Research on the Recognition of Infrasound Signal of Nuclear Explosion by SVM and CNN

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Abstract. Infrasound monitoring is a nuclear test monitoring technology of the CTBTO’s international monitoring system. In order to improve the accuracy rate of atmospheric infrasound signal recognition, the recognition effectiveness of convolutional neural network (CNN) and support vector machine (SVM) are studied. According to the features of nuclear explosion infrasound, the related features are extracted from other types of signals. SVM model and CNN model are used in the experiment, and a method is designed to improve the recognition efficiency. It converts infrasound signals into images, and then uses CNN to recognize them, and the learning process is improved by combining with GAN. Compared with SVM method based on artificial design features, the experimental results show that in the case of small training data set, CNN with improved learning process can dig out the potential features of signals, and has the same recognition ability as SVM. But the recognition ability of nuclear explosion and chemical explosion is slightly better than that of SVM.

1. Introduction

Nuclear weapons have great power. Nuclear explosion will not only directly kill people, but also have a disastrous impact on the ecological environment. The radiation pollution produced will also affect public health for a long time. However, the global nuclear power report 2020(SIPRI 2020 Yearbook) released by the Stockholm International Peace Research Institute(SIPRI) on June 15, 2020 shows that, although the number of nuclear warheads in the world is generally reduced in 2019, all countries with nuclear weapons continue to modernize their nuclear arsenals[1].

In order to limit the development of nuclear weapons and monitor nuclear tests, CTBTO has established an international monitoring system worldwide, and infrasound monitoring is one of the monitoring means[2]. However, there are many kinds of infrasound signals in nature. How to analyze and identify these signals in real time is a problem to be solved in infrasound monitoring, which needs effective technical methods to support. The rapid development of machine learning and its increasing performance provide another way to solve this problem[3].

In this paper, firstly, the characteristics of infrasound of nuclear explosion are analyzed, and the SVM and CNN in machine learning are studied. Then, the infrasound signals of nuclear explosion, chemical explosion, lightning and typhoon are extracted according to these features, and the multi classification SVM and CNN are constructed for recognition experiments. Finally, the learning process is improved and good performance is obtained.
2. Analysis of nuclear explosion infrasound characteristics

At the moment of nuclear explosion in the atmosphere, the energy produced by nuclear explosion is limited in a small volume with extremely high temperature and pressure. In less than 1μs, this high-temperature gas produces a large number of soft X-rays, which are absorbed by the surrounding air within 1 m, causing them to expand rapidly. In about 1 ms, a hot, extremely high-temperature incandescent fireball with a diameter of more than 100m is produced. The fireball continued to expand at supersonic speed and rose slowly at the speed of about 100m/s. Then, the nearly spherical rising fireball becomes a mushroom cloud with a central updraft. The fireball continues to rise and cool in the atmosphere until the gravity of the radioactive cloud equals its buoyancy in the atmosphere[4].

A strong shock wave is generated in less than 1s during the nuclear explosion, and the fireball expands at supersonic speed in the initial few seconds, and the overpressure on the front of the shock wave is 2~3 times higher than that in the fireball. After 50s, the shock wave can propagate to about 20km away from the explosion center[5]. After the shock wave generated by atmospheric nuclear explosion is slowly attenuated into sound wave, dispersion phenomenon will occur. The propagation speed of secondary component is fast and the attenuation is slow, and the propagation speed of high frequency component is slow and the attenuation is fast. Due to the geometric diffusion and high-frequency components being absorbed by the atmosphere, they gradually evolve into infrasound signals[6]. Because the high frequency signal decays faster than the secondary signal, the long period infrasound wave is the main signal observed far away from the source. In addition, the time of arrival of the thermoelastic waves is different from that of a series of acoustic waves which arrive in the stratosphere at about 100km.

**Figure 1** is the infrasound signals of the Soviet Union's nuclear test. The time-frequency diagrams obtained by short-time Fourier transform are shown in **Figure 2**.

According to the observation and research on infrasound of nuclear explosion at home and abroad, its characteristics mainly include the following aspects:

1) The frequency of the signal is about 0.002Hz to 20 Hz, and for small equivalent (several KT) nuclear explosions, the frequency is about 0.02Hz to 4Hz.

