NOISE REDUCTION BASED ON CROSS TF ε-FILTER

Tomomi Abe
Major in Pure and Applied Physics, Waseda university 55N-4F-10A, 3-4-1 Okubo, Shinjuku-ku, Tokyo, 169-8555, Japan

Mitsuharu Matsumoto, Shuji Hashimoto
Department of Applied Physics, Waseda university 55N-4F-10A, 3-4-1 Okubo, Shinjuku-ku, Tokyo, 169-8555, Japan

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Abstract: A time-frequency ε-filter (TF ε-filter) is an advanced ε-filter applied to complex spectra along the time axis. It can reduce most kinds of noise while preserving a signal that varies frequently such as a speech signal. The filter design is simple and it can effectively reduce noise. It is applicable not only to small amplitude stationary noise but also to large amplitude nonstationary noise. However when we consider the noise that varies much frequently along the time axis, TF ε-filter cannot reduce noise without the signal distortion. When we consider the noise where the neighboring frequency bins have similar powers such as impulse noise, we can reduce the noise by using ε-filter applied to the complex spectra not along the time axis, but along the frequency axis. This paper introduces an advanced method for noise reduction that applies ε-filter to complex spectra not only along the time axis but also along the frequency axis labeled cross TF ε-filter. We conducted the experiments utilizing the sounds with stationary, nonstationary and natural noise.

1 INTRODUCTION

Noise reduction plays an important role in speech recognition and individual identification. When we consider the instruments like hearing-aids and phones, noise reduction for a monaural sound is strongly expected. It will also be easy to miniaturize the system size because it requires only one signal. The spectral subtraction (SS) is a well-known approach for reducing the noise signal of the monaural-sound (Boll, 1979). It can reduce the noise effectively despite of the simple procedure. However, it can handle only the stationary noise. It also needs to estimate the noise in advance. Although noise reduction utilizing Kalman filter has also been reported (Kalman, 1960; Fujimoto and Ariki, 2002), the calculation cost is large. Some authors have reported a model based approach for noise reduction (Daniel et al., 2006). In this approach, we can extract the objective sound by learning the sound model in advance. However, it is not applicable to the signals with the unknown noise as well as SS. There are some approaches utilizing comb filter (Lim et al., 1978). In this approach, we firstly estimate the pitch of the speech signal, and reduce the noise signal utilizing comb filter. However, the estimation error results in the degradation of the speech quality. Some authors have reported the method utilizing ε-filter (Harashima et al., 1982; Arakawa et al., 2002). ε-filter is a nonlinear filter, which can reduce the noise signal with preserving the signal. ε-filter is simple and has some desirable features for noise reduction. It does not need to have the model not only of the signal but also of the noise in advance. It is easy to be designed and the calculation cost is small. It can reduce not only the stationary noise but also the nonstationary noise. However, it can reduce only the small amplitude noise in principle. To solve the problems, the method labeled TF ε-filter was proposed (Abe et al., 2007). TF ε-filter is an improved ε-filter applied to the complex spectra along the time axis in time-frequency domain. By utilizing TF ε-filter, we can reduce not only small amplitude stationary noise but also large amplitude nonstationary noise. However TF ε-filter cannot reduce the noise without distortion when the noise changes frequently along the time axis such as impulse noise. To solve the problem, we apply ε-filter to complex spectra not only along the time axis but also along the

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frequency axis labeled cross TF ε-filter. By applying ε-filter to the complex spectra along the two axes, we can reduce the noise even if it changes frequently along the time axis. It need not estimate the noise as well as TF ε-filter in advance. We also show the experimental results of the proposed method compared to the other methods such as SS and TF ε-filter.

2 NOISE REDUCTION UTILIZING TD ε-FILTER AND TF ε-FILTER

To clarify the problems of a time-domain ε-filter (TD ε-filter)(Harashima et al., 1982; Arakawa et al., 2002), we firstly explain the TD ε-filter algorithm. Let us define $x(k)$ as the input signal at time k. Let us also define $y(k)$ as the output signal of the ε-filter at time k as follows:

$$y(k) = x(k) + \sum_{i=-P}^{P} a(i)F(x(k+i) - x(k)), \quad (1)$$

where $a(i)$ represents the filter coefficient. $a(i)$ is usually constrained as follows:

$$\sum_{i=-P}^{P} a(i) = 1. \quad (2)$$

The window size of the ε-filter is $2P+1$. $F(x)$ is the nonlinear function described as follows:

