Research on Sound Signal State Diagnosis Technology of Chemical Columns Based on Support Vector Machine

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Abstract: The safety monitoring in the operation of chemical equipment is related to the national economic development and the safety of people's life and property. Existing online monitoring devices are larger in size, fewer characteristic parameters, and lower degree of intelligence. This paper takes Chemical columns equipment as the research object. Firstly, it is to collect the acoustic signals generated during the column operation process. Then the acoustic and vibration signals will serve as the input signals of a signal transmission and processing system, with the intelligent signal processing procedure of weak signal detection and enhancement, multi-variate feature extraction, multi-modal information fusion, and the online fault diagnosis and recognition by Support Vector Machine method. After 10 experimental runs, the diagnostic accuracy was measured to reach an average of 94%. The results verify the effectiveness of our proposed approach under limited data conditions.

Keywords: Chemical Process Safety; Chemical Columns; Intelligent Monitoring; Support Vector Machine; Acoustic Feature Fusion

1. Introduction

In modern chemical production processes, chemical columns (such as distillation columns, reaction columns, etc.) are among the core equipment, whose stable operation is directly related to product quality, production efficiency, and safety. Traditionally, condition monitoring of chemical columns has mainly relied on physical parameters such as temperature, pressure, and flow rate; however, these parameters often fail to comprehensively reflect the health status of equipment, particularly exhibiting limitations in early fault detection. In recent years, acoustic signals have received extensive attention as a novel monitoring approach [1-3], as they can provide rich information about equipment operating conditions-abnormal phenomena such as friction, leakage, and blockage manifest themselves through specific acoustic characteristics. Acoustic signal monitoring offers the advantages of non-intrusiveness, straightforward installation, and low cost, making it particularly suitable for long-term health monitoring of chemical equipment.

Support vector machine (SVM) [4], a statistical theory-based pattern recognition method, has been gradually applied to mechanical fault diagnosis since 1999 [5]. Relevant studies have extended its application from engine knock detection to bearing and motor fault diagnosis, and further developed its variant support vector regression for equipment condition assessment via function fitting and residual analysis. Afterwards, SVM-based fault diagnosis has gained increasing attention and been widely adopted in chemical industry [6], precision instruments [7], power systems [8-9] and other industrial areas with continuous technical improvements. Characterized by excellent performance in small-sample scenarios, SVM requires no elaborate mathematical models or systematic mechanism analysis, and can effectively mine implicit classification information from limited samples to learn complex nonlinear systems. It well satisfies the demands of modern industrial equipment fault diagnosis, thus becoming a research hotspot with promising application prospects.

This paper addresses the non-stationary characteristics of acoustic signals from chemical equipment, extracts joint time-frequency domain features from the acoustic signals of chemical column operating states, and performs operational state diagnosis for small-sample chemical column data based on the Support

Vector Machine (SVM) method.

2. Algorithm Principle

SVM is considered to be one of the most widely used classifiers, which is a generalization of support vector classifier. It can be applied to linear non-separable data sets and has become more and more popular since its introduction.

2.1 Constructing Support Vector Classifier

Support vector classifier is also called soft interval classifier. Instead of looking for a possible maximum interval, it is better to allow some observations to fall on the wrong side of the interval plane or even on the wrong side of the hyperplane.

Support vector classifiers allow certain observations not to satisfy constraints

$$y_i(b^{\mathrm{T}}x_i + a) \ge 1 \tag{1}$$

At the same time, the number of observations that do not meet the constraints should be as small as possible. The optimization objectives are as follows

$$\min_{b,a}\left\{\frac{1}{2}\|b\|^2 + C\sum_{i=1}^{m} L_{0/1}(y_i(b^{\mathrm{T}}x_i + a) - 1)\right\}. \tag{2}$$

Where C>0 is the adjustment parameter, and the 0/1 loss function maintain a trade-off between the size of the interval and the number of observations over the interval, L0/1 is the 0/1 loss function

$$L_{0/1}(z) = \begin{cases} 1, & z < 0, \\ 0, & z \ge 0, \end{cases} \tag{3}$$

Clearly, all the training observations satisfy the constraint (1) when the C takes positive infinity, so the formula (2) is equivalent to

$$\begin{cases} \min\limits_{b,a} \dfrac{1}{2}\|b\|^2 \\ \text{s.t.} \quad y_i(b^{\mathrm{T}}x_i + a) \ge 1, \quad i = 1,\cdots,m. \end{cases} \tag{4}$$

Some training observations can not satisfy the constraint (1) when the C takes a limit value.

