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Infrasound signal classification based on combining spectral and sound features

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Abstract

The speed and accuracy of data classification are essential factors in the online monitoring of infrasound waves. The available techniques for classifying these data are relatively high accuracy but not high-speed online. In this paper, using the combination of sound and spectral features, the speed of runtime and accuracy of classification have been improved. This method uses spectral entropy, a spectral feature, and the Linear Predictive Coding (LPC) sound features. The proposed approach classifies the infrasound waves generated from the three classes of the rocket launcher, volcano, and shuttle re-entry with a precision of 97% and a runtime of 1.0 seconds that are accurate to the existing methods. The obtained results show that this method has better speed and accuracy rather than existing methods.

Keywords: Infrasound, feature extraction, spectral features, sound features, wavelet transform, spectral entropy.

I. INTRODUCTION

The term "infrasound" refers to sound waves below the frequencies of the threshold of hearing (TOH). These waves, also known as low-frequency sounds, have a frequency of less than 20Hz. Because of their very long wavelengths and their deficient absorption and damping coefficients can be emitted into the atmosphere due to their long distances. The frequency of infrasound signals typically ranges from 0.01 Hz to 20 Hz, which is lower than audible sounds. Infrasound signals attenuate slowly and can propagate hundreds of kilometres. So infrasound signal detection is beneficial in disaster warning systems, such as the Comprehensive Nuclear-Test-Ban Treaty (CTBT) International Monitoring System (IMS).

Therefore feature extraction and recognition of infrasound signals are essential for disaster monitoring. The greater the frequency, the more pronounced this is in the area where frequencies are waves. Approximately 0.01 Hz can be taken several times by the Earth [1]. The processing of infrasound waves is essential due to their long-distance propagation. These data are used in critical applications such as earthquakes, rocket launcher detecting infrasound, etc. But, the different types of noise on these waves cause detection and classification of these signals to become a challenging task. In this paper, we study other proposed methods, then an algorithm for better classification is presented based on spectral and acoustic features. In this method, we use two steps of wavelet transformation and smoothing filtering, which increase the rate of detection of the infrasound events. After infrasound event detection, the spectral and acoustic features have been extracted. Spectral entropy and Linear Predictive Coding (LPC), spectral and acoustic features, respectively, are used here. Spectral features represent the power density of a spectrum of a signal and can extract the linear properties of a signal. Linear acoustic features are high-speed linear prediction coefficients that extract the acoustic features of the infrasound data. Finally, a supervised method is performed to classify these waves. We then compared the proposed method with other state-of-art methods regarding classification accuracy and the algorithm’s complexity.

The paper has been organised as follows; a literature review is collected in section 2. The algorithms are explained in section 3 with the experimental results, and then section 4 concludes the paper with a discussion of future works.

The International Monitoring System (IMS) development has led to more attention in infrasound signals to inspect atomic organisations. In addition, in recent years, with the installation of low-frequency sensors in seismic centres, large and heterogeneous data sets have been provided to researchers in real-time. The processing of this massive amount of data and the need to examine it in real-time requires methods for extracting significant higher-speed properties used for various applications. The randomness of the infrasound signal is one reason that reduces the efficiency in classifying the infrasound signal. Therefore, it is necessary to define the main features of the signal. The classifier can also classify high-performance input data according to the main features described.

A lot of research has been done to detect infrasound signals. In 2005, Ham and colleagues proposed a bank of radial base neural networks to identify six human events [2]. For this method, Cepstral Coefficients were used to extract the features. They improved their way by a bank of parallel neurons with the same feature vector [3].

In [4], a classification method based on the Hilbert Huang Transform (HHT) and support vector machine are presented, divided into three natural events. The features of the infrasound frequency spectrum are signals generated by various events, such as volcanoes, that are unique, which

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provides a field for the classification of the infrasound signal. First, the HHT method extracts feature vectors from different types of infrasound events from the Hilbert Boundary Spectral. Then, feature vectors were classified by the SVM method.

