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# Performance evaluation of a neural network-based beamformer with a small-scale microphone array

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**ABSTRACT**

**Beamforming has been one of the most important techniques in noise reduction under adverse acoustic environments. Traditional beamformers were designed in analytical and adaptive schemes. On the other hands, recent neural network-based beamformers achieve the great success in signal enhancement. The authors have also proposed a broadband neural network-based beamformer, which can deal with wide-band speech signals. The performance of the proposed beamformer was confirmed in computer simulation with an 8-ch equally-spaced linear microphone array, of which the spacing between neighbouring microphones was 10 cm, respectively. In this paper, the performance of the proposed beamformer is evaluated with a hand-held small-scale microphone array, which is developed with miniature MEMS microphones. It is confirmed that the nonlinear beamformer could sharpen the main lobe even with the small-scale microphone array, although an analytical linear beamformer, that is, delay-and-sum beamformer, could not achieve signal enhancement. It is considered that the nonlinear neural network-based beamformer could enhance minute differences in amplitude and phase among multi-channel observations. The performance evaluation is also carried out under a real environment.**

**Keywords:** Noise, reduction, Non-linear beamforming, MEMS microphones
**I-INCE Classification of Subject Number:** 74

## 1. INTRODUCTION

Beamforming has been one of the important issues in acoustical signal processing [1] as well as radar and radio applications. It enables to detect and enhance target signals in adverse conditions. A wide variety of beamformers have proposed for several decades. The traditional beamformers have been analytically and adaptively designed such as a delay-and-sum beamformer [2] and the AMROR [3]. In the field of information processing, machine learning with a huge amount of training data is a representative approach in non-linear optimization problems. A neural network can be an alternative

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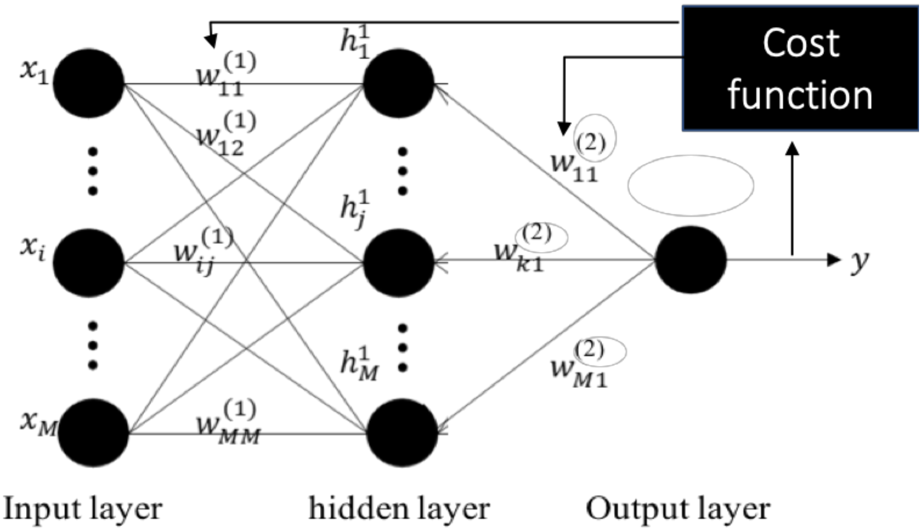


**Figure 1.** Basic structure of a non-linear beamformer with a three-layered neural network.

approach to optimizing the beamformers. Kobatake et al. proposed a pioneering superdirective beam-former with a three-layered neural network structure [4]. Neural network-based beamformers became popular for narrow-band antenna applications [5-7]. It is, however, difficult for those beamformers to deal with wide-band acoustical signals, although various non-linear beamformers with the learning schemes based on neural networks have been investigated for acoustical applications [8-10].

In this paper, the performance of the neural network-based beamformer with an 8-ch small-scale microphone array. It is easily imagined that the delay-and-sum beamformer could not form a sharp main lobe when the microphone spacing is small. The performance of beamforming is evaluated based on directivity patterns and spectral distortion.