2) The signal period is about 0.01s to 100s.

3) Because of one or more reflections in stratosphere and thermoionosphere, the reduction of high frequency signal is faster than that of low frequency signal, the final signal is composed of several layered acoustic components, and obvious dispersion phenomenon appears.

4) The waveform changes in a "compressed" manner.

These features are the basis of signal recognition. Through the establishment of the corresponding mathematical model of these features, the characteristic value of the signal is calculated, and then machine learning is carried out to achieve the purpose of identifying events.
3. Preparation of experimental data

In this paper, InSAS2008 capacitive infrasound sensor is used to build experimental stations in Hainan, Xichang, Baicheng and other places. The experimental station consists of infrasound monitoring array, data processing center and communication equipment. Among them, the infrasound monitoring array is a 3-element array, and each infrasound sensor is equipped with a noise reduction tube array; the data information processing center is responsible for the data receiving and processing of each array element. The structure of the experimental station is shown in Figure 3. A total of 600 sample data were collected, including 16 chemical explosion data, 36 typhoon data, 248 lightning data and 300 noise data. In addition, 20 samples of nuclear explosion are added to be 620 samples form the machine learning sample set.

![Infrasound array, data acquisition terminal, wireless communication, data processing center](image)

**Figure 3.** Structure of experimental station.

According to the basic characteristics of infrasound of nuclear explosion, this paper extracts eight numerical features and time-frequency image features of mean value, variance, amplitude modulation, effective value, skewness, short-time average zero crossing rate, waveform complexity, frequency cubic moment and time-frequency image features from five infrasound signals of nuclear explosion, chemical explosion, thunder and lightning, typhoon and noise.

- **Mean value:** the average value of the data at each sampling point of the signal, expressed in $\mu$.
- **Variance:** the average of the sum of squares of the difference between the data at each sampling point of the signal and the mean value, expressed by $\sigma$.
- **Amplitude modulation:** can measure the amplitude change of signal, expressed in $Ma[7]$.

\[
Ma = \frac{\max |x_i| - \min |x_i|}{\max |x_i| + \min |x_i|}
\]  

(1)  

Where $x_i$ is the sound pressure value at the sampling point after background and atmospheric disturbance is removed from the original signal.

- **Effective value:** energy effect of signal can be measured, expressed by $Ev[8]$.

\[
Ev = \left( \frac{\sum (x_i)^2}{n} \right)^{1/2}
\]  

(2)  

- **Skewness:** it measures the skew direction and degree of data distribution, and can represent the distribution direction of waveform, which is represented by $Sc[9]$.

\[
Sc = \frac{\sum (x_i - \mu)^3}{\sigma^3}
\]  

(3)  

- **Short time average zero crossing rate:** refers to the number of times the signal passes through zero value in each frame, which can reflect the frequency information of the signal to a certain extent, expressed by $Zn[10]$.

\[
Zn = \frac{1}{2N} \left| \text{sgn}(x_i) - \text{sgn}(x_{i-1}) \right|
\]  

(4)  

$N$ is the number of sampling points and $\text{sgn}(x)$ is the symbol function. While $x \geq 0$, $\text{sgn}(x) = 1$, $x < 0$, $\text{sgn}(x) = -1$. 


Waveform complexity: used to indicate the complexity of signal waveform in energy distribution, represented by $C_p[11]$.

$$C_p = \frac{\int_{t=L}^{t=H} f^2(t) dt}{\int_{t=L}^{t=H} f^2(t) dt}$$  \hspace{1cm} (5)$$

Frequency cubic moment: used to represent the spectrum characteristics of signals, represented by $F_t[12]$.

$$F_t = \frac{\int_{f=L}^{f=H} F(f) f^3 df}{\int_{f=L}^{f=H} F(f) df}$$  \hspace{1cm} (6)$$

Due to the different calculation methods of each dimension feature, the value of each dimension is very different. Before the experiment, each feature dimension should be normalized.

Wavelet transform and Fourier transform can be used to express the signal frequency with time[13]. Figure 4 shows the time-frequency diagram characteristics of chemical explosion, lightning, typhoon and noise after short-time Fourier transform.