However, L0/1 is a nonconvex and discontinuous function, and its mathematical properties are not very good, which makes equation (2) difficult to solve directly. Therefore, the L0/1 function is usually replaced by some other functions, which is called "replacement loss function". Substitution loss functions usually have good mathematical properties. For example, they are convex continuous functions and the upper bound of L0/1 functions. The hinge function is commonly used

$$L_{\text{hinge}}(z) = \max(0, 1 - z) \tag{5}$$

By using the hinge loss, the formula (2) can evolve into

$$\min_{b,a}\left\{\frac{1}{2}\|b\|^2 + C\sum_{i=1}^{m} \max(0, 1 - y_i(b^{\mathrm{T}}x_i + a))\right\} \tag{6}$$

A relaxation variable ξi≥0 is introduced and the upper formula can be written as:

$$\begin{cases} \min\limits_{b,a,\xi_i}\left\{\dfrac{1}{2}\|b\|^2 + C\sum\limits_{i=1}^{m}\xi_i\right\} \\ \text{s.t.} \quad y_i(b^{\mathrm{T}}x_i + a) \ge 1 - \xi_i, \\ \qquad \xi_i > 0, i = 1,\cdots,m. \end{cases} \tag{7}$$

The relaxation variable represents the level of which the observation does not satisfy the constraint (1).

The judgment rule of the support vector classifier is determined only by part of the training observation, which means that the classifier is very robust for observations far from the hyperplane. This feature of support vector classifier makes it completely different from other classification methods, such as linear discriminant analysis. The discriminant rules of linear discriminant analysis depend on the mean value of within-group observations and the within-group covariance matrix calculated from all observations.

2.2 Support Vector Machine Model

SVM is a promotion of support vector classifier. SVM uses a special way, namely kernel function, to expand the feature space. If the dependent variable has only two categories and the two categories are linearly separable, then the support vector classifier can be used to classify. In practice, support vector classifiers sometimes encounters failure. If the relationship between independent variables and dependent variables is nonlinear in regression analysis, the linear regression model established by using the suspected term of independent variables will not perform well. In this case, the quadratic term, cubic term and even higher order polynomial of the independent variable can be used to expand the feature space, and then the regression model can be established. For the linear indivisible classification problem, we can map the sample from the original space to a higher dimensional feature space, so that the sample is linearly separable in this feature space.

$\varphi(x)$ represents the eigenvector after the mapping of the x. Substitute the variables in the corresponding formula from(1) to (7), we can obtain the calculation model corresponding to the segmentation of the hyperplane in the feature space.

Because the dimension of the feature space may be very high or even infinite. To avoid this problem, it can be written as

$$\kappa(x_i, x_j) = \phi^{\mathrm{T}}(x_i)\phi(x_j) \tag{8}$$

The inner product of xi and xj in the feature space is equal to the result obtained by function κ(.) in the original sample space. With the function, it is not necessary to directly calculate the inner product in the space of high dimensional or even infinite Witt's sign. Thus, the dual problem formula (7) can be rewritten as

$$\begin{cases} \min\limits_{\alpha} \left\{ \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j \kappa(x_i, x_j) \right\} \\ \text{s.t.} \quad \sum_{i=1}^{m} \alpha_i y_i = 0, \\ \qquad 0 \le \alpha_i \le C, i = 1, \cdots, m. \end{cases} \tag{9}$$

Where κ(.) is kernel function. There are several kernel functions commonly used in SVMs

Linear kernel

$$\kappa(x_i, x_j) = x_i^{\mathrm{T}} x_j \tag{10}$$

polynomial kernel

$$\kappa(x_i, x_j) = \left(x_i^{\mathrm{T}} x_j\right)^d \qquad d \ge 1 \tag{11}$$

radial basis (RBF) nuclei

$$\kappa(x_i, x_j) = e^{\left(-\gamma \|x_i - x_j\|^2\right)} \qquad \gamma > 0 \tag{12}$$

Laplace nuclearc

$$\kappa(x_i, x_j) = e^{\left(-\frac{\|x_i - x_j\|}{\sigma}\right)} \qquad \sigma > 0 \tag{13}$$

Sigmoid nuclear

$$\kappa(x_i, x_j) = \tanh\left(\beta x_i^{\mathrm{T}} x_j + \theta\right) \qquad \beta > 0, \theta < 0 \tag{14}$$

The kernel function operation can effectively solve the recognition problem in nonlinear mode, avoid the complex inner product operation in feature space and greatly reduce the computational cost. Kernel function implies the mapping from low dimensional space to high dimensional space, and this mapping can make the two types of points in low dimensional space linearly separable, making the data easy to be segmented and effectively avoiding the "dimension disaster" brought by high-dimensional space.

This paper mainly adopts polynomial kernel function to classify and judge the running state of chemical industry by analyzing the classification characteristics of kernel function.