The authors of the paper [5], using the spectral entropy method and the supporting vector machine, were able to increase the speed of operation of the infrasound data classification algorithm in general and reduce the processing time by a second, but their classification accuracy was low. This makes the proposed method suitable for real-time monitoring and analysis of infrasound signals. This method extracts the spectral features of the subwoofer according to the three features of the wavelet domain (Fig. 1):

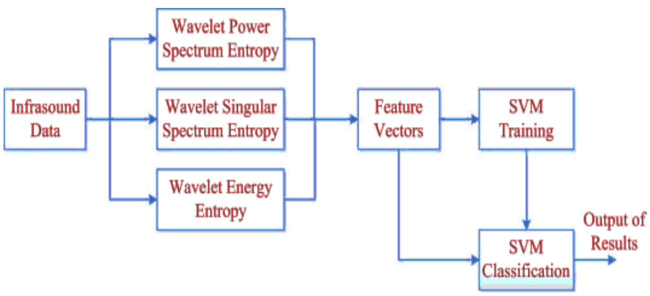


Fig. 1. The general schema of the method of extracting the character and classification of the article [5]

In an article published in 2011 [6], to identify the presence of the elephants, linear prediction coefficients were used to extract the infrasound features of the elephants and then the Hidden Markov Model for data classification. In this paper, one of the features of the extraction method is based on the formants analysis using the correlation method as an alternative method for using the signal spectrum. Then a hidden Markov model is then used to automatically detect the presence of an elephant, according to a record of the acoustic signal.

The main issue here is how subnets can be distinguished from different sources by combining spectral features with high-precision high-noise environments while retaining the real-time nature of the algorithm.

II. Proposed Method

In this paper, by combining the entropy spectrum of the signal spectrum and linear prediction coefficients, in addition to the features of the infrasound signal spectrum, extraction of its sound Features is obtained, and then by classifying methods such as K-NN and SVM are three space shuttle events, rockets and volcanoes. The general block diagram of the proposed method is shown in Fig. 2. The spectral and acoustic properties used are described below[7,8].

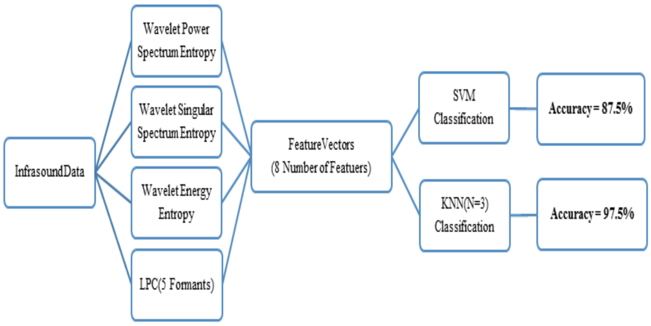


Fig. 2. Block diagram of the proposed method in this article

A. *Extraction of spectral properties using the spectral entropy method*

Information entropy is a quantitative evaluation index for signal uncertainty or system status. This variable provides a better reflection of the intrinsic information of a system and can be used to extract the features of a signal [9]. According to entropy information, research on the extraction of the feature was done in three types of infrasound events. The entropy features of the information are transformed into different spaces. These extracted property vectors can be used to classify the infrasound signal. The spectral properties used in this study are referenced from [5]

A.1. Wavelet Singular Spectrum Entropy (WSE):

WSE data measurement is an extraction method that obtains special values of entropy wavelet waveform signal transformation matrices. The WSE reflects the uncertainty of the energy distribution of the infrasound signal in the time domain-frequency defined by Equation 1, the entropy of the wavelet of the special value spectrum:

$$WSE = -\sum_{i=1}^{k} p_i \times \ln p_i \qquad (1)$$

WSE entropy extracts special values of the wavelet transform of the waveform spectrum of the sub-sound signal. $.\ p_j = \frac{\lambda_j}{\sum_{j=1}^{k} \lambda_j}$ represents the normalised values of the wavelet transform matrix from a frame of the sub-sound signal spectrum. λ_j is an exceptional value of the wavelet transformation matrix. k is the number of special values of the wavelet transformation matrix.

