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An improved EEMD model for feature extraction and classification of gunshot in public places

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Abstract

Ensemble empirical mode decomposition (EEMD) is a noise-assisted adaptive data analysis method. The key of EEMD is to add Gauss white noise into the signal to overcome mode-mixing problem caused by original empirical mode decomposition (EMD). Because the noise in public places is natural noise with alpha stable distribution, in this paper we proposes an improved EEMD by using symmetric alpha stable ($S\alpha S$) distribution instead of the Gauss distribution, and applies the improved EEMD for extracting gunshot feature. Using the improved EEMD, firstly we decompose gunshot signals into a finite number of intrinsic mode functions (IMF). Then, we use the energy ratio of each IMF components to original signal as gunshot feature for classification. The results of simulating experiment show that the improved EEMD method has good generalization abilities for the feature extraction of gunshot in public noise places.

Keywords: Feature extraction of gunshot, ensemble empirical mode decomposition (EEMD), symmetric alpha stable distribution, IMF components, energy ratio

1. Introduction

Gunshot happened in public places, such as airport, banks and square, indicates the malignant event's occurrence. The feature extraction and classification of gunshot in public places are very important for public security. Gunshot sounds are made up of different frequency components, one of which called the muzzle blast, caused by the explosion of the charge that propels the bullet, the sounds correlated with mechanical actions on the gun, between times a shock wave from supersonic projectiles, and sounds related to environmental perturbations that can be commonly arisen from impulsive sounds[1].

The methods from the territory of speech processing are adopted for extracting gunshot feature, such as mel frequency cepstrum coefficient (MFCC), linear predictive cepstral coding (LPCC)[2]. Dufaux [3] has applied these methods to impulsive sounds detection and classification. But these methods may not be suitable to realistic applications.

Empirical mode decomposition (EMD) is a novel and effective method for sound signal analysis[4-9], but the main drawback of EMD is an inescapable mode mixing phenomenon. Thus, ensemble empirical mode decomposition (EEMD)[10] is proposed to solve the problem. The crucial point of EEMD is to add random white noise into the analyzed signal. But noise in public places is natural noise, which is considered to be symmetric alpha stable ($S\alpha S$) distribution[11]. So in this paper we proposes an improved EEMD by using symmetric alpha stable ($S\alpha S$) distribution sequence, instead of the Gauss distribution, for the feature extraction of gunshot in public places.

The steps of the feature extraction of gunshot in the proposed method: firstly, we adopt the improved EEMD to decompose the gunshot signals into a finite number of intrinsic mode functions (IMF); secondly, we take the energy ratio of each IMF components to original signal as gunshot feature; thirdly, we input the gunshot feature to neural network classifier for gunshot classification.

The remainder of this paper is organized as follows. In Section 2, a brief review of improved EEMD model for the feature extraction and classification of gunshot in public places is introduced. The results of our experiments are discussed in Section 3. Conclusion is made in Section 4.

2. Improved EEMD model for the feature extraction and classification of gunshot

2.1. Symmetric alpha stable distribution

Symmetric alpha stable distribution has attracted considerable attention since it describes the non-Gaussian characteristics of signals [12].

The probability density functions of the symmetric alpha stable distribution can be expressed as follows:

$$f_a(x) = \frac{\alpha}{|1-\alpha|\pi} x^{1/(\alpha-1)} \int_0^{\pi/2} v(\theta) \exp[-x^{\alpha/(\alpha-1)} v(\theta)] d\theta, (\alpha \neq 1, x > 0) \tag{1}$$

where

$$\boldsymbol{v}(\theta) = \frac{1}{\sin(\alpha\theta)^{\alpha/(\alpha-1)}} \cos[(\alpha-1)\theta] \cos(\theta)^{1/(\alpha-1)}$$

$$f_1(x) = \frac{1}{\pi(1+x^2)} \quad \text{and} \quad f_2(x) = \frac{1}{2\sqrt{\pi}} e^{-x^2/4}$$