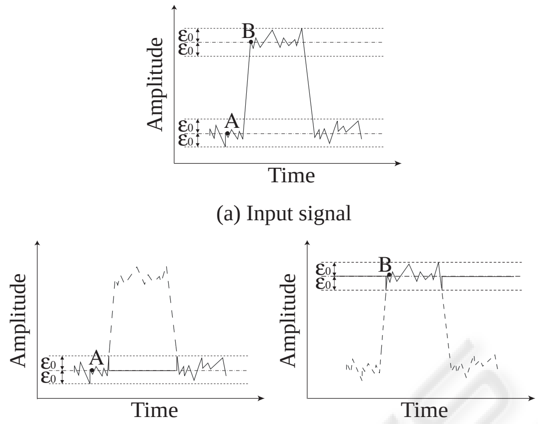
$$|F(x)| \leq \varepsilon_0 : -\infty \leq x \leq \infty, \quad (3)$$

where ε_0 is a constant. This method can reduce small amplitude noise while preserving the speech signal. For example, we can set the nonlinear function $F(x)$ as follows:

$$F(x) = \begin{cases} x & (-\varepsilon_0 \leq x \leq \varepsilon_0) \\ 0 & (otherwise). \end{cases} \quad (4)$$

Figure 1 shows the basic concept of an ε-filter when Eq.4 is utilized as $F(x)$. Figure 1(a) shows the waveform of the input signal.

Executing the ε-filter at point A in Figure 1(a), we first replace all the points where the distance from A is larger than ε_0 by the value of point A. We then summate the signals in the same window. Figure 1(b) shows the basic concept of this procedure. The dotted line represents the points where the distance from A is larger than ε_0. In Figure 1(b), the continuous line represents the values replaced through this procedure. As a result, if the points are far from A, the points are ignored. On the other hands, if the points are close to A, the points are smoothed. Due to this procedure, the



(a) Input signal

(b) When a TD ε-filter is applied to the point A

(c) When a TD ε-filter is applied to the point B

Figure 1: The basic concept of a TD ε-filter.

ε-filter reduces noise while preserving the precipitous attack and decay of the speech signal. In the same way, by executing the ε-filter at point B in Figure 1(a), we replace all the points where the distance from B is larger than ε_0 by the value of the point B. The points are ignored if they are far from B, while the points are smoothed if the points are close to B as shown in Figure 1(c). Consequently, we can reduce small amplitude noise near by the processed point while preserving the speech signal.

An ε-filter can reduce small amplitude noise in the time domain. However, due to the procedure, it is not applicable to large amplitude noise. To solve this problem, Time-Frequency ε-filter (TF ε-filter) was proposed (Abe et al., 2007). TF ε-filter utilizes the distribution difference of the speech signal and the noise in the frequency domain. The following assumptions regarding the sound sources are used:

- **Assumption 1.** Speech signal has greater variation in power than noise signal in the time-frequency domain.
- **Assumption 2.** Noise signal is distributed more uniformly and with less variation in the time-frequency domain.

Figure 2 depicts the speech signal and the white noise signal in the time and the time-frequency domains.

As shown in Figure 2, assumptions 1 and 2 are fulfilled in the case of various noise like white noise and natural noise such as the sound of a cooling fan. In Figures 2(b) and (d), the power is normalized using the maximal power of the speech signal. When we consider frequency bins where there are signals, the ratio of noise power to signal power is smaller than the ratio of noise amplitude to signal amplitude in the time domain. In TF ε-filter, we utilize this feature to

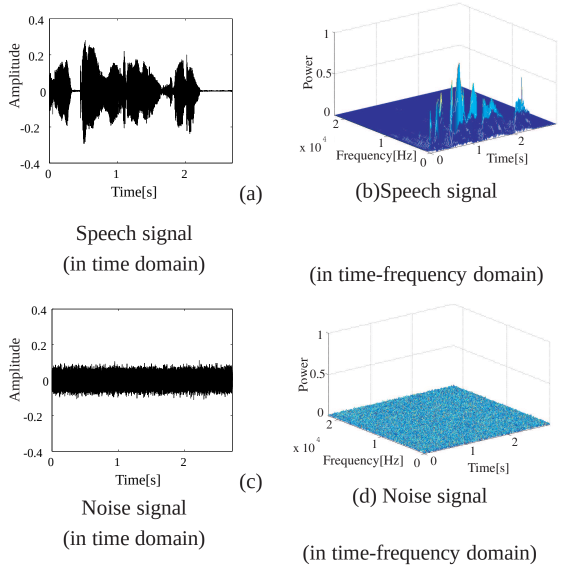


Figure 2: A speech signal or noise signal in the time and frequency domains.