A.2. Wavelet Power Spectrum Entropy (WPE):

This property indicates the energy distribution of the infrasonic signal in the frequency domain, representing the power spectrum's entropy m. Power spectrum entropy is effective for classifying types of infrasonic signals. In the following relation, X (t) is equivalent to the main signal and S (ω) represents the signal of the power spectrum in the frequency domain:

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

In this respect X (ω) represents the fast discrete Fourier transform. N is the number of Fourier transform points. The entropy of the power spectrum is also according to Equation (3):

S_j represents the j-th power of the spectrum. The power entropy of the subsonic signal spectrum is obtained according to the following equation:

$$WPE = -\sum_{i=1}^{k} p_i \times \ln p_i \qquad (3)$$

In this relation, $p_j = \frac{S_j}{\sum_{j=1}^{k} S_j}$ which indicates the power of the normalized spectrum of each wavelet transform component. k is the number of powers of the signal spectrum.

A.3. Wavelet Energy Spectrum Entropy (WEE):

The time and frequency domains represent two different dimensions of the signal. In this way, to obtain all the signal information, we use the WEE property index, which is a combination of the frequency-time domain, to analyse the signal. WEE can reflect the uncertainty of the distribution of signal properties in the time-frequency domain. We perform the wavelet transform on the final signal energy to obtain the wavelet energy spectrum, and then the entropy of the wavelet energy can be calculated using the following equation:

$$WEE = -\sum_{i=1}^{k} p_i \times \ln p_i \quad (4)$$

In this relation, $p_j = \frac{E_j}{\sum_{j=1}^{k} E_j}$ represents energy at any scale of wavelet transform. k is the number of wavelet transform scales. The images in Figure 3 are spectral features extracted in this method:

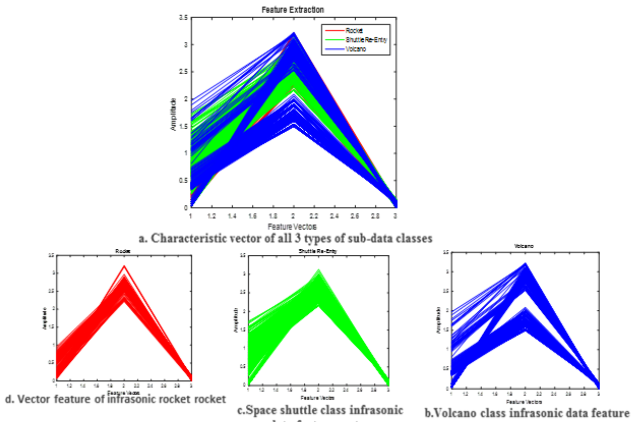


Fig. 3. Feature vector extracted from spectral entropy method (spectral characteristics of subsonic signal)

B. Audio Attribute Extraction: Linear Projection Coefficients (LPC):

The LPC is a method for encoding a low bit rate audio signal. Signal derivatives are the focal point of this method. The main purpose is to express each sample of a signal as a mixture of its past. The LPC designs a full-pole filter model that is a variable-time filtered conversion function in the form of (5):

$$H(z) = \frac{G}{1-\sum_{k=1}^{p} a_k z^{-k}} \quad (5)$$

Where G is the filter value, a_k is the LPC coefficients and p is the filter order. The steps for calculating the LPC coefficients are shown in Fig. 4.