![Figure 4](image)

**Figure 4.** Example of time-frequency diagram for four types of signals.

4. Infrasound signal recognition experiment

4.1. Recognition experiment based on SVM

4.1.1. Experimental method and theory. SVM is a machine learning method proposed by Dr. Vapnik of the AT&T Bell laboratory based on statistical learning theory. According to the structural risk minimization criterion, it improves the generalization ability of classifier as much as possible on the premise of minimizing the classification error of training samples[14].

SVM is a two class data classification method. The object studied in this paper contains the infrasound signals generated by multiple events, which is a multi class data classification problem, and can not be directly classified by SVM. There are mainly two methods to construct multi classification model of SVM. One is to directly construct multiple classification which faces to divide all samples. The parameter solution of multiple classification surfaces is combined into one optimization problem, and multi class classification is realized by solving the optimization problem of multi-objective function, which is referred to as direct method[15]. The other method is to decompose the multi classification problem into multiple binary classification problems, and construct multiple classifiers indirectly by combining these two classifiers, which is referred to as indirect method[16].
Because of the complexity of the data structure model, only five types of data can be constructed. Taking SVM as the hidden layer node of neural network, nuclear explosion, chemical explosion, thunder and lightning, typhoon and noise are taken as one class, and the other four types of samples are classified into another. Five SVMs are needed to be constructed. In the process of discrimination, five output values are obtained from the input data through the five SVMs. The output values are compared through a linear activation function, and the largest one corresponds to the category of the input data, so as to realize the recognition of the five types of data.

For each SVM, the hyperplane partition can be described by the linear equation shown in equation (7):

\[ W^T x + b = 0 \]  \hspace{1cm} (7)

Where \( W \) is the normal vector, which determines the direction of the hyperplane; \( b \) is the displacement, which determines the distance between the hyperplane and the origin. For training samples \((x_i, y_i)\), the following formula is satisfied:

\[
\begin{align*}
W^T x_i + b &\geq +1, & y_i = +1, \\
W^T x_i + b &\leq -1, & y_i = -1.
\end{align*}
\]  \hspace{1cm} (8)

The sample points which are nearest to the hyperplane satisfy \( y_i(W^T x_i + b) = 1 \), which are called "support vectors". The dotted line is called the boundary, and the distance between the two dotted lines is called the interval, represented by \( \gamma \):

\[ \gamma = \frac{2}{||W||} \]  \hspace{1cm} (9)

By finding the minimum value of \( ||W|| \), the optimal hyperplane can be obtained.

However, the sample linear is not separable, and the above method cannot solve the problem effectively. In this case, the method of SVM is to map the training samples from the original space to a higher dimensional space, so that the samples are linearly separable in this space. Let \( \phi(x) \) denote the eigenvector after mapping \( x \). Therefore, in the feature space, the corresponding model of hyperplane partition can be expressed as formula (10).

\[ f(x) = W^T \cdot \phi(x) + b \]  \hspace{1cm} (10)

Finding the minimum value of \( ||W|| \), can be transformed into the solution of its dual problem. That is, using a kernel function to calculate the value in the original sample space, so as to save the complexity of high-dimensional computation.

When a small number of sample points fall between the hyperplane and the boundary in the training sample, in order to prevent over fitting, a relaxation variable \( \zeta_i \geq 0 \) can be introduced to each sample point, so that the interval plus the relaxation variable is greater than or equal to 1, which is approximately linearly separable, and the constraint condition can be expressed as formula (11).

\[ y_i(W^T x_i + b) \geq 1 - \zeta_i \]  \hspace{1cm} (11)

In order to get the minimum value of equation (9), the interval should be as large as possible, and the number of misclassification points should be as small as possible. So, parameter \( C \) is introduced to reconcile the two, and the objective function expressed as formula (12). Then, the same learning method as linear separable SVM can be used.

\[ \frac{1}{2} ||W||^2 + C \sum_{i=1}^{m} \zeta_i \]  \hspace{1cm} (12)

4.1.2. Experimental results and data analysis. For the identification of nuclear explosion events, 15 groups of characteristic data are randomly selected as positive samples (the remaining five groups are used for testing), and six groups of characteristic data are randomly selected from each of the four types of data of chemical explosion, lightning, typhoon and noise as negative samples to form a
training set to train a SVM. The penalty factor is 0.22, and the amplitude feature and mean value feature are selected for visualization. The training results are shown in Figure 5.