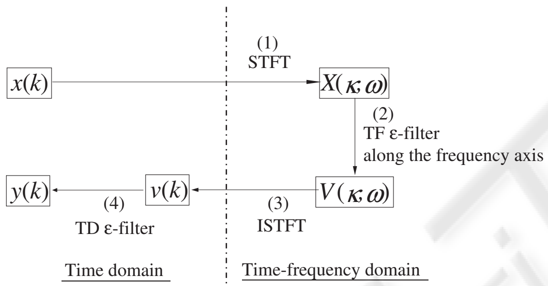


Figure 3: Block diagram of combining TF ε-filter and TD ε-filter.

apply an ε-filter to high-level noise.

Figure 3 illustrates the method combining TF ε-filter and TD ε-filter with a block diagram. As shown in Figure 3(1), we firstly transform the input signal $x(k)$ to the complex amplitude $X(\kappa,\omega)$ by short term Fourier transformation(STFT) as follows:

$$X(\kappa,\omega) = \sum_{l=-\infty}^{\infty} x(\kappa+l)W(l)e^{-j\omega l}, \tag{5}$$

where W, κ and ω represent the window function, the time frame in the time-frequency domain and the angular frequency, respectively. j represents the imaginary unit. Next we execute a TF ε-filter, which is an ε-filter applying to complex spectra along the time axis in the time-frequency domain, as shown in Figure 3(2). In this procedure, $V(\kappa,\omega)$ is obtained as follows:

$$V(\kappa,\omega) = \sum_{i=-Q}^{Q} a(i)X'(\kappa+i,\omega), \tag{6}$$

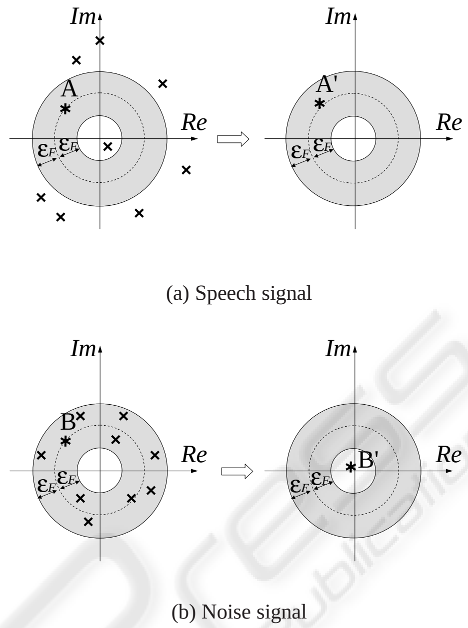


Figure 4: Differences in performance when a TF ε-filter is applied to the speech signal and noise.

where the window size of ε-filter is $2Q+1$,

$$X'(\kappa+i,\omega) = \begin{cases} X(\kappa,\omega) \\ (||X(\kappa,\omega)|-|X(\kappa+i,\omega)|| > \varepsilon_T) \\ X(\kappa+i,\omega) \\ (||X(\kappa,\omega)|-|X(\kappa+i,\omega)|| \le \varepsilon_T) \end{cases} \tag{7}$$

and ε_T is a constant.