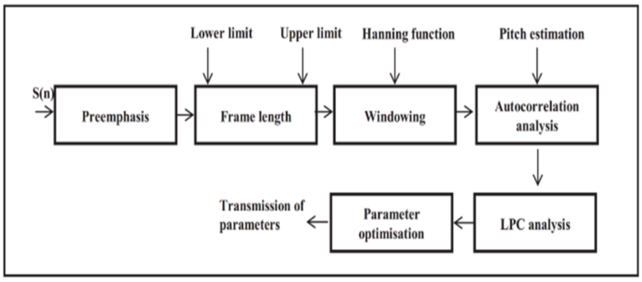
Fig. 4. Block diagram of the steps for calculating LPC coefficients

In LPC conversion, the signal is excited and reconstructed, assuming that $P(z) = \sum_{k=1}^{p} a_k z^{-k}$ ، $A(z) = 1 - P(z)$ and $H(z) = \frac{1}{A(z)}$ are calculated from the sound as follows [10]:

$$E(z) = X(z)A(z) \quad (6)$$

$$\tilde{X}(z) = \tilde{E}(z)H(z) \quad (7)$$

In LPC-based noise cancellation, the processing is usually



performed on the exciting signal, and then the signal is reconstructed. LPCs are the basic formants of an audio signal. The images in Figure 5 are the extracted elements (audio features):

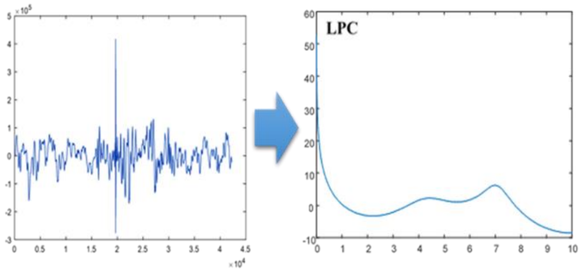


Fig. 5. An example of applying an LPC algorithm to an infrasonic signal

In the figure above, the peaks on the left are the formants of the audio signal. The following is a figure 6 showing the feature vectors extracted for the three classes of the LPC method.

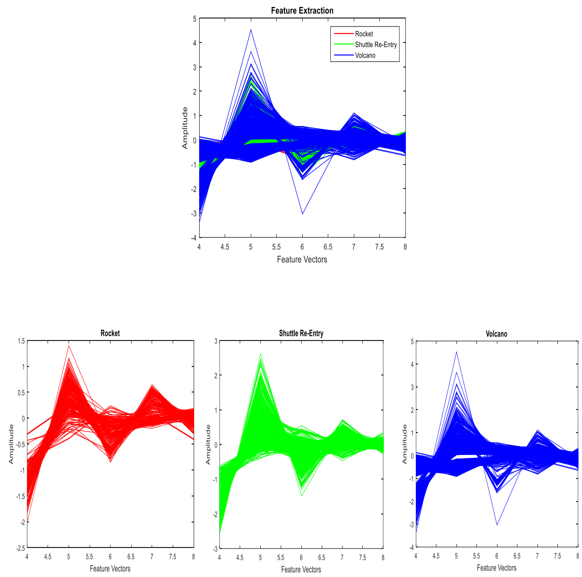


Fig. 6. Attribute vector extracted for three classes of LPC method (Audio characteristics of the sub-sound signal)

In Fig. 7, all spectral and audio characteristics are presented after applying the proposed feature extraction algorithms.

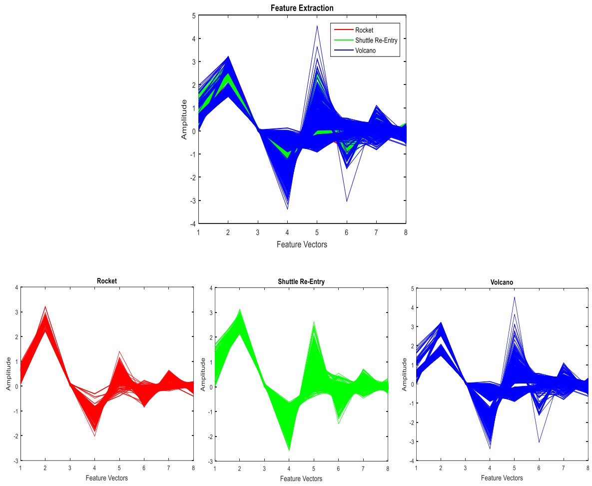


Fig. 7. Extracted property vector for three classes of a combination of two methods of LPC and entropy of the spectrum (spectral and sound characteristics of the sub-sound signal)

C. *Classification Of Data*

C.1. Classification method k The nearest neighbour (KNN):

K is the nearest neighbour of a learning-monitoring algorithm. In general, this algorithm is used in two ways: to estimate the density function of the distribution of training data and to categorise test data based on training patterns.

