Applied Acoustics 113 (2016) 116–120

Contents lists available at ScienceDirect

Applied Acoustics

journal homepage: www.elsevier.com/locate/apacoust

Infrasound signal classification based on spectral entropy and support vector machine

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ARTICLE INFO

Article history:
Received 21 September 2015
Received in revised form 11 January 2016
Accepted 21 June 2016
Available online 29 June 2016

Keywords:
Feature extraction
Spectral entropy
Infrasound signal
Support vector machines
Pattern recognition

ABSTRACT

The operation speed of the algorithm is the critical factor in the real-time monitoring of infrasound signals. The existing methods mainly focus on how to improve the accuracy of classification and can't be used in real time monitoring because of their slow running speed. We adopt spectral entropy into the feature extraction of infrasound signals. Combined with the support vector machine algorithm, the proposed method effectively extracted the signal features meanwhile greatly improved the operation efficiency. Experimental results show that the running speed of the proposed method is 1.0 s, which is far less than 4.7 s of the comparison method. So the proposed method can be applied in real-time monitoring of earthquakes, tsunamis, landslides and other infrasound events.

1. Introduction

Many natural phenomena and human activities such as earthquakes, volcanic eruptions, tsunamis, landslides, explosions, lightning, and rocket launching bring about infrasound signals. The frequency of infrasound signals typically ranges from 0.01 Hz to 20 Hz which is lower than that of audible sounds. Infrasound signals attenuate slowly and can propagate hundreds of kilometers. So infrasound signal detecting is very useful in disaster warning system, such as the Comprehensive Nuclear-Test-Ban Treaty (CTBT) International Monitoring System (IMS). Therefore characteristic extraction and recognition of infrasound signal are very important for disaster monitoring.

A great amount of theoretical research and engineering applications have been focused on both the detection and identification of the different characteristics of infrasound sources. An exploratory study of feature extraction, launched by Liszka and Holmstrom [1], performed a scale spectrum of continuous wavelet transform on infrasound signals. Schmitter formed a feature vector by combining the energy of wavelet decomposition at different scales with kurtosis and skewness of time series signal [2]. Ham et al. proposed a set of feature vectors by use of Mel-frequency scale cepstral coefficients and their associated derivatives for each infrasound signal which was effective to classify the infrasound signals of volcanic eruptions and avalanches [3–6]. In an effort to classify time series type of infrasound signals, Chilo proposed a method for filtering and extracting features from infrasound data and compared three feature extraction techniques [7,8]. In the research of Liszka, the spectral entropy was used for extracting the feature of infrasonic data. The research proved that the spectral entropy feature is one of the useful distribution parameters of relevant variables [9].

On the basis of previous research results, Liu et al. presented a new classification method based on Hilbert–Huang transform (HHT) and a support vector machine (SVM) [10]. This method was used to discriminate between three different natural events and was shown to successfully improve the classification accuracy. However, these feature extraction methods are complex, due to the complexity of the algorithm and long running time, it was difficult to implement using the FPGA and other hardware. These methods are not suitable for real-time monitoring and analysis of infrasound signals.

In the classification theory of SVM, the support vectors of different categories of data are most similar. Therefore, the entropy of the support vectors is the largest by comparison since the entropy is greater as the information is more confusing. The best classification interface on the feature vectors extracted by information entropy can therefore be found by SVM algorithm. The SVM algorithm was used for the detection of infrasound signals from snow avalanche and volcanic activity, which achieved a significant reduction of false detections [11,12].

An attempt to combine the spectral entropy theory with the SVM algorithm was undertaken in the field of face recognition by Ye et al. [13]. In the medical field, Mehta et al. and Rud et al.

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http://dx.doi.org/10.1016/j.apacoust.2016.06.019
0003-682X/

applied an entropy-based algorithm for the detection of low frequency heart murmur using support vector machine [14,15]. The numerical results indicated that the algorithm achieved a good detection rate. The combination of approximate entropy and support vector machines showed strong generalization ability for the electroencephalogram signal classification [16,17].

In this study, we proposed a feature extraction method based on information entropy and then applied it to infrasound signal classification. We then compared the proposed method with Liu's method [10] on the effect of classification and the complexity of algorithm. The results indicate that, in comparison to other methods, the proposed method is a little bit less accurate; however, the operating speed of the classification algorithm is greatly improved. This makes the proposed method to be a feasible method for real-time monitoring and analysis of infrasound signals.

2. Materials and methods

In this study, a classification framework combining information spectrum entropy [18,19] with SVM method [20,21] is proposed to extract effective feature vectors of infrasound signals generated by earthquakes, tsunamis and volcanic events, followed by infrasound signal classification. The integrated classification framework proposed in this study is also shown in Fig. 1.