For the identification of chemical explosion events, 12 groups of chemical explosion characteristic data are randomly selected as positive samples (the remaining four groups of chemical explosion characteristic data are used for testing), and six groups of characteristic data are randomly selected from each of the three types of data as negative samples to form a training set to train a SVM. The penalty factor is 0.25, and the amplitude feature and mean value feature are selected for visualization. The training results are shown in Figure 6.

For the identification of typhoon events, 27 groups of typhoon characteristic data were randomly selected as positive samples (the remaining 9 groups of typhoon characteristic data were used for testing), and 10 groups of characteristic data were randomly selected from chemical explosion, lightning and noise data as negative samples to form a training set to train a SVM. The penalty factor was 0.20, and the amplitude feature and mean value feature were selected for visualization. The training results are shown in Figure 7.

For the identification of lightning events, 186 sets of lightning characteristic data are randomly selected as positive samples (the remaining 62 sets of lightning characteristic data are used for testing), 134 groups of noise characteristic data, all chemical explosion and typhoon characteristic data are randomly selected to form a training set to train a SVM. The penalty factor is 0.15, and the amplitude feature and mean value feature were selected for visualization. Training results are shown in Figure 8.

Figure 5. Training results of SVM for nuclear explosion recognition.

Figure 6. Training results of SVM for chemical explosion recognition.

Figure 7. Training results of SVM for typhoon recognition.

Figure 8. Training results of SVM for lightning recognition.
For noise identification, 400 groups of noise characteristic data are randomly selected as positive samples, all chemical explosion, lightning and typhoon feature data are taken as negative samples to form a training set to train SVM. The penalty factor is 0.10. The short-term average zero crossing rate feature and waveform complexity feature are selected for visualization. The training results are shown in Figure 9.

Four SVM models are trained to classify the test samples, and each sample gets the score of four prediction categories, and the category with the highest score is the recognition result of the sample. The short-term average zero crossing rate feature and waveform complexity feature are selected to visualize the recognition results, and the real distribution of test samples and the prediction distribution of SVM are obtained. Figure 10 shows the result of SVM on test set.

SVM is used for classification test for many times, and the results of each operation are counted. The recognition accuracy of various events is shown in Table 1.

Table 1. Test result of SVM.

|                        | nuclear explosion | chemical explosion | typhoon | thunder | noise | total |
|------------------------|-------------------|--------------------|---------|---------|-------|-------|
| Number of test samples | 7                 | 6                  | 13      | 93      | 112   | 231   |
| Mean value of correct recognition number | 5.62              | 3.85               | 12.22   | 90.56   | 111.68 | 223.93 |
| Average number of misidentifications | 1.38              | 2.15               | 0.78    | 2.44    | 0.32  | 7.07  |
| Recognition accuracy   | 80.3%             | 64.2%              | 94%     | 97.4%   | 99.7% | 96.9% |
8

From the above experimental result, it can be seen that the eight features have good classification performance for typhoon, lightning and noise data, and only four classifiers need to be trained, so the calculation speed is relatively fast. However, for nuclear explosion and chemical explosion, the recognition rate is relatively low due to the small number of samples.

4.2. Recognition experiment based on CNN

4.2.1. Experimental method and theory. CNN is a kind of feedforward neural network with depth structure including convolution calculation. It is one of the representative algorithms of deep learning. It is mainly used for image recognition, and its recognition ability has far exceeded that of human brain in some aspects[17]. The hidden layer of convolution neural network generally includes three kinds of common structures: convolution layer, pooling layer and full connection layer. In some new algorithms, there may be some complex structures such as concept module and residual module. Convolution layer and pooling layer are unique to convolution neural network[18].