3. State Diagnosis Based on SVM

Running state diagnosis, also known as fault diagnosis, is generally divided into three steps. The first step is data acquisition, which is to obtain relevant data that can reflect the operating state of the device. The second step is feature extraction. The proper method is adopted to extract the feature information hidden in the signal so that the running state information of the equipment is more prominent. The third step is to judge the state, which is to analyze and judge the current running state of the equipment on the basis of obtaining the running state information. Fault diagnosis technology can be divided into three categories including hardware redundancy based fault diagnosis technology, analytical model based fault diagnosis technology and data driven fault diagnosis technology. The fault diagnosis technology based on support vector machine is one of the main methods of data-driven technology. The data-driven fault diagnosis method does not require complex mathematical models and prior information such as expert experience. The method is based on the collected data information. The deep information hidden in the data is mined by various data processing methods, and then the running state information of the system is distinguished to achieve the purpose of fault diagnosis. Support Vector Machine is one of the methods of pattern recognition and fault diagnosis based on data analysis and intelligent computing.

This paper takes the audio signal of the equipment as the research object, and establishes the fault diagnosis model based on support vector machine, which is shown in Figure 1. The biggest advantage of support vector machine technology in fault diagnosis is that it is suitable for small sample decision-making. It can learn complex nonlinear system with only a few data samples, which meets the requirements of fault diagnosis for modern industrial equipment.

4. Analysis of Acoustic Signal Operation State of Chemical Tower

Chemical tower is one of the core equipment in chemical static equipment. It is not only the main equipment of chemical separation, but also the reaction equipment. Packing tower and plate tower are commonly used chemical tower equipment. Compared with other chemical static equipment, the operation state of the tower is relatively complex because there is a large amount of vapor-liquid phase fluid flow inside and the composition changes greatly. Liquid flooding, leakage, blockage of drop pipe, abnormal plate hole and entrainment are common abnormal operating states in chemical tower. It can be installed, measured and analyzed without intervention because the sound sensor has the advantages of non-contact and easy processing. It is feasible to analyze the operation status of chemical tower by using sound signal.

According to some symmetrical arrangement structure, the off-line collection of sound data of plate tower and packed tower in various working states is completed by manual cooperation and the sound resource bank of running state is established.

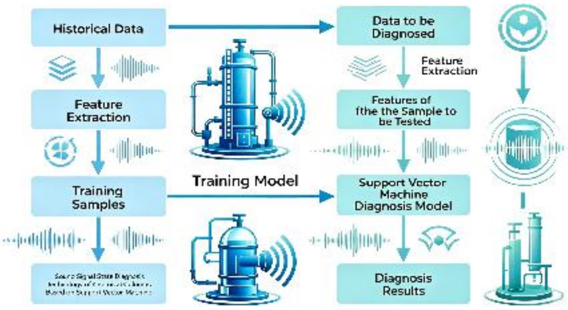
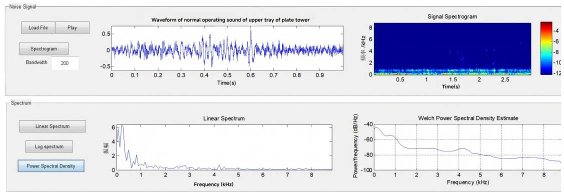


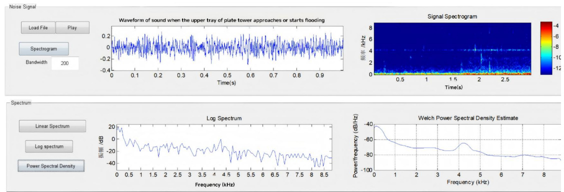
Figure 1. Fault Diagnosis Model Based on Support Vector Machine

Figure 2 shows the time domain and frequency domain characteristics of the sound waveform of the upper tray of the plate tower during normal operation and liquid flooding. Each figure consists of four subgraphs: the time domain waveform of sound, the time-frequency speech spectrum of sound signal, the line spectrum after short time Fourier transform and the power spectrum density of Welch method. Figure 2(a) shows the time-frequency characteristics of the upper tray of the plate tower. Figure 2(b) shows the time-frequency characteristics of sound when approaching or starting fluid flooding. Figure 2(c) shows the sound time-frequency characteristics of liquid flooding failure. Comparing the language spectrum diagram and power spectrum density diagram of the three subgraphs, it can be seen that there will be a spectral peak near 5 kHz when there is a liquid flooding fault in the upper tray of the plate tower. Figure (b) also shows significant transition characteristics.

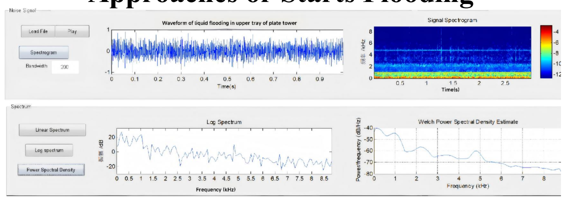
Figure 3 shows the time domain and frequency domain characteristics of the sound waveform of the lower tray of the packing tower during normal operation and liquid flooding. Figure 3(a) is the time-frequency characteristic of normal operation. Figure 3(b) is the sound time-frequency characteristic of beginning liquid flooding. Figure 3(c) is the sound time-frequency characteristic of severe liquid flooding. By comparing the spectrogram, line spectrum and power spectral density diagram of the three subgraphs, it can be seen that, there is a spectrum peak at about 0.7kHz at the initial stage of liquid flooding fault. The spectrum peak appears at 0.7kHz and 1kHz respectively in case of serious flooding fault. We can also hear a relatively significant howl through the subjective audition.