Figure 4 illustrates the differences in performance when we apply a TF ε-filter to the speech signal and the noise. The horizontal axis and the vertical axis represent the real axis and the imaginary axis, respectively. In Figure 4, $*$ and $\times$ represent the processed point and the other signal points in the same window, respectively. Point A in Figure 4(a) and point B in Figure 4(b) represent the complex amplitude of the processed point. A' and B' represent the complex amplitudes of the outputs when we apply the TF ε-filter to the points A and B, respectively. Executing the TF ε-filter, we firstly replace the complex amplitude of the signal outside of the shadow area by that of A. We then summate the complex spectra of all the points in the same window. Due to handling complex spectra, when we have many signals that have similar amplitudes but different phases, the real part and imaginary part cancel each other. In other words, even if the amplitude of the noise is large, the noise is reduced because they cancel each other. Note that the noise is reduced not only when the amplitude of the noise is small but also when the amplitude of the noise is large because of this procedure. Figure 4(a) represents the basic concept in the case that the power varies drastically like a speech signal. When we consider a signal whose power varies frequently, the difference between the absolute value of A and that of the other signals is large as shown in Figure 4(a). For this reason, many signals in the same window as the point A are replaced by A. As a result, when we handle the speech signal, the complex amplitude of the processed point is intact. Figure 4(b) represents the basic concept in case that the power does not vary so much like a noise signal. When we consider a noise signal, the difference between the absolute value of B and that of the other signals is relatively small compared with the speech signal. Hence, few signals in the same window as point B are replaced by B. In other words, when handling noise, the complex amplitude of the processed point becomes smaller when the TF ε-filter is applied. Based on these aspects, we can reduce noise while preserving the signal by setting ε_T appropriately.

Hence, the TF ε-filter is effective even when the power of the noise to signal is large. Additionally, under assumption 2, the TF ε-filter becomes more effective. When assumption 2 is satisfied, the variation of the noise to the signal in the frequency domain becomes smaller than that in the time domain. As a consequence, even if the noise varies frequently in the time domain, the ε-filter can be applied in the time-frequency domain.

Next, we transform $V(\kappa,\omega)$ to $v(k)$ by inverse STFT as shown in Figure 3(3).

To reduce the remaining noise, we additionally apply the ε-filter in the time domain to $v(k)$ as shown in Figure 3(4). Note that the ε-filter in the time domain can be utilized because large amplitude noise has already been reduced in the previous procedure. The output $y(k)$ can be obtained as follows:

$$y(k) = \sum_{i=-P}^{P} a(i)v'(k+i), \tag{8}$$

where

$$v'(k+i) = \begin{cases} v(k) & (|v(k+i) - v(k)| > \varepsilon_t) \\ v(k+i) & (|v(k+i) - v(k)| \le \varepsilon_t) \end{cases} \tag{9}$$

and ε_t is a constant.

3 NOISE REDUCTION UTILIZING CROSS TF ε-FILTER

TF ε-filter can reduce the various types of noise effectively. However, when we use the noise that varies much frequently along the time axis, TF ε-filter cannot reduce noise without the signal distortion. When we consider the noise where the neighboring frequency bins have similar powers such as impulse noise, we can reduce the noise by using ε-filter applying to complex spectra not along the time axis, but along the frequency axis.

Figure 5 shows the basic concept of the proposed method. At first, as shown in Figure 5 "Step 1", we apply the ε-filter to the complex spectra along the frequency axis to reduce the noise where the neighboring frequency bins have similar power although the noise amplitude varies drastically such as the impulse noise and white noise whose amplitude varies. Next we apply ε-filter to complex spectra along the time axis to reduce the noise that distributes wider than the speech signal in the frequency domain as shown in Figure 5 "Step 2".

Figure 6 illustrates the proposed method with a

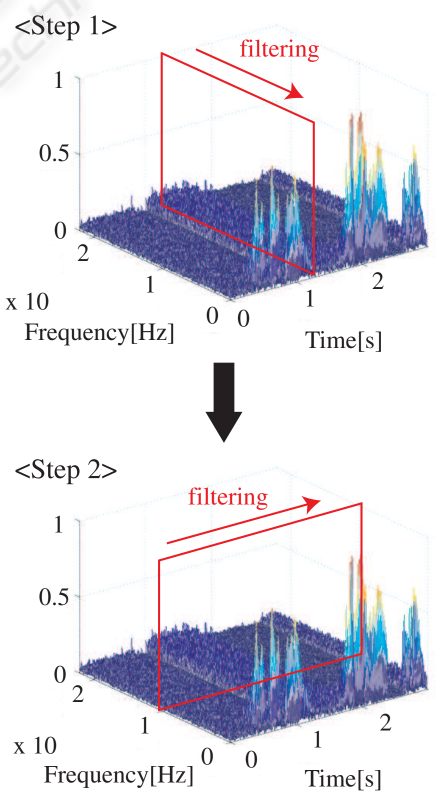


Figure 5: The basic concept of cross TF ε-filter.

