound source with high spatial diversity and speech enhancement at the same time. MA beamforming exploits the a priori spatial information about characteristics of surrounding noise, the designed MA distribution, the assumed steering vector, the observed coherence between array signals to obtain advantage in reducing noise level while saving the clean speech data without speech distortion.

Generalized sidelobe canceller (GSC) beamformer [1]-[6] is an efficient technique for extracting the desired talker and removing background noise. GSC beamformer steers the pattern in a certain direction and uses other signal processing algorithms for extracting the clean speech data while removing unwanted noises. The common applications of GSC beamformer is speech enhancement and interference suppression [7]-[9], robust far-field speech recognition [10], [11], medical ultrasound and image quality enhancement [12]-[14], robust adaptive beamforming for radar and antenna arrays [15]-[17].

However, in a realistic recording scenario, the internal electrical noise, the error of microphone array geometry, the different frequency, the movement of speaker during conversation, the imprecise estimation of related transfer function, the existence of non-directional noise degrade GSC beamformer's output signal. GSC beamformer depends on the precise impinging angle of a useful signal, the quality of microphones, the accurate distribution of microphones, the homogeneous environment of the situation, the movement of talkers during conversation. As a result, the speech component is not preserved at the upper branch, the speech leakage still exists at reference signals or the correlation between reference signals often reduces beamformer's performance. Consequently, speech distortion, large musical noise and residual noise are the limitations of GSC beamformer.

Many researchers attempt to enhance the GSC beamformer's performance under realistic recording scenarios. Li *et al.* [18] attempted to reduce the influence of diffusion noise by applying the power ratio of the output signal of GSC beamformer and blocking matrix. This method adaptively updated the weight coefficient of the adaptive noise canceller. The simulations have shown the effectiveness of the suggested technique under a realistic recording environment.

Wang *et al.* [9] proposed an efficient rule of adjusting coefficient of adaptive interference canceller (AIC) for removing the effect of interference and alleviating speech distortion. The author's proposed method is based on time-varying Gaussian distribution. The results have been confirmed in different conditions with prospective robustness and advantage over the existing techniques.

Middelberg and Doclo [19] presented an idea of incorporating external microphones in a minimum power distortionless response beamformer with precise estimation of related transfer function. The simulation results show the better output signal in the terms of noise reduction and interference reduction under complex and adverse conditions.

Park *et al.* [20] described a two-stage noise suppression technique, wherein an input signal is primarily filtered by a determinant-based Wiener filter and a subsequent noise canceller. This method modified the weights at noise-only regions. The simulation was measured by five objective metrics, the spectrogram, the mean opinion score and different other competing methods with real recording signals.

Joel *et al.* [21] addressed the problem of lack of precise source location information from estimation errors or the presence of a moving source. The author proposed region-of-interest (ROI) beamformer based on GSC beamformer framework while suppressing noise and attenuating effect of different signals. The author presented several performance metrics for evaluating the effectiveness under real-life situations.

Unfortunately, due to the imprecise frequency sampling, the existence of complex surrounding noise fields, the different start time of recording between microphones, the different simulated configuration of experiment, the different purpose of mentioned techniques, so these methods can not deal with realistic problems. The authors' idea is utilizing the covariance of speech, which is contained in MA signals and beamformer's output signal to improve the GSC beamformer's evaluation. Therefore, in this article, the author presented a perspective gain function, which is based on the computation about real-imaginary part of cross power spectral densities for overcoming this drawback of conventional MA beamformer with recovering the speech.

2. GENERALIZED SIDELOBE CANCELLER BEAMFORMER

GSC beamformer has three parts for extracting the desired speech component from the noisy mixture. The scheme of GSC beamforming technique can be shown in Figure 1. The upper branch uses a fixed beamformer (FBF) to steer the pattern at a certain sound source location while the blocking matrix (BM) blocks the

speech component for obtaining the only noise component. And the third part is an efficient adaptive noise canceler (ANC), which recovers the clean speech data from FBF beamformer's output by using BM's output signal as the reference signal. In this contribution, delay-and-sum (DAS) beamformer is presented as FBF beamformer. The signal subtraction operator plays the role of BM and Wiener filter was implemented as ANC.

Dual-microphone array (DMA2) has a compact size, low complexity and easy installation in several acoustic equipment. Therefore, in this section, the author describes the formulation of received array signals of DMA2.