In the definition of the law, the closest neighbor k is considered to be equal to one. We assume that $\boldsymbol{D^n} = \{\boldsymbol{x_1}, \dots, \boldsymbol{x_n}\}$ is the set of n input patterns and $\boldsymbol{x'} \in \boldsymbol{D^n}$ is the closest input pattern to the test neighbours The nearest neighbours law classifies it in a class similar to the class $\boldsymbol{x'}$. The law of the nearest neighbour is a sub-optimal procedure, the error rate of which is usually greater than the minimum possible error rate, the error rate of the binary algorithm. But it is proved that if an unlimited number of input patterns are used, the error rate in the worst case will not exceed twice the algorithm'. The law k is the closest neighbour of the extension of the law of the nearest neighbour, and as it is clear, this rule classifies x in a category that has the most frequent occurrence in k between k's nearest neighbours [11].

D. *Support Vector Machine (SVM)*

The SVM, first introduced by Corinna Cortes and Vapnik in 1995 [12], has a significant advantage in classifying and predicting regression in solving small, nonlinear, and large-scale problems [13, 14]. The support vector machine supports relatively simple training and, unlike neural networks, does not get trapped at the maximum local level.[15]

SVM is a binary separator. Multi-class pattern recognition can be achieved by combining two-class subsample vector machines. Normally there are two views for this purpose. One is the one-on-one strategy for classifying each pair of classes and classes left. Another strategy is "one vs one" to classify each pair. When the first category leads to ambiguous classification. For multi-class issues, the general approach to reducing the multi-class problem is to several binary issues. Each issue is solved with a binary separator. Then the output of the SVM binary separators is combined and thus the problem of several classes is solved.[16,17]

III. Results of Simulations and Experiments

A. *Collecting databases and preparing them for training and testing data*

Infrasound data is collected by sensors sensitive to frequencies from 0.01 to 20 Hz. The data used in this research is data provided by the Research Institute of the Worldwide Undergraduate Archives of Canada from 1996 to 2003 in Ottawa, Canada. [18] These data are used to predict the earthquake, track down the space shuttle, know about volcanic activity from a distance of several hundred kilometres, and so on. The data includes the sub-sound data of different months from 1995 to 2003 and is provided to users. These data have a variety of sources of sub-audio data such as:

- Bolide
- Earthquake
- Explosion
- Rocket
- Shuttle Re-Entry
- Volcano

Figure.8 shows an example of the Rocket Infrared Data recorded in 1999. Table.1 also offers information on the station names, the number of samples received, and the sampling frequencies for these data.

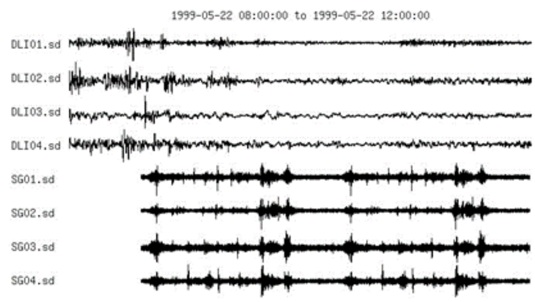


Fig. 8. Rocket Infrasonic Data

The project uses Rocket, Shuttle Re-Entry and Volcano data for the following reasons:

• a Large number of samples in this data for training

• Use most of the available articles to simulate and compare results from this data.

