PARAMETER OPTIMIZATION IN TIME-FREQUENCY ε-FILTER BASED ON CORRELATION COEFFICIENT

Tomomi Abe
Waseda university, 55N-4F-10A, 3-4-1 Okubo, Shinjuku-ku, Tokyo, 169-8555, Japan

Mitsuharu Matsumoto
The University of Electro-Communications, 1-5-1, Chofugaoka, Chofu-shi, Tokyo, 182-8585, Japan

Shuji Hashimoto
Waseda university, 55N-4F-10A, 3-4-1 Okubo, Shinjuku-ku, Tokyo, 169-8555, Japan

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Abstract: Time-Frequency ε-filter (TF ε-filter) can reduce most kinds of noise from a single-channel noisy signal with preserving the signal that varies drastically such as a speech signal. The filter design is simple and it can effectively reduce noise. It can reduce not only small stationary noise but also large nonstationary noise. However, it has some parameters and we need to set them appropriately based on empirical control. So far, there are few studies to evaluate the appropriateness of the parameter setting of ε-filter in general. In this paper, we employ correlation coefficient of the filter output and the difference between the input and the filter output as the evaluation function of the parameter setting. We also show the algorithm to set the optimal parameter of TF ε-filter. We conducted the experiments to compare the value of the correlation coefficient and the mean square error when we change ε value. The experimental results show the applicability of our criterion in parameter setting of ε-filter.

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 single-channel signal is required. The spectral subtraction (SS) is a well-known approach for reducing the noise signal of the monaural-sound (Boll, 1979; Lim, 1978). 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 constructing 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 a nonlinear filter named ε-filter for noise reduction (Harashima et al., 1982) with preserving the signal. We call it "TD ε-filter" as it treats signal shape in time domain. TD ε-filter is simple and has some desirable features for noise reduction. It does not require 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 time-frequency ε-filter (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 has some parameters and we need to set them adequately based

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on empirical control. Moreover, as we only have a single-channel noisy signal, it is difficult to evaluate whether the parameter is optimal or not. We cannot know the difference between the original signal and the filter output from the observed signal. So far, there are few studies on the appropriateness of the parameter setting of ε-filter in general.

As a simple criterion, we assume that the signal and noise are noncorrelated. And we employ the correlation coefficient of the filter output and the difference between the input signal and the filter output to set ε adequately. We introduce a method to determine the parameter utilizing the correlation coefficient. When we utilize the proposed method, we can set the parameters adequately without the information about the noise and the signal. In Sec.2, we explain TF ε-filter to clarify the problem. In Sec.3, we describe the algorithm of the method to determine the parameter adequately. In Sec.4, we show the experimental results. Experimental results show that the proposed method can estimate the optimal parameter of the TF ε-filter. Conclusions are given in Sec.5.

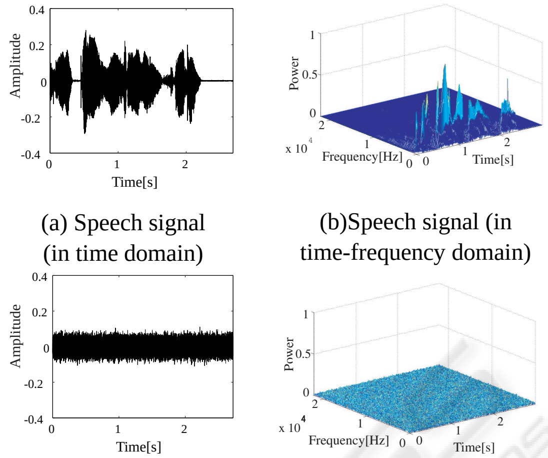
2 TIME-FREQUENCY ε-FILTER

To clarify the problems of a TF ε-filter, we briefly explain the TF ε-filter algorithm. 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 (Abe et al., 2007):

- **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 becomes less variation in the time-frequency domain compared to in the time domain.

Figure 1 depicts the speech signal and the white noise signal in the time and the time-frequency domains.