2.1. Feature extraction based on information entropy

Entropy was first introduced into the information theory by Claude Elwood Shannon and defined as the uncertainty of a discrete random variable. Information entropy is a quantitative assessment indicator for the uncertainty of a signal or system status. It is a better reflection of the inherent information of a system and can be used to extract the characteristics of a signal [22]. On the basis of information entropy, the research of feature extraction on three types of infrasound events was performed. The information entropy features were extracted in different transform space. These extracted feature vectors can be used for infrasound signal classification.

2.1.1. Wavelet Singular Spectrum Entropy (WSE)

The information measure of WSE is a type of feature extraction method that integrates the singular value decomposition of the wavelet transform with feature extraction based on entropy. WSE has the capability to reflect the uncertainty of the infrasound signal energy distribution in the time–frequency domain. Wavelet Singular Spectrum Entropy is defined by the following formula (1):

$$Wse = -\sum_{i=1}^{K} p_i \times \ln p_i \tag{1}$$

where W_{se} represents the extracted wavelet singular spectrum entropy. $p_i = \frac{\lambda_i}{\sum_{i=1}^{K}\lambda_i}$, represents a proportion of the *i-th* singular value in the singular value spectrum. λ_i represents the *i-th* singular value and K represents the number of effective singular characteristic values that are used to calculate the wavelet singular entropy.

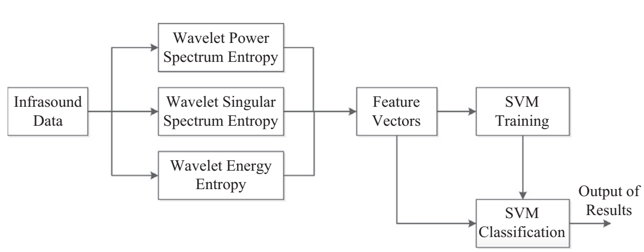

Fig. 1. Classification model framework proposed in this paper.

2.1.2. Wavelet Power Spectrum Entropy (WPE)

The distribution of the infrasound signal energy in the frequency domain is reflected in the power spectral entropy [10]. This indicates that the power spectral entropy is effective to extract the features from each type of infrasound signal.

Suppose $x(t)$ is the original signal and the signal power spectrum $S(\omega)$ can be expressed as follows:

$$S(\omega) = \frac{1}{2\pi N}|X(\omega)|^2 \tag{2}$$

In Eq. (2), $X(\omega)$ represents the discrete Fourier transform of the original signal $x(t)$, N is the points number of Fourier transform.

S_i represents the *i-th* value of power spectrum. $S = \{S_1, S_2, \ldots, S_K\}$ can be seen as a type of split on the original signal power division [23]. In the frequency domain the power spectral entropy is defined as:

$$Wpe = -\sum_{i=1}^{K} p_i \ln p_i \tag{3}$$

In Eq. (3), $p_i = \frac{S_i}{\sum_{i=1}^{K} S_i}$, it represents a proportion of the *i-th* power value in the whole power spectrum, K represents the number of power value.

2.1.3. Wavelet Energy Spectrum Entropy (WEE)

The time domain and the frequency domain represent two different dimensions of a signal. In order to obtain the whole information, we use the feature indicator WEE, in a joint time–frequency domain, to analyze the signals. WEE can reflect the uncertainty of the feature distribution of the signals in the time–frequency domain.

A wavelet transform on the signal of finite energy is performed in order to obtain wavelet energy spectrum E, then the wavelet energy entropy can be calculated using the following Eq. (4):

$$Wee = -\sum_{i=1}^{K} p_i \ln p_i \tag{4}$$

In the above Eq. (4), $p_i = \frac{E_i}{\sum_{i=1}^{K} E_i}$ represents a proportion of the energy of the *i-th* scale in the energy of all scales, K represents the decomposition number of scale.

2.2. Infrasound signal classification based on support vector machine

Support vector machine has many unique advantages for the classification and regression prediction in solving small sample, nonlinear and high dimension problems [24,25]. Due to the small amount of simulation data and high dimension of feature vectors, we chose SVM as a classifier.

The support vector machine constructs a hyperplane in a high- or infinite-dimensional space, which can be used for classification.

$$f(x) = \mathbf{w} \cdot \mathbf{x} + b. \tag{5}$$

where $\mathbf{x}$ is the training data, $\mathbf{w}$ is the normal vector of the hyperplane, and b is the offset.

The problem of maximizing the distance of data points of two classes can be expressed as a quadratic programming optimization problem. The method introduces non-negative slack variables, ξ_i, which measure the degree of misclassification of the data $\mathbf{x}_i$, $i = 1, 2, \ldots, N$, where N is the number of training data. The objective function is then increased by a function which penalizes non-zero