(a) Time-Frequency Characteristics of Normal Operating Sound Of Upper Tray Of Plate Tower

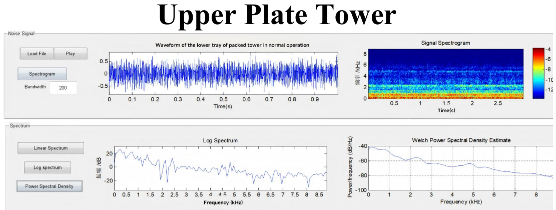


(b) Time-frequency Characteristics of Sound When the Upper Tray of Plate Tower Approaches or Starts Flooding

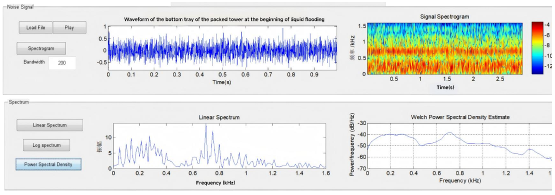


(c) Sound Time-Frequency Characteristics of Liquid Flooding In Upper Tray of Plate Tower

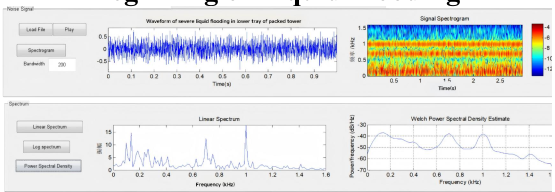
Figure 2. Comparison of Time-Frequency Characteristics of Sound Waveforms During Normal Operation and Liquid Flooding in Upper Plate Tower



(a) Sound Time-Frequency Characteristics of the Lower Tray of Packed Tower in Normal Operation



(b) Sound Time-Frequency Characteristics of the Bottom Tray of the Packed Tower at the Beginning of Liquid Flooding



(c) Sound Time-Frequency Characteristics of Severe Liquid Flooding in Lower Tray of Packed Tower

Figure 3. Comparison of Time-Frequency Characteristics of Sound Waveform in Normal Operation and Liquid flooding of Lower Packing Tower

In this paper, support vector machine is used to classify and identify the normal and liquid flooding states of plate tower and packed tower.

5. Audio Signal Feature Extraction

5.1 Pretreatment of Audio Signals

Preprocessing is one of the most important parts in audio signal processing. The preprocessing process of audio signal refers to the process that the signal is converted into digital signal after sampling and quantization. Then, the digital signal is divided into frames and windowed, which mainly provides convenience for the next feature extraction.

The audio signal is divided into frames. The frame length ranges from 10ms to 30ms in the process of framing. If the frame length is too long, the signal may be non-stationary and have adverse effects on the subsequent feature extraction. On the contrary, if the frame length is too short, it may lead to too little information contained in a frame signal. In order to avoid the large change between two adjacent frames, there is usually about 1/2 of the overlap between adjacent frames and the overlap area is called frame shift. There are almost discontinuities at the beginning and end of each frame. Therefore, the more frames are divided, the greater the error with the original signal. Adding windows can solve this problem. Windowing makes the signal continuous so that every frame can show the characteristics of periodic function. Window functions include rectangular windows, Bartlett windows (triangular windows), Hanning windows, Haiming windows, Brakman windows, etc. This subject uses Hanning window to process audio signal.

In addition to the usual statistical features of mean, variance and kurtosis, there are also special features of audio signal in time domain, frequency domain or time frequency domain.

The other spectrum characteristics of the signal are analyzed based on the short-time spectrum coefficient.

5.2 Frequency Domain Characteristics

The frequency domain characteristic parameters involved in this paper include frequency domain energy, subband energy ratio energy ratio, frame based spectrum centroid, frame based spectrum bandwidth, segment based spectrum centroid and segment based 3dB bandwidth.

(1) Frequency domain energy

The calculation formula of frequency domain energy is as follows.

$$PE_n = \int_0^{\omega_0} \left|F_n(\omega)\right|^2 \mathrm{d}\omega \tag{15}$$

Where ω_0 is half of the sampling frequency.

Frequency domain energy refers to the energy of audio signal in time domain after Fourier transform. Frequency domain energy can be used to determine whether the frame signal is a silent frame. First, a threshold value of frequency domain energy is set. If the frequency domain energy is less than the threshold value, the frame is determined as silent frame. On the contrary, if the frequency domain energy is greater than this threshold, the frame is determined to be non mute frame.