As shown in Figure 1, assumptions 1 and 2 are fulfilled in the case of various noises like white noise and natural noise such as the sound of a cooling fan. In Figures 1(b) and (d), the power is normalized based on the maximal power of the speech signal. When we consider frequency bins corresponding to the presence of active speech signal, the power of the noise with respect to the power of the signal is smaller than the power of the noise with respect to the power of the signal in the time domain. In TF ε-filter, we utilize this feature to apply an ε-filter to high-level noise.



(a) Speech signal (in time domain)

(b)Speech signal (in time-frequency domain)

(c) Noise signal (in time domain)

(d) Noise signal (in time-frequency domain)

Figure 1: A speech signal or noise signal in the time and time-frequency domains.

Let us define $x(k)$ as the input signal sampled at time k. In TF ε-filter, we firstly transform the input signal $x(k)$ to the complex amplitude $X(\kappa,\omega)$ by short term Fourier transformation (STFT). where κ and ω represent the time frame in the time-frequency domain and the angular frequency, respectively. κ and ω are discrete numbers. 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. In this procedure, $Y(\kappa,\omega)$ is obtained as follows:

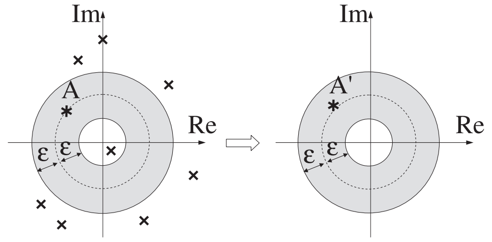
$$Y(\kappa,\omega) = \sum_{i=-Q}^{Q} a(i)X'(\kappa+i,\omega), \tag{1}$$

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

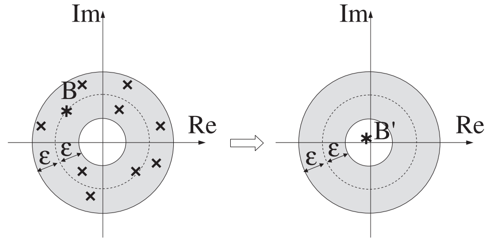
$$\begin{aligned} & X'(\kappa+i,\omega) \\ = & \begin{cases} X(\kappa,\omega) & (||X(\kappa,\omega)|-|X(\kappa+i,\omega)||>\varepsilon) \\ X(\kappa+i,\omega) & (||X(\kappa,\omega)|-|X(\kappa+i,\omega)||\le\varepsilon), \end{cases} \end{aligned} \tag{2}$$

and ε is a constant.

Figure 2 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 the following explanations, we basically use the word "signal" when we handle them as the symbols while we use the word "complex spectra" when we handle them as the values. We used the word "signal" as the mean of "all the signal points". We also used the word "complex spectra of the points" as the "all the complex amplitudes of the points". In Figure 2, $*$ and $\times$ represent the processed point and the other signal points in the same window, respectively.



(a) Speech signal



(b) Noise signal

Figure 2: Performance difference when a TF ε-filter is applied to the speech signal and noise.

Point A in Figure 2(a) and point B in Figure 2(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 powers but different phases, they are filtered out by the TF ε-filter and the complex amplitudes of the filter outputs become small. Figure 2(a) represents the basic concept in the case that the power varies frequently like in 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 2(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 almost preserved. Figure 2(b) represents the basic concept in case that the power does not vary so much like in 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. Based on these aspects, we can reduce noise while preserving the signal by setting ε appropriately. Hence, the TF ε-filter is effective even when the power of the noise with respect to the power of the signal is large. Additionally, under assumption 2, the TF ε-filter becomes more effective. When assumption 2 is satisfied, the variation of the noise with respect to the variation of the signal in the frequency domain becomes smaller than the case 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.

Then, we transform $Y(\kappa,\omega)$ to $y(k)$ by inverse STFT.

In TF ε-filter, ε is an essential parameter to reduce the noise appropriately. If ε is set to excessively large values, the TF ε-filter becomes similar to linear filter and smoothes not only the noise but also the signal. On the other hand, if ε is set to an excessively small value, it does nothing to reduce the noise anymore. Due to these reasons, ε value should be set adequately.