$$\sum_{i=1}^{N} \log[f_\alpha(z_i)] = N \log \alpha - N \log(\alpha - 1) + \sum_{i=1}^{N} (\log z_i)/(\alpha-1) + \sum_{i=1}^{N} \log \int_0^{\pi/2} v(\theta) \exp[-z_i^{\alpha/(\alpha-1)} v(\theta)] d\theta \tag{2}$$

where $\boldsymbol{z_i} = |\boldsymbol{x_i}|/\boldsymbol{c}$, $\boldsymbol{c} = \gamma^{1/\alpha}$ .For symmetric alpha stable ($S\alpha S$) distribution $\beta = 0$ .Therefore, through observing the value of $\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_N$ we use maximum likelihood method to estimate parameters α and γ .

Generate two independent random variables $\boldsymbol{V}$ and $\boldsymbol{W}$, where $\boldsymbol{V}$ is with uniform distribution in range of $(-\frac{\pi}{2}, \frac{\pi}{2})$, $\boldsymbol{W}$ is with the mean of 1 exponential distribution+.

Define the following variables:

$\varepsilon = 1 - \alpha$, $\tau = -\varepsilon \tan(\alpha\Phi_0)$, $\boldsymbol{u} = \tan(0.5\boldsymbol{V})$, $\boldsymbol{b} = \tan(0.5\varepsilon\boldsymbol{V})$, $\boldsymbol{B} = \boldsymbol{b}/(0.5\varepsilon\boldsymbol{V})$, $\boldsymbol{d} = \frac{\boldsymbol{z}^{\varepsilon/\alpha} - 1}{\varepsilon}$

$z = \frac{\cos(\varepsilon\boldsymbol{V}) - \tan(\alpha\Phi_0)\sin(\varepsilon\boldsymbol{V})}{\boldsymbol{W}\cos(\boldsymbol{V})}$. Generate symmetric alpha stable ($S\alpha S$) random variable X:

$$X = \frac{2(u-b)(1+ub) - \Phi_0 \tau B(b(1-u^2) - 2u)}{(1-u^2)(1+b^2)}(1+\varepsilon d) + \tau d \tag{3}$$

2.2. Improved ensemble empirical mode decomposition method

Because the noise in public places is considered to be with symmetric alpha stable ($S\alpha S$) distribution this paper proposes an improved EEMD by using symmetric alpha stable ($S\alpha S$) distribution instead of gauss distribution. So, the original signal is restructured:

$$x^i(t) = x(t) + \varepsilon_k X \tag{4}$$

The first order IMF is:

$$\overline{IMF}_1(t) = \frac{1}{I} \sum_{i=1}^{I} IMF_1^{\,i}(t) \tag{5}$$

At the first stage(k=1) ,calculate the first residue:

$$r_1(t) = x(t) - \overline{IMF}_1(t) \tag{6}$$

Decompose realizations $r_1(t) + \varepsilon_1 E_1[X]$; get the second order IMF is:

$$\overline{IMF}_2(t) = \frac{1}{I} \sum_{i=1}^{I} E_1\{r_1(t) + \varepsilon_1 E_1[X]\} \tag{7}$$

where $k = 2, \cdots, K$, K is the final decomposition order, k-th residue can be expressed:

$$r_k(t) = r_{k-1}(t) - \overline{IMF}_k(t) \tag{8}$$

Decompose realizations $r_{k-1}(t) + \varepsilon_{k-1} E_{k-1}[X]$; get the k-th order IMF is:

$$\overline{IMF}_k(t) = \frac{1}{I} \sum_{i=1}^{I} E_1\{r_{k-1}(t) + \varepsilon_{k-1} E_{k-1}[X]\} \tag{9}$$