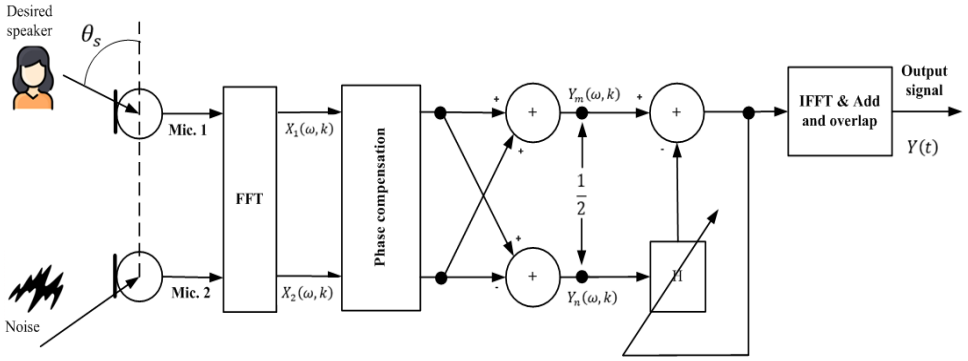


Figure 1. The structure of GSC beamformer for preserving the clean speech data

With the preferred direction of arrival of interest useful signal θ_s, the range between two mounted microphones is d, the representation of observed microphone array signals $X_1(\omega,k), X_2(\omega,k)$ at current considered frequency f, $\omega = 2\pi f$ and frame l in the frequency-domain can be expressed as:

$$X_1(\omega,k) = S(\omega,k)e^{j\Phi_s} + N_1(\omega,k) \tag{1}$$

$$X_2(\omega,k) = S(\omega,k)e^{-j\Phi_s} + N_2(\omega,k) \tag{2}$$

Where $N_1(\omega,k), N_2(\omega,k)$ means the third-party speaker, interference, non-directional noise or diffuse noise field; $S(\omega,k)$ is the clean speech data from the desired target speaker, $\Phi_s = \pi f \tau_0 cos(\theta_s)$ contains the information about phase delay between the original speech to the microphone, $\tau_0 = \frac{d}{c}$, with $c = 343(m/s)$ is speed propagation of speech in the fresh air.

The upper branch's output signal is named the main signal $Y_m(\omega,k)$ and the BM block's output signal is reference signal $Y_r(\omega,k)$. These signals can be derived as:

$$Y_m(\omega,k) = \frac{X_1(\omega,k)e^{-j\Phi_s} + X_2(\omega,k)e^{j\Phi_s}}{2} \tag{3}$$

$$Y_r(\omega,k) = \frac{X_1(\omega,k)e^{-j\Phi_s} - X_2(\omega,k)e^{j\Phi_s}}{2} \tag{4}$$

The AND extracts the desired target speaker from the main reference by using reference signal. The Wiener filter calculates the auto and cross power spectral densities (PSD) of $Y_r(\omega,k)$, $Y_m(\omega,k)$ and $Y_r(\omega,k)$:

$$P_{Y_mY_r}(\omega,k) = (1-\alpha)P_{Y_mY_r}(\omega,k-1) + \alpha Y_m(\omega,k)Y_r^*(\omega,k) \tag{5}$$

$$P_{Y_rY_r}(\omega,k) = (1-\alpha)P_{Y_rY_r}(\omega,k-1) + \alpha Y_r(\omega,k)Y_r^*(\omega,k) \tag{6}$$

with α is an appropriate smoothing parameter in range of 0 to 1.

Hence, the coefficients of Wiener filter is defined as:

$$H_{GSC}(\omega,k) = \frac{P_{Y_mY_r}(\omega,k)}{P_{Y_rY_r}(\omega,k)} \tag{7}$$

The final beamformer output signal is computed as:

$$Y(\omega,k) = Y_m(\omega,k) - Y_r(\omega,k) * H_{GSC}(\omega,k) \tag{8}$$

In real-life situations, due to many reasons, the error of sampling rate, the difference of microphone quality, the moving head of talker, the internal electrical noise, GSC beamformer's output signal often degrades. In the next section, the author introduced a gain function to recover the desired target speaker.

3. THE REAL AND IMAGINARY PART-BASED GAIN FUNCTION

The author's idea is exploiting the cross PSD between the received array signals to compute the original variance of speech $\sigma_s^2(\omega,k)$ to recover the amplitude of GSC beamformer's output signal.

In the presence of noise source with the direction θ_n, the (1) and (2) can be rewritten as:

$$X_1(\omega,k) = S(\omega,k)e^{j\Phi_s} + N_1(\omega,k)e^{j\Phi_n} \tag{9}$$

$$X_2(\omega,k) = S(\omega,k)e^{-j\Phi_s} + N_2(\omega,k)e^{j\Phi_n} \tag{10}$$

where $\Phi_n = \pi f \tau_0 cos(\theta_n)$.