3 PARAMETER OPTIMIZATION UTILIZING CORRELATION COEFFICIENT

As described in the previous section, when the TF ε-filter is employed, we need to set ε value adequately to reduce the noise. However, we cannot estimate optimal parameter because the noise and signal are not known throughout all the procedures.

To solve the problem, we pay attention to the correlation of the speech signal and the noise signal. We make the following assumption concerning the sound source and noise:

- **Assumption 1.** The speech signal is noncorrelated with the noise signal.

Let us define $s(k)$ and $n(k)$ as the objective signal and the noise, respectively. Let $R(s(k),n(k))$ be the correlation coefficient of $s(k)$ and $n(k)$ described as follows:

$$R(s(k),n(k)) = \frac{\sum_{k=1}^{L}(s(k)-\overline{s(k)})(n(k)-\overline{n(k)})}{\sqrt{\sum_{k=1}^{L}(s(k)-\overline{s(k)})^2}\sqrt{\sum_{k=1}^{L}(n(k)-\overline{n(k)})^2}}, \tag{3}$$

where L is the data length. $\overline{s(k)}$ and $\overline{n(k)}$ represent the average of $s(k)$ and $n(k)$, respectively. $\overline{s(k)}$ and $\overline{n(k)}$ are described as follows:

$$\overline{s(k)} = \frac{1}{L}\sum_{k=1}^{L} s(k). \tag{4}$$

$$\overline{n(k)} = \frac{1}{L}\sum_{k=1}^{L} n(k). \tag{5}$$

When L is large enough, it is expected that the assumption 1 satisfies:

$$R(s(k), n(k)) = 0. \tag{6}$$

As described above, $s(k)$ and $n(k)$ are unknown throughout the filtering procedures. Instead of $s(k)$ and $n(k)$, we consider the correlation coefficient of the filter output and the difference between the input signal and the filter output. Let us consider $x(k)$ and $y(k)$ as the input signal and the output signal of TF ε-filter, respectively. $x(k)$ can be described as follows:

$$x(k) = s(k) + n(k). \tag{7}$$

When the TF ε-filter can reduce the whole noise, while it preserves the signal completely, the filter output $y(k)$ equals the signal $s(k)$. The noise $n(k)$ can be described as follows:

$$\begin{aligned} n(k) &= x(k) - s(k) \\ &= x(k) - y(k). \end{aligned} \tag{8}$$

Although actual TF ε-filter does not reduce the whole noise and also reduces the signal, if ε value is set optimally, it is expected that the correlation coefficient of $y(k)$ and $x(k) - y(k)$, $R(y(k), x(k) - y(k))$ has a smaller value than $R(y(k), x(k) - y(k))$ in other ε. Hence, the optimal parameter ε_{opt} can be obtained as

$$\varepsilon_{opt} = \arg\min_{\varepsilon} R(y(k), x(k) - y(k)), \tag{9}$$

where

$$\begin{aligned} &R(y(k), x(k) - y(k)) \\ &= \frac{\sum_{k=1}^{L}(y(k) - \overline{y(k)})(x(k) - y(k) - \overline{x(k) - y(k)})}{\sqrt{\sum_{k=1}^{L}(y(k) - \overline{y(k)})^2}\sqrt{\sum_{k=1}^{L}(x(k) - y(k) - \overline{x(k) - y(k)})^2}}, \end{aligned} \tag{10}$$

where $\overline{x(k)}$ and $\overline{x(k) - y(k)}$ represent the average of $x(k)$ and $x(k) - y(k)$, respectively. $\overline{x(k)}$ and $\overline{x(k) - y(k)}$ are described as follows:

$$\overline{x(k)} = \frac{1}{L}\sum_{k=1}^{L} x(k). \tag{11}$$

$$\overline{x(k) - y(k)} = \frac{1}{L}\sum_{k=1}^{L} (x(k) - y(k)). \tag{12}$$

We test its adequateness in the following section.