TABLE 1. Number of samples from each sub-audio data class

Sampling frequency (Hz)	Number and name of events	Station name and number of samples received at each station
20 18 20 20 40	Volcano (234)	BORG(9) IRF(6) IS26(200) ESLA(6) DIA(13)
10 20	Rocket (36)	DLIAR(16) SGAR(16)
40 20 20	Shuttle Re-Entry (738)	TXI(428) LS(141) SG(169)

When the raw data was prepared, then the files, because they had different times (which was almost every file for at least 60 seconds and a maximum of 1 hour), first extracted the sub-audio data by the detector algorithm. Then, in 2-second frames, With a 1-second overlap, the extraction property is separated.

We apply the detection algorithm first to raw data because, as shown in Fig. 5, it may be silent at the beginning or end of the file. There is no sub-audio signal, or it is only a noise algorithm. Extremely accurate subliminal data extraction. In this project, 70% of the features are for training, and 30% of the features are for testing.

B. Preprocessing

High noise and long-range are the most critical features of this signal. One of the challenges is the high noise in the infrared data, which challenges the extraction of the correct feature of the original signal data. Because subliminal waves, like sound waves, have acoustic properties and are mechanical waveforms, they are affected by climate change, which causes the level of noise in the environment. For example, the height of the sensor, temperature, humidity, wind, seasons, night and day acts as a noise in the acoustic environment.

In this paper, in the preprocessing stage, the intermediate passage barterture filter was used, and the frequencies between 0.01 to 10 Hz were filtered and separated. Then the detection algorithm is used to detect sub-sound data from background noise.

C. Simulator and experiment results

After the data were prepared using the algorithm of the three closest neighbours to the three space shuttle classes, the rocket and volcano rocket resulted in the following results:

Below is a Table of Confidence that shows rocket data from 69 samples correctly detecting 62 specimens and detecting seven false space shuttles, seven of the space shuttle data the rocket detected a mistake, and the 231 space shuttle data, 224 were correctly identified.

TABLE 2. Results after running the simulator

Classification accuracy (in per cent)	Classification method	Feature extraction methods
89.8576	KNN, K = 2	**Proposed Method(LPC + Spectral Entropy)**
87.5468	KNN, K = 2	**Spectral Entropy**
88.5712	KNN, K = 2	**LPC**
97.5779	KNN, K = 3	**Proposed Method(LPC + Spectral Entropy)**
90.3702	KNN, K = 3	**Spectral Entropy**
95.1557	KNN, K = 3	**LPC**
96.8564	KNN, K = 4	**Proposed Method(LPC + Spectral Entropy)**
80.5621	KNN, K = 4	**Spectral Entropy**
91.6997	KNN, K = 4	**LPC**
90.8547	SVM	**Proposed Method(LPC + Spectral Entropy)**
86.4706	SVM	**Spectral Entropy**
60.3564	SVM	**LPC**

TABLE 3. Confidence table

Volcano	Shuttle Re-Entry	Rocket	Class
0/69 = 0	7/69 = 0.10	62/69 = 0.89	Rocket
0/231 = 0	224/231 = 0.96	7/231 = 0.03	Shuttle Re-Entry
278/278 = 1	0/278 = 0	0/278 = 0	Volcano

IV. CONCLUSION AND FUTURE WORK

In this research, a method is proposed for classifying sub-sound data using spectral and audio properties to have high speed and accuracy. To do this, preprocessing was performed on sub-audio data to highlight these features. Then the spectral properties of the violent domain, including the entropy of the special values of the wavelet transformation matrix, the energy entropy of the wavelet transform, and the entropy of the signal strength of the wavelet transform plus the sound characteristics, including the linear prediction coefficients, were extracted, which ultimately yielded a grading accuracy of over 97%.

Future work can be better for noise reduction Hilbert-Huang transformation algorithms, Wien filter, Wolf-Gaddel filter, etc. In the block for better categorisation of the Viterbi and Hidden Markov algorithms. Which uses (non-stationary signals such as sub-audio and voice signals to detect better).

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