The cross PSD of $X_1(\omega,k), X_2(\omega,k)$ can be recursively determined as the following:

$$P_{X_1X_2}(\omega,k) = \beta P_{X_1X_2}(\omega,k-1) + (1-\beta)X_1(\omega,k)X_2^*(\omega,k) \tag{11}$$

with β in smoothing parameter in range $\{0...1\}$.

From the (9) and (10), the cross PSD can be defines as:

$$P_{X_1X_2}(\omega,k) = E\{X_1(\omega,k)X_2^*(\omega,k)\} \tag{12}$$

$$= \sigma_s^2(\omega,k)e^{j2\Phi_s} + \sigma_n^2(\omega,k)e^{j2\Phi_n} \tag{13}$$

with the assumption that the speech and noise component are uncorrelated, $E\{S(\omega,k)N^*(\omega,k)\} = 0$.

From the (13), we can easily take the real and imaginary part:

$$Re\{P_{X_1X_2}(\omega,k)\} = \sigma_s^2(\omega,k)cos(2\Phi_s) + \sigma_n^2(\omega,k)cos(2\Phi_n) \tag{14}$$

$$Im\{P_{X_1X_2}(\omega,k)\} = \sigma_s^2(\omega,k)sin(2\Phi_s) + \sigma_n^2(\omega,k)sin(2\Phi_n) \tag{15}$$

where $Re\{.\}$, $Im\{.\}$ denote the real part and imaginary part operator.

From the described in (14) and (15), we can easily compute the variance of speech $\sigma_s^2(\omega,k)$ the following way:

$$T = \cos(2\Phi_s)\sin(2\Phi_n) - \sin(2\Phi_s)\cos(2\Phi_n) \tag{16}$$

$$= \sin(2(\Phi_n - \Phi_s)) \tag{17}$$

$$Ts = Re\{P_{X_1X_2}(\omega,k)\} * sin(2\Phi_n) - Im\{P_{X_1X_2}(\omega,k)\} * cos(2\Phi_n) \tag{18}$$

and:

$$\sigma_s^2(\omega,k) = \frac{Ts}{T+\gamma} \tag{19}$$

where γ is a small constant.

With the definition, steering vector $\boldsymbol{D}_s(\omega,\theta_s) = [e^{j\Phi_s} \quad e^{-j\Phi_s}]^T$, $\boldsymbol{X}(\omega,k) = [X_1(\omega,k) \quad X_2(\omega,k)]^T$ and the covariance matrix of observed microphone array signals $\boldsymbol{\Phi}_{X_1X_2}(\omega,k) = E\{\boldsymbol{X}(\omega,k)^H\boldsymbol{X}(\omega,k)\}$, the covariance of speech after using the GSC beamformer can be determined through the speech component at the main signal as:

$$\sigma_{s_{GSC}}^2(\omega,k) = \frac{1}{4}\boldsymbol{D}_s^H(\omega,\theta_s)\boldsymbol{\Phi}_{X_1X_2}(\omega,k)\boldsymbol{D}_s(\omega,\theta_s) \tag{20}$$

therefore, the gain function can be expressed as:

$$reimGain(\omega, k) = \frac{\sigma_s^2(\omega, k)}{\sigma_{s_{GSC}}^2(\omega, k)} \tag{21}$$

the amplitude of GSC beamformer's output signal is gained as:

$$\hat{Y}(\omega, k) = reimGain(\omega, k) \times Y(\omega, k) \tag{22}$$

In the next section, the author will conduct an experiment to demonstrate the effectiveness of gain function with the purpose of recovering the clean speech data while attenuating the effect of background noise.

4. EXPERIMENTS

The purpose of this experiment is demonstrate the effectiveness of the author's described gain function (re-imGain) and the conventional GSC beamformer, modified GSC beamformer [22] with adaptive using ratio power between upper branch's and lower branch's output signal and traditional minimum variance distortionless response (MVDR) beamformer [23] in realistic recording environment. The author used DMA2 for recording the clean speech data in the presence of a third-party talker, the sound of washing machine, television and fan. For estimating the speech quality, an objective measurement [24] was applied for calculating the obtained SNR of MA signals and processed signals by GSC beamformer and re-imGain. The scheme of the demonstrated experiment was shown in Figure 2.