(2) Subband energy ratio

The frequency domain of the signal is divided into four sub-bands with different bandwidth, namely $[0,\frac{\omega_0}{8}]$, $[\frac{\omega_0}{8},\frac{\omega_0}{4}]$, $[\frac{\omega_0}{4},\frac{\omega_0}{2}]$, $[\frac{\omega_0}{2},\ \omega_0]$. The energy of each sub-band is calculated respectively and the ratio of each sub-band energy to the total energy is calculated.

The calculation formula of subband energy ratio is as follows.

$$DE_{ni} = \frac{1}{PE_n}\int_{\omega_{il}}^{\omega_{ih}} \left|F_n(\omega)\right|^2 \mathrm{d}\omega \tag{16}$$

Where DE_{ni} is the ratio of the frequency domain energy of the i-th sub-band in the n-th frame signal to the total frequency domain of the frame signal, ω_{il} and ω_{ih} represents the lower and upper boundary frequencies of the *i*-th sub-band of the frame signal, respectively. The frequency-domain energy of each subband varies greatly with different audio types.

(3) Frame based spectral centroid

The centroid of spectrum is an important parameter to describe the timbre property of sound, and it is also one of the key information of frequency distribution and energy distribution in audio signal. The bright part of the sound has a relatively high frequency and a high spectral centroid. On the contrary, the dark and deep part of the sound has a relatively low frequency and a low spectral centroid. The spectrum centroid based on the frame mainly reflects the spectrum center of the frame signal. The larger the value is, the more high-frequency components are in the frame signal. The smaller the value is, the lower the low frequency components in the signal is.

The calculation formula of spectrum centroid based on frame is as follows.

$$ZC_n = \frac{\sum_{\omega=l_n}^{h_n} \omega \left|F_n(\omega)\right|^2}{\sum_{\omega=l_n}^{h_n} \left|F_n(\omega)\right|^2} \tag{17}$$

Where ZC_n is the spectrum centroid of the nth frame signal, ln and hn are the minimum and maximum frequencies in the spectrum of the frame signal, respectively.

(4) Frame based spectrum bandwidth

Spectrum bandwidth is an important parameter to describe the frequency domain of audio. The absolute value of the difference between the highest frequency and the lowest frequency is the spectrum bandwidth of the signal. The larger the spectrum bandwidth, the larger the frequency range of the signal; on the contrary, the smaller the spectrum bandwidth, the smaller the frequency range of the signal.

The calculation formula of spectrum bandwidth based on frame is as follows.

$$ZB_n = \sqrt{\frac{\int_0^{\omega_0} (\omega - ZC_n)^2 \left|F_n(\omega)\right|^2 \mathrm{d}\omega}{\int_0^{\omega_0} \left|F_n(\omega)\right|^2 \mathrm{d}\omega}} \tag{18}$$

Where ZB_n represents the spectrum bandwidth of the nth frame signal.

(5) Segment based spectral centroid

The spectrum centroid based on the segment corresponds to the frame based spectral centroid mentioned above. The Fourier transform object based on the spectral centroid of the frame is a frame in the audio signal after framing while the Fourier transform object based on the spectral centroid of the segment is a segment of audio.

The calculation formula of spectrum centroid based on segment is as follows.

$$ZC(k) = \frac{\sum_{n=1}^{L} [x_k(n) \cdot F_k(n)]}{\sum_{n=1}^{N} F_k(n)} \tag{19}$$

Where $ZC(k)$ is the spectrum centroid of the *k*th audio segment, $x_k(n)$ represents the amplitude of the *n*th sampling point in the kth audio segment, and *L* represents the number of sampling points in the audio segment.

(6) Segment based 3dB bandwidth

The 3dB bandwidth is the bandwidth corresponding to the half power reduction. The corresponding frequency range is the 3dB bandwidth based on segment when its size is equal to the times of the maximum amplitude in frequency domain for audio signal.

5.3 Mel Frequency Cepstrum Coefficient(MFCC)

Mel cepstrum coefficient is an acoustic characteristic parameter derived from the auditory characteristics of human ears. In general, the human ear is more sensitive to sound below 1kHz. There is a linear relationship between the perceptual ability of human ear and the frequency of sound within 1kHz. However, the perception ability of human ear is not so sensitive when the sound is above 1kHz. At this time, there is a certain linear relationship between the perception ability of human ear and the frequency of sound in logarithmic coordinates. The relationship between Mel frequency and linear frequency is as follows.

$$\mathrm{Mel}(f) = 2595 \times \log_{10}\left(1 + \frac{f}{700}\right) \tag{20}$$

The feature parameter extraction of Mel spectrum coefficient is mainly to preprocess the acoustic signal and get the energy spectrum of the acoustic signal based on fast Fourier transform. 23 (number of filters) output vectors are obtained after Mel triangular filter bank, in which MI is the output of the ith triangular filter. The MFCC parameters of each order can be obtained by using discrete cosine transform (DCT) after taking the natural logarithm.

$$C(n) = \sum_{i=1}^{23} \log(m_i) \cos\left[n(i + \frac{1}{2})\frac{\pi}{24}\right] \tag{21}$$

Where P is the order of MFCC parameter and $C(n)$ is the nth dimension MFCC parameter. In this paper, $P = 12$.