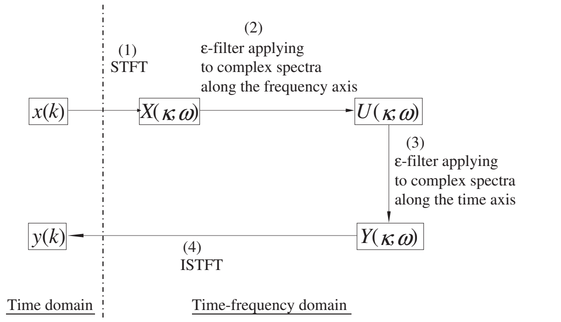


Figure 6: The block diagram of the proposed method.

block diagram. Let us consider $x(k)$, and $X(\kappa,\omega)$ transformed from $x(k)$ by STFT as well as Eq.5 as shown in Figure 6(1). Next we apply ε-filter to complex spectra along the frequency axis as shown in Figure 6(2). In this procedure, $U(\kappa,\omega)$ is obtained as follows:

$$U(\kappa,\omega) = \sum_{i=-N}^{N} a(i)X'(\kappa+i,\omega), \tag{10}$$

where

$$X'(\kappa+i,\omega) \tag{11}$$
$$= \begin{cases} X(\kappa,\omega) \\ (||X(\kappa,\omega)| - |X(\kappa,\omega+i)|| > \varepsilon_F) \\ X(\kappa,\omega+i) \\ (||X(\kappa,\omega)| - |X(\kappa,\omega+i)|| \leq \varepsilon_F). \end{cases}$$

ε_F is a constant and $2N+1$ is window size. Then we employ ε-filter applying to complex spectra along the time axis as shown in Figure 6(3). In this procedure, $Y(\kappa,\omega)$ is obtained as follows:

$$Y(\kappa,\omega) = \sum_{i=-M}^{M} a(i)U'(\kappa+i,\omega), \tag{12}$$

where

$$U'(\kappa+i,\omega) \tag{13}$$
$$= \begin{cases} U(\kappa,\omega) \\ (||X(\kappa,\omega)| - |X(\kappa+i,\omega)|| > \varepsilon_T) \\ U(\kappa+i,\omega) \\ (||X(\kappa,\omega)| - |X(\kappa+i,\omega)|| \leq \varepsilon_T). \end{cases}$$

ε_T is a constant and $2M+1$ is the window size. Next we transform $Y(\kappa,\omega)$ to $y(k)$ by inverse STFT as shown in Figure 6(4). We label this process "cross TF ε-filter".

4 EXPERIMENT

4.1 Experimental Condition

We conducted the experiments utilizing a speech signal with a noise signal. As the speech signal, we utilized "Japanese Newspaper Article Sentences" edited by the Acoustical Society of Japan. We also prepared three kinds of noise signals: stationary noise, nonstationary noise and natural noise. The signal and the noise are mixed in the computer. To compare the effectiveness of the proposed method to other methods, we conducted the experiments utilizing three methods; spectral subtraction (SS), the method combining TF ε-filter and TD ε-filter and cross TF ε-filter. Table 1 shows the value of common parameters for all the experiments.

Table 1: Common parameters.

Parameter		Value
Sampling frequency		44100
STFT	Block size	512
	Hop size	256
	Window function	Hanning window

To evaluate the performance of noise reduction, we use signal-to-noise ratio (SNR) and signal-to-distortion ratio (SDR). SNR is defined as follows:

$$SNR = 10 \cdot \log_{10} \left(\frac{\sum_{k=1}^{L} s(k)^2}{\sum_{k=1}^{L} n(k)^2} \right), \tag{14}$$

where $s(k)$, $n(k)$ and L represent the speech signal at time k, the noise signal at time k, and the length of the signal, respectively. To calculate SNR of the output signal, we separately applied each method to the signal and noise, and calculated the output SNR by using the obtained signal and noise. SDR can be represented as follows:

$$SDR = 10 \cdot \log_{10} \left(\frac{\sum_{k=1}^{L} s_{in}(k)^2}{\sum_{k=1}^{L} (s_{in}(k) - s_{out}(k))^2} \right), \tag{15}$$

where $s_{in}(k)$ and $s_{out}(k)$ represent the input signal and the output signal at time k respectively, when we used only the speech signal. SDR represents how much the signal is distorted by reducing the noise. Throughout all the experiments, the parameters of SS and the method combining TF ε-filter and TD ε-filter are set optimally. On the other hand, in cross TF ε-filter, ε_T was set at 0.1. We only change ε_F depending on the noise to show the robustness concerning the parameter setting although we can reduce the noise more effectively. SNR of the input signal is set at 10[dB] throughout all of the experiments.