## 2. NON-LINEAR BEAMFORMING

Beamforming can be achieved by linear signal processing, where multiple observed signals are phase-adjusted and summed up [1, 2]. It means that the target signal is emphasized and interference signals coming from the undesired directions are weakened by phase interference. The target signal coming from the desired direction is not distorted by the linear beamforming. This advantage makes the delay-and-sum beamformer popular in acoustical signal processing. On the other hand, the delay-and-sum beamformer is not superior in controlling the directivity pattern compared with the state-of-the-art beamformers. The delay-and-sum beamformer needs a number of microphones to form the sharp main lobe, especially in the low-frequency range and does not turn attention to the directions except the look direction.

Kobatake et al. proposed a novel framework of non-linear beamforming, where a three-layered neural network as shown in Fig. 1 was employed to achieve superdirectivity [4]. The neural network is trained as an autoencoder. The neural network is allowed to output the input signal as it is, only when the signal comes from the target direction. Otherwise, the neural network is trained not to output any signal in the training phase. It can achieve superdirectivity for the narrowband signal such as sinusoidal signals. However, the non-linear activation functions used in the neural network-based beamformers cause the non-linear distortion on the target signal. Non-linear distortion should be reduced for wide-band acoustic applications.

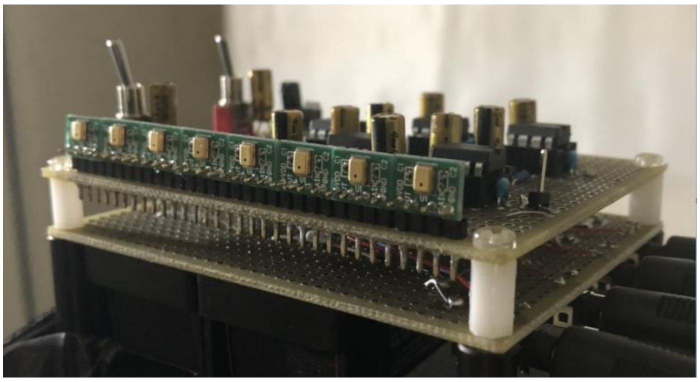

**Figure 2.** Appearance of a 8-ch small-scale microphone array.

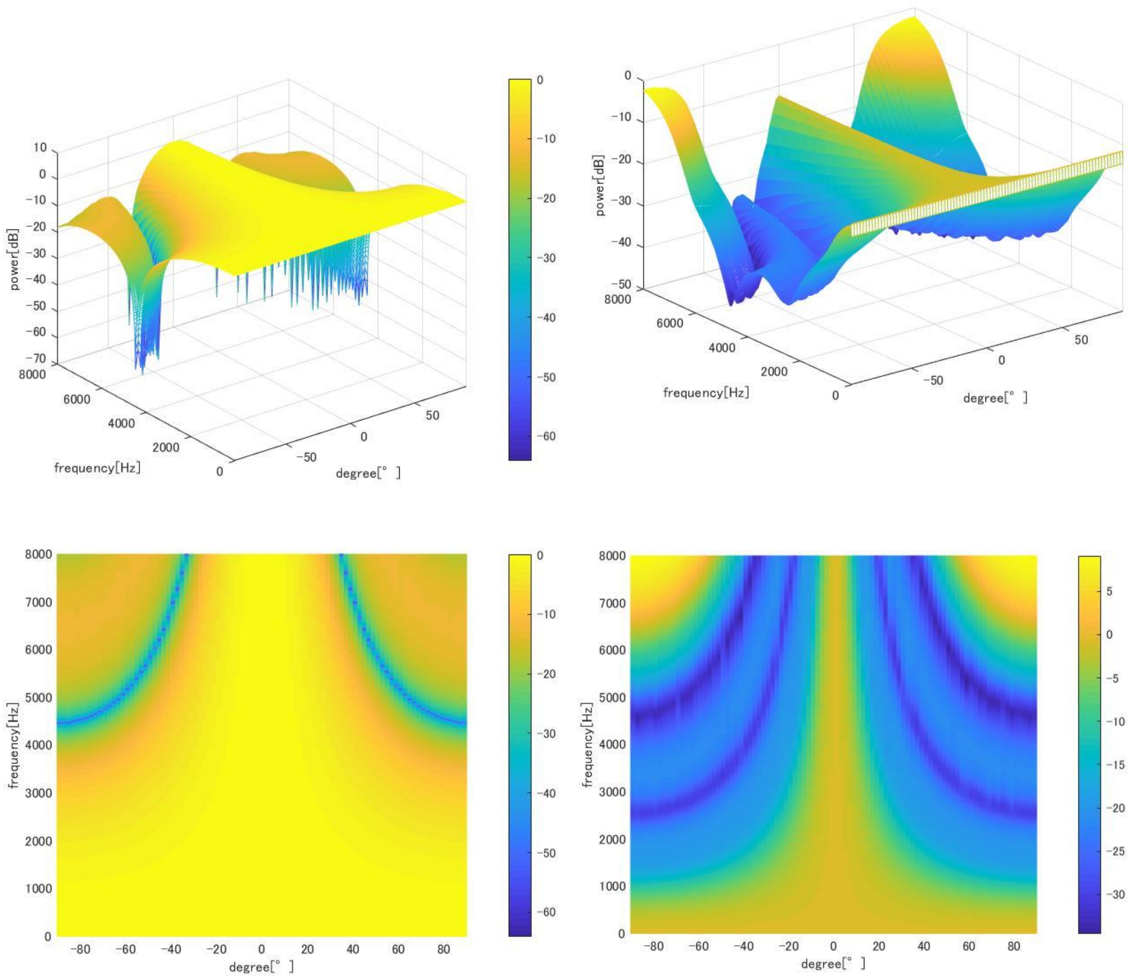


**Figure 3.** Beampatterns of delay-and-sum beamformer and non-linear beamformer in left and right pannels, respectively.

## 3. DESIGN OF A SMALL-SCALE MICROPHONE ARRAY

A small-scale handheld microphone array is designed using eight MEMS microphones (Knowles Electronics SPU0414HR5H－SB). The spacing between neighboring microphones is 10 mm approximately. The pre-amplifier is laboratory-made and the amplified analog signals are imported into a PC through a USB audio interface.