6. Experimental Scheme and Result Analysis

6.1 Master Plan

This experiment is mainly divided into two parts: feature extraction and fault diagnosis. The principle block diagram of the experimental scheme is shown in Figure 1. At the feature extraction part, the audio signal is first read, then each audio signal is preprocessed by frame division and other preprocessing and each eigenvalue of the audio signal in time domain, frequency domain, cepstrum domain is calculated. Finally, all the feature data are written into the Excel. In the fault diagnosis part, the characteristic data table output from the previous experiment is first read, and then the training sample and the test sample in the fault sample and the normal sample are divided respectively. The training samples are used to train the SVM classifier. Finally, the test samples are used for classification test. The test results are compared with the correct classification situation to obtain the correct rate of fault diagnosis.

6.2 Algorithm Programming

In this paper, the classification algorithm based on support vector machine completes the fault diagnosis experiment and the whole experiment is carried out in MATLAB environment. MATLAB algorithm program mainly includes feature extraction and fault diagnosis. The program of feature extraction reads into audio file and outputs feature data set. The program of the fault diagnosis part reads the characteristic data set and outputs the fault diagnosis results. The program design flow chart of feature extraction process is shown in Figure 4. The program design flow chart of fault diagnosis is shown in Figure 5.

The steps of the feature extraction procedure are as follows.

(1) Read audio files from all audio folders.

(2) Enter the loop: read the data information of the first audio signal for preprocessing and calculate each feature parameter. All feature parameters are saved as feature matrix, and the data in this feature matrix is written into the first row of Excel table.

(3) In the next loop, the feature parameters of the second audio are written to the second line in the Excel table. Until the data information of all audio signals is read and a series of calculations are carried out, the characteristic parameters are written into the same excel table, and the cycle ends.

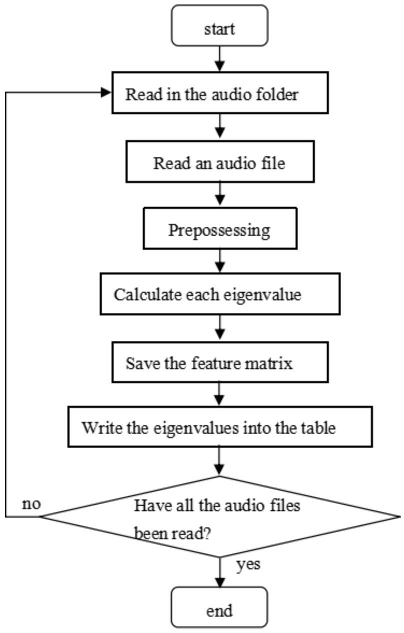


Figure 4. Program Design Flow Chart of Feature Extraction

The specific steps of the fault diagnosis procedure are as follows.

(1) Read the feature data table output by feature diagnosis program.

(2) Read the category information of feature data.

(3) Some samples are selected as training data in two kinds of samples.

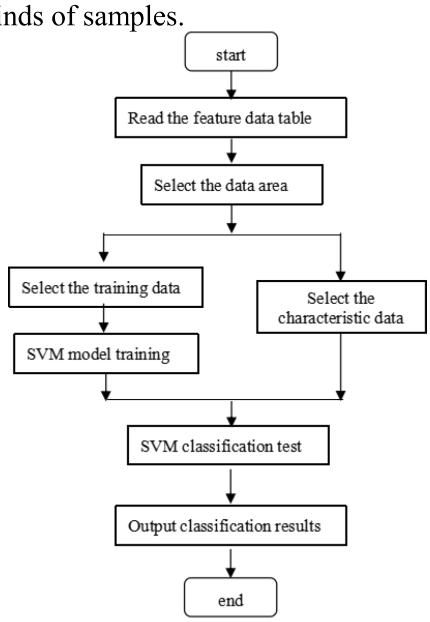


Figure 5. Programming Processes for Fault Diagnosis

(4) In addition to the training data, some or all of

the data are selected as the test data.
(5) Using training data to train SVM model.
(6) The trained SVM model is used to classify the test data and output the classification results.
(7) The classification results are compared with the correct classification and the classification accuracy is calculated and output.
At this time, the algorithm of fault diagnosis has been completed. The fault diagnosis results and diagnosis accuracy are obtained.