The function of convolution layer is to use convolution kernel to convolute input data and generate characteristic graph. Each element of convolution kernel corresponds to a weight coefficient and a deviation, which is similar to the neurons of a feedforward neural network. In the convolution calculation, the convolution kernel slides in the input matrix. Every time the convolution kernel slides to a position, the input features are multiplied by matrix elements according to their size, and the deviation is added. If $Z$ is the characteristic graph of the $l$ layer, the calculation method of the characteristic diagram of the $l+1$ layer is shown in equation (13).

$$Z^{l+1}(i, j) = [Z^l \otimes w^{l+1}](i, j) + b$$

(13)

In formula (13), $(i, j)$ is the subscript of the feature image pixel, $w$ is the convolution kernel, and $b$ is the deviation. Let the characteristic graph of the $l$ layer be a square matrix whose row and column are all $L_l$, the size of convolution kernel is $f$, the convolution step size is $s_0$, and the number of filling layers is $p$.

$$L_{l+1} = \frac{L_l + 2p - f}{s_0} + 1$$

(14)

After feature extraction in convolution layer, the output feature map is transmitted to pooling layer for feature selection and information filtering, which can compress data and reduce the number of parameters. In the pool layer, the points in some adjacent areas in the characteristic map are replaced by a unified measurement, and the maximum value or average value in the pool area is generally taken. The process of pooling is similar to that of convolution kernel scanning feature map, which is controlled by pooling size $f$, step size $s_0$ and filling layers $p$. It is generally expressed as formula (15).

$$A^{l}_k(i, j) = \left[ \sum_{x=1}^{f} \sum_{y=1}^{f} A^{l}_k(i, j) + x, s_0(j + y) \right]^{1/2}$$

(15)

The last part of CNN is a full connection layer, which is equivalent to the hidden layer of traditional feedforward neural network. It is only used for nonlinear combination of extracted features to get the output.

4.2.2. Experimental results and data analysis. In the experiment, 3/5 samples are randomly selected from the infrasound signal time-frequency characteristic graph data set as the training set, and the remaining samples as the test set to test the classification ability of the trained network. During the training process, the network converges quickly. After 75 iterations, the network error reaches the set value. The network training accuracy and loss rate change as shown in Figure 11.
Figure 11. Variation curve of training accuracy and loss rate.

In order to eliminate the influence of random selection of training set and test set, the time-frequency characteristic graph of training samples is input into CNN to run for many times. The results of each operation are counted. The recognition accuracy of various events is shown in Table 2. It can be seen that the overall recognition rate of this method is similar to that of support vector machine, but for chemical explosion with less sample data, its recognition effect is still not ideal.

Table 2. CNN test results.

|                      | nuclear explosion | chemical explosion | typhoon | thunder | noise | total |
|----------------------|-------------------|--------------------|---------|---------|-------|-------|
| Number of test samples | 7                 | 6                  | 13      | 93      | 112   | 231   |
| Mean value of correct recognition number | 5.89              | 3.18               | 12.14   | 87.47   | 112   | 220.68 |
| Mean value of misidentifications  | 1.11              | 2.82               | 0.89    | 5.53    | 0     | 10.35 |
| Recognition accuracy  | 84.1%             | 53.0%              | 93.4%   | 94.1%   | 100%  | 95.5% |

4.2.3. Improvement of experimental process. Due to the lack of chemical explosion data in the real environment, a large number of effective data cannot be collected as training samples. In order to solve the problem of low recognition rate caused by insufficient sample size of chemical explosion, this paper combines generative countermeasure network with CNN, and inputs the enhanced chemical explosion data into CNN for training.

GAN was established by Ian Goodfellow in 2014, it defines two probability functions $P_t$ and $P_f$. $P_t$ is the probability distribution function describing the characteristics of real data, and $P_f$ is the probability distribution function describing the characteristics of generated data. After maximum likelihood estimation of the input data, the generation model outputs the data closest to the probability $P_t$ distribution, so that the generation model can learn to approximate the real data without prior knowledge, and finally achieves the goal of $P_f$ being approximately $P_t$ [19] [20] [21]. The objective function is defined in the form of equation (16).

$$\min_G \max_D V(D, G) = E_{x \sim P_t(x)}[\log D(x)] + E_{z \sim P_f(z)}[\log(1 - D(G(z)))]$$ (16)
In equation (16), $x$ is the input real data, $z$ is the input noise data, $D(x)$ is the probability that the discrimination model $D$ will recognize $x$ as the real data, and $G(z)$ is the generated data obtained by mapping the input noise by the generation model.