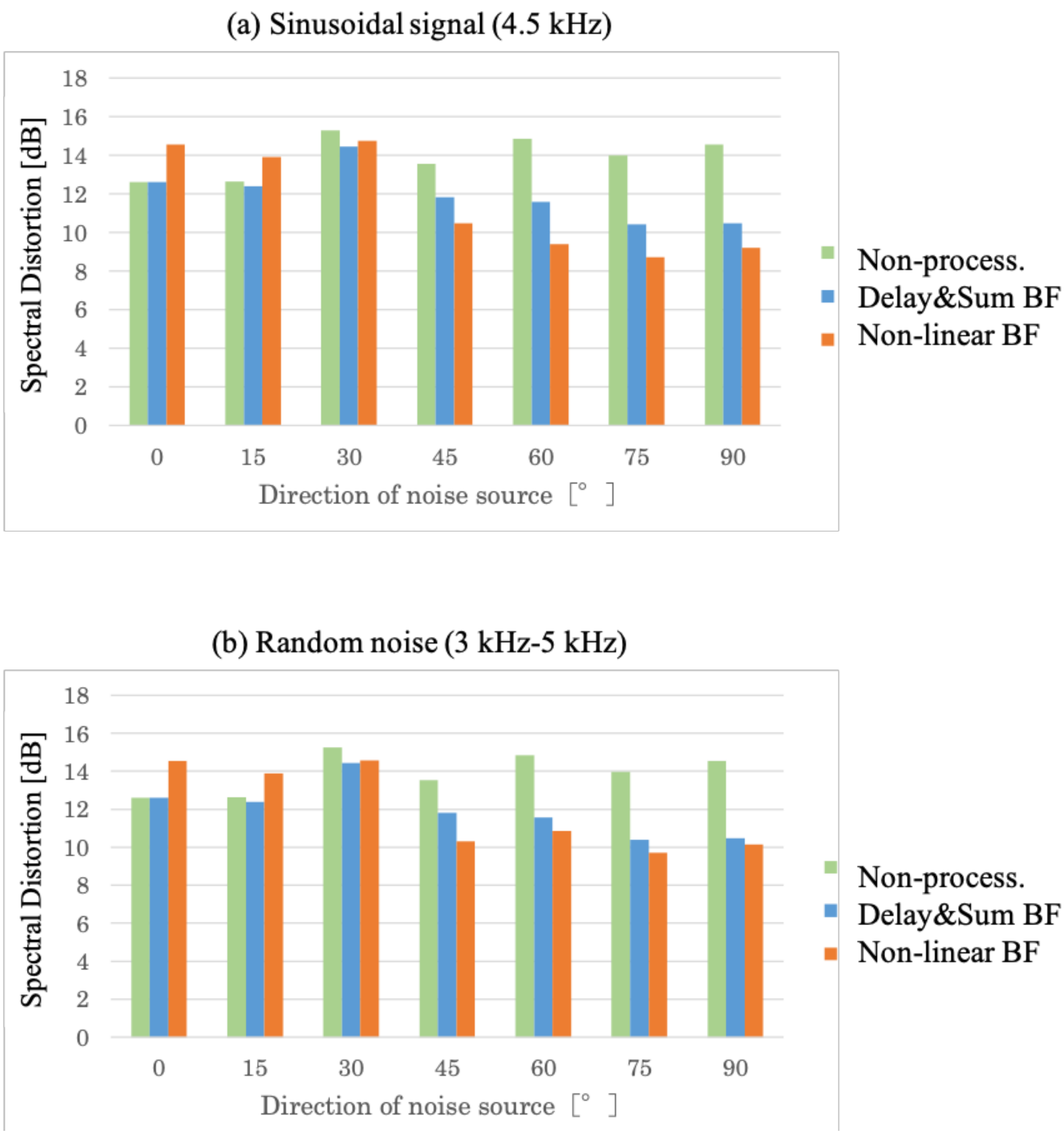


**Figure 4.** Spectral distortion of non-processed signals, delay-and-sum beamformer outputs, and non-linear beamformer outputs for the sinusoidal signal of 4.5 kHz and band-limited random noise (3 kHz – 5 kHz) in upper and lower panels, respectively.

Figure 2 shows the appearance of the 8-ch small-scale MEMS microphone array. Each microphone is omnidirectional and plate-mounted so that diffraction and reflection cause distortion.

## 4. PERFORMANCE EVALUATION

The performance of the beamformers with the 8-ch small-scale MEMS microphone array is evaluated based on the directivity patterns and spectral distortion. The evaluation data were recorded in a sound-proofed room, where the distance between the microphone array and the loudspeaker is fixed at 2.0 m. The loudspeaker was set at either of 0 degrees, that is, the front of the array, and 15, 30, 45, 60, 75, 90 degrees. The target signal was male utterance. The sinusoidal signal of 4.5 kHz and random noise in the frequency range from 3 kHz to 5 kHz were prepared as test signals. The non-linear beamformer is trained with the random noise (3 kHz – 5 kHz).