6.3 Audio Feature Set Construction and Result Analysis

Feature extraction is a key step in fault diagnosis of audio signals. Different information contained in audio signals is analyzed by feature extraction to identify the types of audio signals. In the selection of feature parameters, not only the calculation method and the amount of calculation should be considered, but also the dimension should be reduced as much as possible.
Audio features are generally divided into two different types in the process of feature extraction of audio signal. One is based on the feature information of audio segment and the other is based on the feature information of audio frame. For the latter case, the audio is divided into frames and then the audio frame is analyzed and processed. The audio signal features to be extracted in this project are shown in Table 1 including 12 kinds of features in time domain, frequency domain and cepstrum domain and 26 dimension feature parameters.

Table 1. Statistics of Characteristic Parameters

Type	Characteristic parameters	Dimension	Location
Time domain features	Short-term energy	1	B column
	Short-term zero-crossing rate	1	C column
	Short-term average amplitude	1	D column
	Short-term autocorrelation coefficient	1	E column
	Short-term average amplitude difference	1	F column
Frequency domain features	Frequency domain energy	1	G column
	Subband energy ratio	4	H-Kcolumn
	Frame based spectral centroid	1	L column
	Frame based spectrum bandwidth	1	M column
	Segment based spectral centroid	1	N column
	Segment based 3dB bandwidth	1	O column
Cepstrum features	MFCC	12	P-AA column

The scatter diagram of characteristic parameters is drawn by MATLAB, in which the red "*" represents the normal sample and the black " o " represents the fault sample. In this paper, several obvious features are discussed. Figure 6 is short time energy. Figure 7 is short time average amplitude difference. Figure 8 is frequency domain energy. Figure 9 is frame-based spectrum centroid. Figure 10 is frame-based spectrum bandwidth. And Figure 11 is frame-based 3 dB bandwidth.

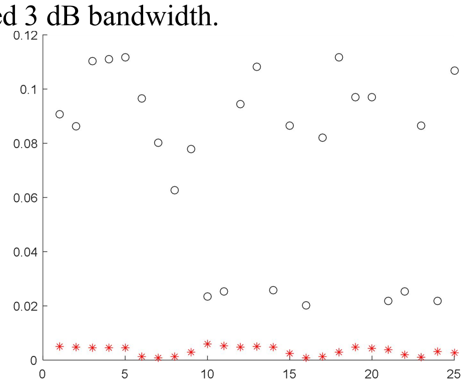


Figure 6. Short Time Energy

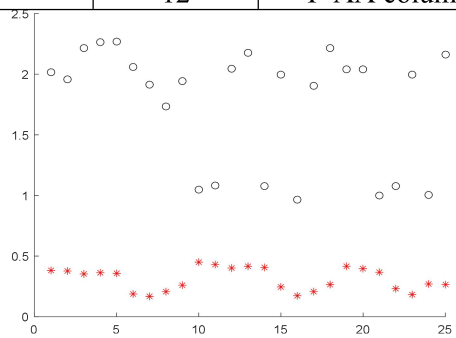


Figure 7. Short Time Average Amplitude Difference

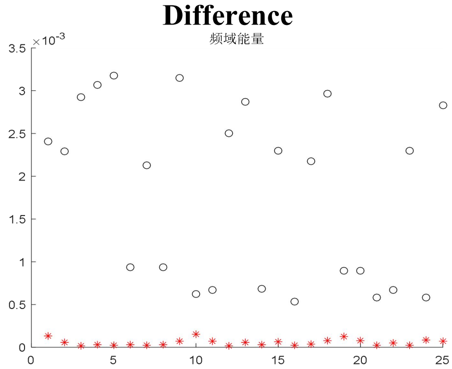


Figure 8. Frequency Domain Energy

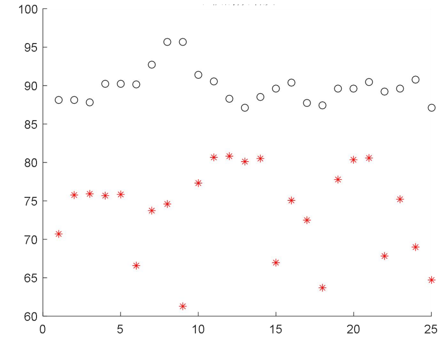


Figure 9. Frame-based Spectral Centroid

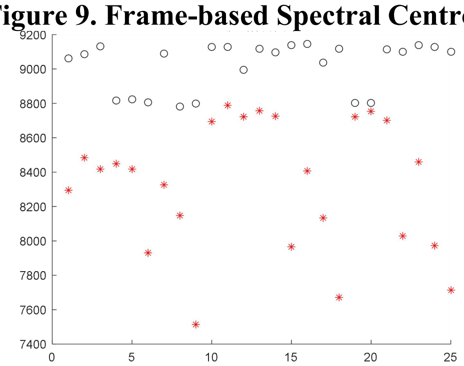


Figure 10. Spectrum Bandwidth Based on Frame

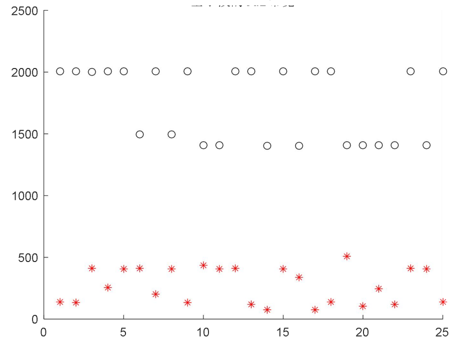


Figure 11. 3dB Bandwidth Based on Frame

It can be seen from Fig. 7 to Fig. 11 that fault samples and normal samples have their own relatively concentrated distribution areas in each scatter diagram. Excel are used to calculate the maximum, minimum and mean values of the six characteristic parameters and the specific statistical results are shown in Table 2.