So, the source signal can be expressed:

$$x^i(t) = \sum_{k=1}^{K} \overline{IMF}_k + r_k^i(t) \tag{10}$$

2.3. Feature extraction and classification of gunshot in public places based on the improved EEMD

We adopt the improved EEMD to decompose the gunshot signals into a finite number of intrinsic mode functions(IMF). We adopt Parseval theorem to find out the original signal energy (E) and the energy of various components (E_i), then we take the energy ratio of each IMF components to original signal as gunshot feature:

$$k_i = \frac{E_i}{E}, \qquad E_i = \frac{1}{N}\sum_{i=0}^{N-1} A_i^2 \tag{11}$$

where A_i is the amplitude of each IMF component, N is the length of the signal, i is the order of IMF. We normalize k_i, take them as the gunshot feature vectors, and then input them to the neural network classifier[13] for gunshot classification. The processing steps are showed as follow.

1.Decomposing original signal of improved EEMD
2.Get each order of IMF
3.Take the energy ratio of each IMF components to original signal as gunshot feature vectors $k_i = \frac{E_i}{E}$
4.Input k_i to the neural network classifier for gunshot classification

3. Experiments and analyses

We performed some experiments on the gunshot data set that contains 240 examples (from http://soundbible.com/). The number of classes is 3(pistols, rifles, machine guns). The sampling rate of each class is 44.1 KHz, and the sample length is 60-120s;The parameter ε_1 is about 0.2 and the iteration times is 1000; The parameter α is 1.8, the parameter γ is 1.0. C_i ($i = 1, \cdots, 9$) is the order of IMF and R is residue as shown in Figure 1. The decomposing results of improved EEMD are shown in Figure 2.Table 1 shows the comparing results of classification by using MFCC, LPCC, EMD, EEMD and our method for feature extraction under no noise environment. In the experiments, 20-40 training samples per class are randomly selected from 80 training set, and the rest of per class is test set. The noise data set (recorded by us) contains the noises of 3 different environments (including roadside, train station and square with dense crowds of people) and white noise. Table 2-5 show the comparing results of classification by using MFCC, LPCC, EMD, EEMD and our method for feature extraction under real noise environment separately. In the experiments, 40 training samples per class are randomly selected from 80 training set, and the rest of per class is test set.

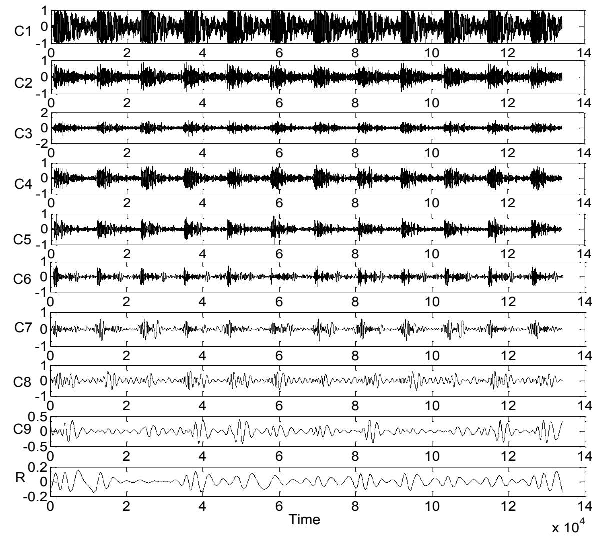

Figure 1 Decomposing results of Improved EEMD

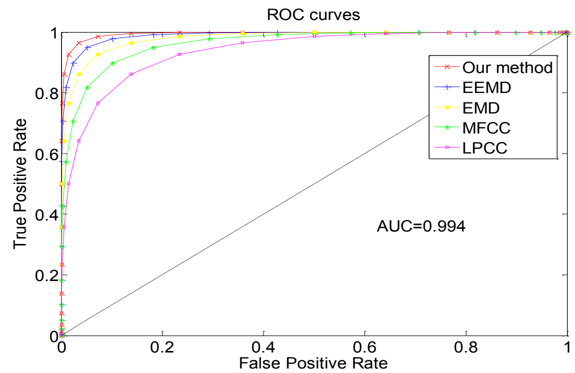

Figure 2 Receiver operating characteristic curves results of five methods

Table 1 Comparing results of gunshot classification under no noise environment (%)