Table 2: *SNR* and *SDR* when a signal with stationary noise is utilized.

	SNR[dB]	*SDR*[dB]
Input signal	10.0	—
SS	18.3	21.7
TD ε-filter processed after TF ε-filter	40.6	18.9
Cross TF ε-filter	44.4	19.3

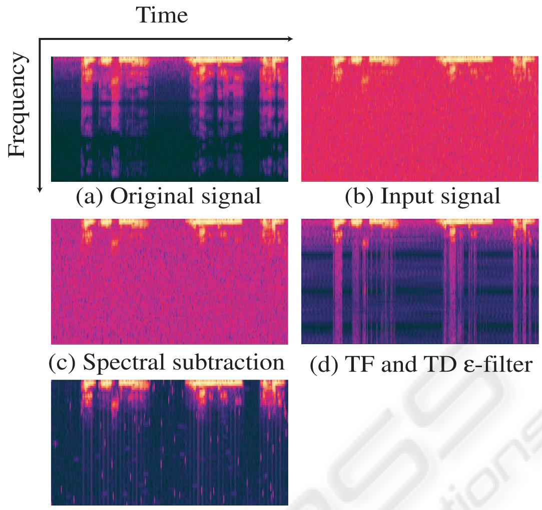
4.2 Experimental Results in the Case of Stationary Noise

We first conducted the experiment utilizing a signal with stationary noise. We prepared a speech signal and white noise as the signal and the stationary noise, respectively. We set ε_F in the proposed method at 0.7. We also set the window size of ε-filter applied to complex spectra in the proposed method along the frequency axis and the time axis at 101 and 11, respectively. Table 2 shows the results of the experiments for stationary noise.

As shown in Table 2, the proposed method could reduce the noise compared to the other methods with preserving the signal. Figure 7 shows the sound spectrograms. In Figure 7, bright color represents that the signal power is high while dark color represents that the signal power is low. Figure 7(a) shows the spectrogram of the original signal. Figure 7(b) shows the spectrogram of the signal with stationary noise. Figures 7(c)-(e) show the spectrograms of the output of SS, the output of the method combining TF ε-filter and TD ε-filter and the output of the proposed method, respectively. As shown in Figure 7, when we used the proposed method, the noise could be reduced more effectively than the other methods.

4.3 Experimental Results in the Case of Nonstationary Noise

The experiment was conducted using a signal with nonstationary noise. We used the same speech signal as in Sec.4.2. We prepared white noise with an amplitude that sometimes varied. We set ε_F in the proposed method at 1.1. We also set the window size of ε-filter applied to complex spectra in the proposed method along the frequency axis and the time axis 81 and 11, respectively. Table 3 shows the results of the experiments on nonstationary noise. As shown in Table 3, the *SNR* of the proposed method is superior to those of the other methods. Figure 8(a) shows the spectrogram of the original signal. Figure 8(b) shows the spectrogram of the signal with nonstationary noise. Figures 8(c)-(e) show the spectrograms of the outputs of SS, the output of the method combining TF ε-filter and TD ε-filter and the output of the proposed method, respectively. The relation between the color and signal power is the same as in Sec.4.2. As shown in Figure 8, when we use the proposed method, the noise could be reduced more effectively than the other methods even if we use the nonstationary noise as noise.



(a) Original signal (b) Input signal

(c) Spectral subtraction (d) TF and TD ε-filter

(e) Cross TF ε-filter

Figure 7: Experimental results when a signal with stationary noise is utilized.

Table 3: *SNR* and *SDR* when a signal with nonstationary noise is utilized.