It can be seen from table 2 that there are obvious differences in these six characteristic parameters between fault signal and normal signal, which can well distinguish fault signal from normal signal. In practice, the audio signal in fault state often appears machine roar while the audio signal in normal state is relatively quiet and gentle. Therefore, the parameters of fault signal such as short-term energy, short-term average amplitude difference, frequency domain energy, spectrum centroid based on frame are relatively large. The results in Table 3 are consistent with the actual situation and have certain reference value. In addition to the six distinct characteristic parameters, the other characteristic parameters have little difference from subjective evaluation while they are still involved in state diagnosis as characteristic parameters.

6.4 Experimental Results and Data Analysis

In the experiment of audio signal fault diagnosis, the audio signal of chemical tower is taken as the experimental sample. There are 25 fault samples, including 20 training samples and 5 test samples. There are 25 normal samples, including 20 training samples and 5 test samples.

Classfication represents the diagnostic results of the support vector machine fault diagnosis experiment and grouptest represents the correct classification result where "1" represents the fault state and "2" represents the normal state. Compared with the classification and group test results, the experimental results and the correct diagnosis results are the same. The experiment successfully classified all the test samples correctly. the output classification accuracy is 100, which is consistent with the fault diagnosis results in the workspace.

Table 2. Statistical statistics of features

	Fault signal			Normal signal		
	Maximum value	Minimum value	Mean value	Maximum value	Minimum value	Mean value
Short-term energy	0.121	1.97E-02	7.64E-02	6.36E-03	7.70E-04	3.29E-03
Short-term average amplitude difference	6.06E-03	-9.91E-03	-2.70E-03	2.38E-03	-7.72E-03	-1.96E-03
Frequency domain energy	3.31E-03	5.22E-04	1.87E-03	1.68E-04	1.70E-05	5.83E-05
Frame based spectral centroid	97.4	85.5	89.7	80.6	60.9	73.5
Frame based spectrum bandwidth	9.15E+03	8.78E+03	9.02E+03	8.82E+03	7.53E+03	8.32E+03
Segment based 3dB bandwidth	2.01E+03	1.41E+03	1.75E+03	508	96.0	244

In order to better test the fault diagnosis system based on support vector machine, more experiments are needed. 20 samples were randomly selected as training samples and the other samples were used as test samples in each sample. The experiment was repeated 10 times to record the test results and diagnostic accuracy, as shown in Table 3.

According to Table 3, the highest diagnostic accuracy is 100%, the lowest diagnostic accuracy is 80%, and the average diagnostic accuracy is 94% in 10 fault diagnosis experiments with multiple test samples. The experimental results show that the average correct rate of fault diagnosis system based on support vector machine is 94% which can reflect the running state of the equipment to a certain extent.

Table 3. Statistics of Fault Diagnosis Results of Multiple Test Samples

Runs	Correct category	Test category	Diagnostic accuracy
1	1111122222	1121122222	90%
2	1111122222	2111122222	90%
3	1111122222	1111122222	100%
4	1111122222	1111122222	100%
5	1111122222	1111122222	100%
6	1111122222	1122122222	80%
7	1111122222	1211122222	90%
8	1111122222	1111122222	100%
9	1111122222	1111222222	90%
10	1111122222	1111122222	100%

7. Conclusion

In the era of rapid development of industry, people have higher and higher requirements for the safety of production. Equipment failure is directly related to people's life and property safety. Therefore, real-time monitoring and fault diagnosis of equipment operation status has become an important research topic. The sound sensor can be installed in a non-contact way and the audio information of the equipment running state is easy to obtain. The audio information state detection and fault diagnosis have research potential. In this paper, the audio information of chemical tower under normal and liquid flooding state is collected for the purpose of detecting and studying the running state of chemical tower. The audio feature extraction and analysis in time-frequency domain are carried out. The sound signal of chemical tower is identifiable in two operating states.

For the small sample signals collected offline, SVM is selected as the pattern classification algorithm to classify and recognize the audio signals in two running states. The simulation results show that the recognition of chemical tower operation state based on SVM is feasible. The on-line identification of various operating states of chemical tower and the further improvement of the effectiveness of the algorithm can be used as the research objectives in the future.

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