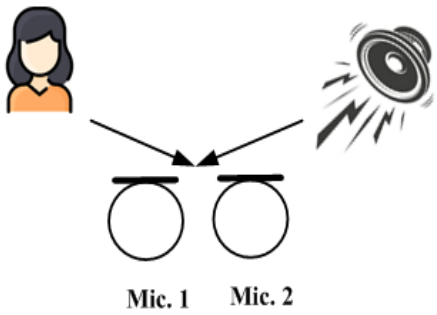
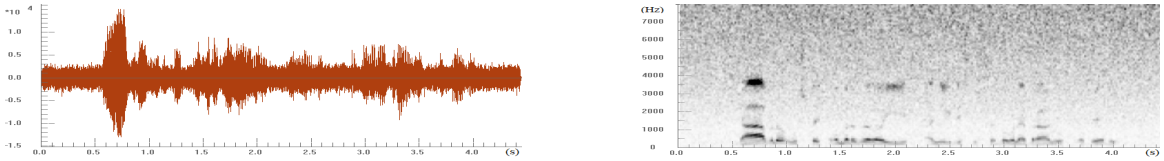


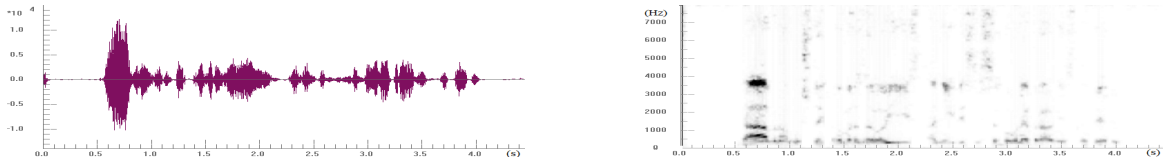
Figure 2. The demonstrated experiment in realistic recording scenario

A speaker stands at distance $L = 5(m)$ to the axis of DMA2 in an anechoic room $3x4x4.5(m)$. The range between two mounted microphones is $d = 4.25(cm)$. The impinging angle of the useful signal is $\theta_s = 45(deg)$ and the direction of arrival of noise is $\theta_n = 120(deg)$. These parameters were set for recording the speech component: sampling frequency $Fs = 16kHz$, the overlap 50%. The observed MA signal is given by Figure 3. Figure 3(a) is spectrogram and Figure 3(b) is received array signals. To further apply the traditional GSC beamformer, the author used $\alpha = 0.1$, $nFFT = 512$ to compute the auto/cross PSD. The output signal yields as in Figure 4. Figure 4(a) is spectrogram and Figure 4(b) is processed signal by applying traditional GSC beamformer.



(a) (b)

Figure 3. The waveform (a) spectrogram and (b) of received array signals

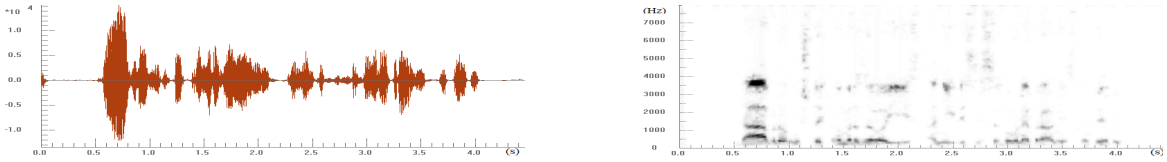


(a) (b)

Figure 4. The waveform (a) spectrogram and (b) processed signal by applying traditional GSC beamformer

From the achieved result, we can see that in complex and annoying environment, due to the microphone mismatches, the error of steering vector, the moving head of speaker, the room acoustic, the presence of non-directional noise, third - party talker, the GSC beamformer's performance often corrupted. The speech component was not recovered as the original signal. Consequently, the necessity of additive gain function is very important for obtaining satisfied speech quality.

The author's proposed gain function contains the variance of speech and allows gaining the amplitude of beamformer's output signal. The promising results are shown in Figure 5. Figure 5(a) is spectrogram and Figure 5(b) is obtained signals by applying re-imGain. The advantage of the suggested re-imGain is described with reducing the speech distortion to 8.1 dB and increasing the speech quality from 7.8 to 8.9 dB, as in Table 1 and Figure 6.