	SNR[dB]	*SDR*[dB]
Input signal	10.0	—
SS	15.5	21.9
TD ε-filter processed after TF ε-filter	40.8	16.3
Cross TF ε-filter	44.2	17.3

4.4 Experimental Results in the Case of Natural Noise

To evaluate the performance of the proposed method for natural noise, we conducted the experiment utilizing a speech signal and a noise generated from the cooling fan of a personal computer. The most power of noise used in this experiment is distributed in the low-frequency range. We set ε_F in the proposed method at 1.8. We also set the window size of ε-filter applied to complex spectra in the proposed method along the frequency axis and the time axis 51 and 11,

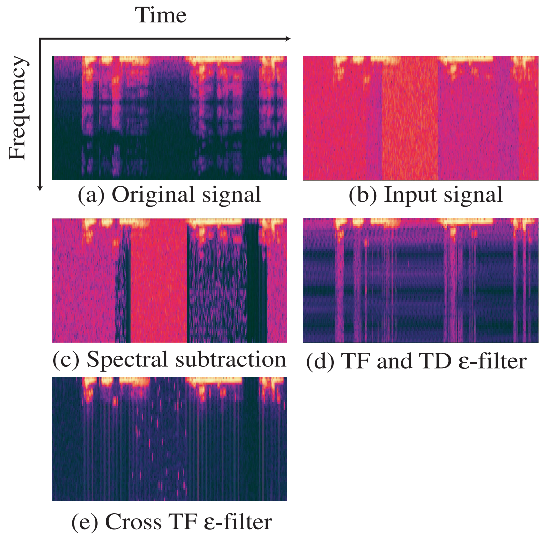


Figure 8: Experimental results when a signal with nonstationary noise is utilized.

Table 4: *SNR* and *SDR* when a signal with natural noise is utilized.

	SNR[dB]	*SDR*[dB]
Input signal	10.0	—
SS	17.4	20.1
TD ε-filter processed after TF ε-filter	38.2	13.4
Cross TF ε-filter	40.2	15.0

respectively. Table 4 shows the results of the experiments for natural noise. As shown in Table 4, the *SNR* of the proposed method is superior to those of the other methods as well as in the case of stationary noise and nonstationary noise. Figure 9(a) shows the spectrogram of the original signal. Figure 9(b) shows the spectrogram of the signal with natural noise. Figures 9(c)-(e) show the spectrograms of the outputs of SS, the output of the method combining TF ε-filter and TD ε-filter and the output of the proposed method, respectively. The relation between the color and signal power is the same as in Sec.4.2. As shown in Figure 9, when we use the proposed method, the noise could be reduced more effectively than the other methods even if the natural noise was used as noise.

5 CONCLUSIONS

In this paper, we introduced an algorithm for noise reduction applying ε-filter to complex spectra not only along the time axis but also along the frequency axis in time-frequency domain. The proposed method can

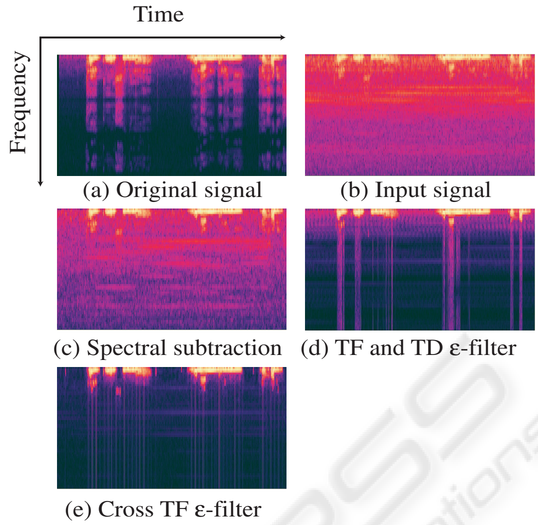


Figure 9: Experimental results when a signal with natural noise is utilized.

reduce not only stationary noise but also nonstationary and natural noise effectively with preserving signal clarity. The experimental results showed that the proposed method could be applied to various kinds of noise. The proposed method could reduce the louder noise compared with the conventional methods such as the method combining TF and TD ε-filter and SS. It is considered that the proposed method can be applied not only to the speech in Japanese but also to the speech in English with noise because the performance of the proposed method depends on only the power change of speech and noise signal. For future works, we would like to confirm the robustness of the proposed method for various input *SNR* and various types of noise. We also aim to determine each parameter adaptively.

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