The GAN constructed in this paper uses a full connection layer as the input layer, and then three convolution layers to extract image features. Batchnorm is used to whiten the input of each convolution layer to make the gradient larger. Finally, a tanh activation function is used to output the results. The discriminant model is a binary classification model. Convolution neural network is used to identify true and false data, and sigmoid activation function is used to output true and false probabilities.

The random noise is used as the input data to generate the model. The false data output by the model in the process of training optimization is shown in Figure 12. Figure 12(a) is the generated image after 10 rounds of network training, which is no different from random noise. Figure 12(b) shows the generated image after 50 rounds of network training, and some contours similar to the time-frequency diagram of chemical explosion begin to appear. Figure 12(c) shows the generated image after 100 rounds of network training. The generated image is very similar to the real chemical explosion time-frequency diagram.

Figure 12. Time frequency image of chemical explosion generated by GAN.

GAN is used to train and generate chemical explosion data, and the pseudo sample data of chemical explosion is doubled. Then CNN is used for identification experiment. The experimental results are shown in Table 3. The training accuracy rate is 98.6%, and the test accuracy rate is 96.3%. Especially for the identification of chemical explosion data, the performance has been greatly improved.

Table 3. Improved test results.

|                  | nuclear explosion | chemical explosion | typhoon | thunder | noise | total |
|------------------|-------------------|--------------------|---------|---------|-------|-------|
| Number of test samples | 14                | 12                 | 13      | 93      | 112   | 244   |
| Mean value of correct recognition number | 12.54             | 9.16               | 11.75   | 89.52   | 112   | 234.97 |
| Mean value of misidentifications | 1.46              | 2.84               | 1.25    | 3.48    | 0     | 9.03  |
| Recognition accuracy | 89.6%             | 76.3%              | 90.4%   | 96.3%   | 100%  | 96.3% |

5. Comprehensive comparative analysis

The above experimental results show the accuracy of event recognition, but the real purpose of the model is to identify the nuclear explosion signal. From this point of view, we comprehensively evaluate the false positive rate (FPR) and true positive rate (TPR) of the model. We eliminate the useless noise data for event recognition, and carry out identification experiments for nuclear explosion, chemical explosion, typhoon and thunder and lightning data. We modify the output of the
model to the probability that each sample data is identified as four events, and calculate their ROC curve and AUC value respectively. The results are shown in Figure 13.

![Figure 13. ROC curve of the model.](image1)

Through many experiments, the AUC value of the model is statistically analyzed and its probability density function is fitted. The results are shown in Figure 14.

![Figure 14. Fitted probability density curve with AUC value.](image2)

The AUC value of SVM model approximately follows the β distribution of parameters (α=97.062, β=4.441), and the expected value E(x)=0.971. However, the AUC value of CNN model approximately follows the β distribution of parameters (α=58.662, β=3.421), and the expected value E(x)=0.945. For the distribution characteristics of infrasound data, the AUC value of SVM model is higher than that of CNN model, that is, SVM model has higher comprehensive performance.

6. Conclusion
In this paper, the overall recognition performance of support vector machine model is better, but it has higher requirements for artificial design features, so researchers need to conduct in-depth study on various characteristics of various signals, so as to find out the signal features with greater difference. And for the classification of multiple types of data, it is necessary to train multiple SVM models. When new categories are added, all models need to be retrained.

Convolution neural network with its excellent performance in image recognition can dig out the time-frequency features ignored in artificial design, so as to identify the spectrum of typhoon and lightning infrasound signals more accurately. However, for the event types with few samples, there is
still a problem of insufficient learning. After the learning process is improved by using generative countermeasure network, the recognition effect of specific events can be improved. The recognition ability of nuclear explosion and chemical explosion is slightly better than that of support vector machine.

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