The beam patterns of the delay and sum beamformer and the non-linear beamformer are shown in Fig. 3, where the target direction is set to 0 degrees. The delay and sum beamformer could not sharpen the main lobe. On the other hand, the non-linear beamformer could form the sharp main lobe, although the attenuation is caused in the higher frequency range at the target direction.

Figure 4 shows the spectral distortions of non-processed signals, delay-and-sum beamformer outputs, and non-linear beamformer outputs for the sinusoidal signal of 4.5 kHz and band-limited random noise (3 kHz – 5 kHz). It is confirmed that the non-linear beamformer is superior to the delay and sum beamformer when the noise source is located from 45 degrees to 90 degrees.

## 5. CONCLUSIONS

In this paper, a small-scale microphone array is designed with eight miniature MEMS microphones. The microphone array device is used for data acquisition in a sound-proofed room. Those data were used for beamforming by a traditional delay-and-sum beamformer and a non-linear neural network-based beamformer. The directivity patterns indicate that the non-linear beamformer has an advantage over the delay-and-sum beamformer. It is found, however, that the spectral distortion is not improved enough.

Future works include the subjective evaluation of noise reduced signals obtained by the linear delay-and-sum and non-linear neural network-based beamformers.

## 6. ACKNOWLEDGEMENTS

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