(a) (b)

Figure 5. The waveform (a) spectrogram and (b) obtained signals by applying re-imGain

Table 1. The comparison obtained SNR (dB)

Method estimation	Microphone array	GSC beamformer	MVDR beamformer	GSC-ratio	re-imGain
NIST STNR	10.5	17.8	18.1	20.2	26.7
WADA SNR	7.6	18.9	19.2	20.3	26.5

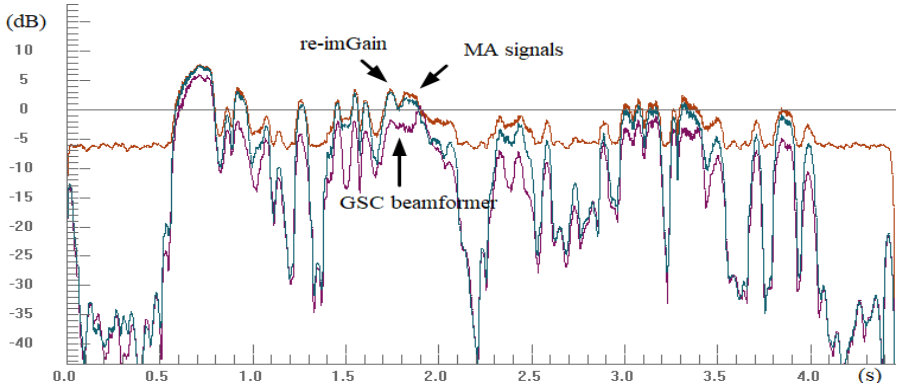


Figure 6. The comparison energy between MA signals and processed signals by GSC beamformer and re-imGain

The appealing characteristic of the author's presented method is low computation and utilizing the observed microphone array signals to calculate the variance of the speech component to form an additive appropriate gain function. This approach allows gaining the amplitude of the beamformer's output signal and reducing the speech distortion. The effectiveness was confirmed by increasing the obtained SNR, which enhanced the perceptual metric listener and speech intelligibility. The suggested technique can easily be installed into various types of speech applications and multi-channel systems for resolving other complicated problems. From the obtained numerical simulations, the paper can derive some interesting opinions:

(a) The MA beamformer has the ability of steering the pattern at a certain location while attenuating the surrounding noise field, interference or noisy acoustic factors. In this experiment, GSC beamformer removes a large amount of noise component while preserving the original speech component talker. At Figures 4(a) and (b), we can easily realize the speech enhancement with promising results.

(b) MVDR beamformer applied the direction of arrival of interest signal and covariance matrix of observed MA signals for obtaining the original speech data while attenuating surrounding noise field. GSC-ratio based on adaptive ratio of power between fixed beamformer and blocking matrix's output signal and the coherence to control the coefficients of adaptive noise canceller. The efficiency of MVDR beamformer and GSC-ratio is presented in Table 1.

(c) Due to the effect of undetermined reasons, such as, internal electrical noise, the movement of speaker during the conversation, the different microphone quality or sensitivities, the imprecise related transfer function, the error of estimating necessary parameters, the difference of time recording between microphones, the displacement of configured microphones, conventional GSC beamformer, MVDR beamformer and GSC-ratio's performance usually degraded. The existence of speech distortion causes reducing clean speech data.

(d) The appealing properties of the author's approach is utilizing the real and imaginary part of cross power spectral between microphone array signals for computing the variance of speech from noisy mixture and variance of speech after performing GSC beamformer. This effective gain function allows saving the amplitude of GSC beamformer's output signal while not gaining noise as in Figures 5(a) and (b).

(e) This article presented an efficient technique, which exploits the priori information about the observed MA signals for calculating the original covariance of speech for gaining the useful signal. The advantage of this method is low complexity and easy installation in various types of acoustic speech applications for addressing speech distortion in several speech applications.

(f) The author's approach depends on cross power spectral densities between microphones, the microphone sensitivities. So with different types of acoustic equipment, this method can not deal with complicated problems in real-life recording situations. In addition, the presented method is based on the assumption of accurate direction of arrival of desired target speaker. Under the condition of error of computing θ_s, moving head of speaker or inaccurate calculation of impinging angle of talker, this method does not resolve mentioned drawbacks.

5. CONCLUSION

In this contribution, a gain function, which is based on the using of the real-imaginary part of cross power spectral densities between received array signals, has been presented. The appealing properties of this approach is exploiting the spatial information about the real-imaginary part and preferred steering vector. The author's proposed method has low complexity and easy implementation, which is suited for almost all acoustic equipment. An experiment was conducted in the presence of a complex environment, third-party talker. The numerical results have shown the reduction of speech distortion to 8.1 dB and enhancing the signal-to-noise ratio from 7.8 to 8.9 dB. The author's suggested technique can be integrated into various types of acoustic speech applications to resolve other complicated problems, such as, dereverberation, automatic speech recognition by utilizing the capability of gaining the amplitude of final output signal for recovering clean speech data and improve the accuracy of recognition.

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