Method	Number of training samples		
	40	30	20
MFCC	62.41 ± 3.54	60.97 ± 4.31	59.73 ± 3.95
LPCC	72.33 ± 4.24	71.22 ± 5.10	70.57 ± 4.65
EMD	85.93 ± 2.77	84.39 ± 3.00	83.25 ± 3.17
EEMD	87.31 ± 3.98	86.74 ± 4.22	85.33 ± 4.57
Our method	93.33 ± 2.63	92.18 ± 2.95	91.65 ± 3.03

Table 2 Comparing results of gunshot classify-cation under white noise environment (%)

Method	Different SNR conditions		
	30db	25db	20db
MFCC	61.67 ± 3.11	60.52 ± 4.56	58.48 ± 4.22
LPCC	71.67 ± 6.01	70.56 ± 5.72	69.81 ± 5.03
EMD	85.26 ± 4.24	82.96 ± 2.97	80.53 ± 4.37
EEMD	85.96 ± 3.44	82.66 ± 3.05	81.69 ± 3.53
Our method	89.23 ± 3.45	88.89 ± 2.88	83.33 ± 4.57

Table 3 Comparing results of gunshot classification under square with dense crowds of people noise environment (%)

Method	Different SNR conditions		
	30db	25db	20db
MFCC	60.27 ± 6.37	57.52 ± 5.71	54.48 ± 5. 17
LPCC	70.34 ± 5.51	68.33 ± 3.53	65.29 ± 4.62
EMD	83.22 ± 3.09	81.48 ± 2.42	80.18 ± 4.27
EEMD	84.44 ± 2.32	81.77 ± 3.05	80.45 ± 4.79
Our method	88.77 ± 2.05	86.18 ± 3.65	81.85 ± 4.16

Table 4 Comparing results of gunshot classification under roadside noise environment (%)

Method	Different SNR conditions		
	30db	25db	20db
MFCC	60.67 ± 5.62	58.35 ± 4.97	56.21 ± 5.35
LPCC	70.19 ± 5.31	69.34 ± 5.17	68.82 ± 4.29
EMD	85.14 ± 4.17	84.22 ± 3.87	81.57 ± 3.59
EEMD	86.92 ± 3.19	85.71 ± 4.19	82.62 ± 3.75
Our method	89.23 ± 2.53	88.57 ± 3.05	83.19 ± 3.13

Table 5 Comparing results of gunshot classification under train station noise environment (%)

Method	Different SNR conditions		
	30db	25db	20db
MFCC	59.35 ± 7.28	56.82 ± 6.39	53.34 ± 5.83
LPCC	69.73 ± 5.71	65.07 ± 6.27	64.21 ± 4.53
EMD	81.67 ± 5.01	80.63 ± 5.32	79.07 ± 4.89
EEMD	82.96 ± 4.98	81.22 ± 4.45	80.18 ± 4.12
Our method	85.92 ± 2.37	84.62 ± 3.62	84.07 ± 3.57

Figure 2 shows the Receiver operating characteristic curves (ROC) of MFCC, LPCC, EMD, EEMD and our method. The more the ROC curves close to the top left corner, the better the performance will be, and the area under curve (AUC) of our method is 0.994.Tables 1 shows the increasing of the training samples can improve classification accuracy and our method improves 5.98~30.92% higher than other methods. Tables 2-5 indicate the increasing of SNR also can improve classification accuracy and our method improves 2.96~30.73% higher than other methods in real noise environment.

4. Conclusion

This paper proposed an improved EEMD method by using the symmetric alpha stable ($S\alpha S$) distribution instead of gauss distribution. We also presented using the energy ratio of each IMF components to original signal as gunshot features for classification in public places. Verified experiments have indicated our method outperforms others such as MFCC, LPCC, EMD and EEMD.

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