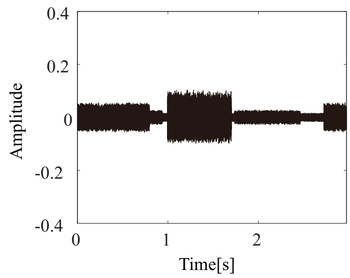


Figure 3: Waveform of the nonstationary noise.

4 EXPERIMENT

4.1 Experimental Condition

To clarify the adequateness of the proposed method, we conducted the experiments utilizing a speech signal with a noise signal. In the experiments, we calculate $R(y(k), x(k) - y(k))$ and the mean square error (MSE) between the original signal $s(k)$ and the filter output $y(k)$. MSE is defined as follows:

$$MSE = \frac{1}{L}\sum_{k=1}^{L} (s(k) - y(k))^2. \tag{13}$$

As the sound source, we used “Japanese Newspaper Article Sentences” edited by the Acoustical Society of Japan. We used the white noise with uniform distribution as the stationary noise. As nonstationary noise, we prepared white noise with the amplitude that sometimes varied as shown in Figure 3. The signal and the noise are mixed in the computer. The sampling frequency and quantization bit rate are set at 44.1kHz and 16bits, respectively. We set the window size of TF ε-filter at 61.

4.2 Relation between the MSE and the Correlation Coefficient

We prepared two noisy signals with stationary noise and nonstationary noise whose SNR are 10.0[dB]. We applied the ε-filter to the signals with changing ε value with range[0.1, 0.5].

Figures 4 and 5 show the experimental results when we use the signal with stationary noise and nonstationary noise as the input signal, respectively. As shown in Figures 4 and 5, the ε value that has the minimal value of correlation coefficient corresponds to the ε value that has the minimal value of MSE in both cases. We could obtain similar results when we utilized other signals.

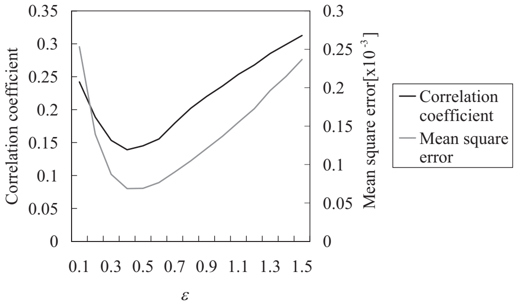


Figure 4: Experimental result when we used the signal with stationary noise.

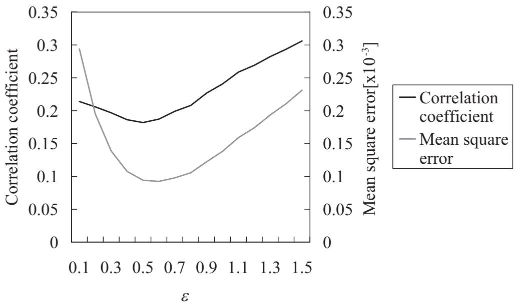


Figure 5: Experimental result when we used the signal with nonstationary noise.

5 CONCLUSIONS

In this paper, we employed correlation coefficient of the filter output and the difference between the input and the filter output as the evaluation function of the parameter setting of TF ε-filter. We also introduced an algorithm to determine the parameter of TF ε-filter automatically. The experimental results showed that we can determine the parameter of TF ε-filter adequately by utilizing our criterion. We can employ ε value which has the minimal value of correlation coefficient between $x(k)$ and $x(k) - y(k)$ when TF ε-filter is used. As the proposed method only assumes the decorrelation of the signal and noise, it is expected that the application range of the proposed method is wide. By using our method, even when we only have the single-channel noisy signal, we can evaluate whether the ε value is adequate or not. The proposed method does not require to estimate the noise in advance. For future works, we would like to evaluate the robustness for changing the window size of the TF ε-filter. We also would like to determine all parameters, that is, not only the ε value but also the window size adequately based on automatic control. Adaptive TF ε-filter, which can change its parameter adaptively depending on the input signal, will be developed in the near future.

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