Fault Diagnosis of Mine Hoist Based on MFCC-SVDD

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Abstract. In the field of coal mine production, mine hoist plays a very important role in the whole mine transportation engineering. Its safety and stability directly affect the production efficiency of coal mine and the life safety of staff. In view of this, a fault diagnosis method of mine hoist based on MFCC-SVDD is proposed. By collecting the audio signal of the elevator, MFCC algorithm was used to extract the sound signal of multiple channels and the MEL frequency cepstrum coefficient was used to extract the fault characteristic parameters. Based on the one-class classifier SVDD, the hypersphere of the elevator was constructed to test and recognize the sound signals in the training, and the classification and recognition of the fault types of the elevator were completed. The MFCC characteristic parameters of 600 training samples were randomly selected as input to train the model, and 200 test samples were identified. The accuracy of fault identification reached 85%-96%, which provided a guarantee for mine production safety.

Keywords: MFCC; SVDD; Fault diagnosis.

1. Introduction

Mine hoist is one of the important equipment connecting mine underground and surface [1-2]. The safety and stability of hoist directly affect the economic benefit of coal mine and the safety of underground workers. Because of the discrete fault interval of spare parts, regular maintenance will cause higher maintenance cost and more equipment failure. The traditional fault diagnosis method of hoist is to use the contact sensor to collect the vibration signal when the equipment is running

By contrast, the audio signal has the advantages of being more sensitive to the fault characteristic information of the elevator, lower signal-to-noise ratio, fast acquisition speed and low cost. In view of this, a fault diagnosis method for mine hoist based on MFCC-SVDD is proposed.

Mel-Frequency Cepstral Coefficient (MFCC) [10-11] is a frequency domain analysis method for sound signals, which has the advantages of no restriction on the types of input audio signals, strong anti-interference and good Rubon.

Support vector domain description algorithm (SVDD) is a closed hypersphere that can make the minimum volume of all or most target samples in the feature space. It is suitable for anomaly detection and fault detection. It has the characteristics of small amount of computation and clear goal. 。

In this paper, Xutuan mine elevator in Huaibei is selected as the research object, and the elevator audio sample library is established. The MFCC algorithm is used to extract the characteristic parameters of the MEL frequency cepstrum coefficient of the elevator sound signal from the elevator audio samples, and a large amount of data training is conducted on the description and recognition model of the abnormal sound support vector data of the elevator. The fault type and fault point of elevator can be diagnosed quickly and accurately, and the real-time on-line monitoring and analysis of elevator state can be realized

2. Extraction of hoist signal features

2.1. Signal processing of hoist

Improve the mechanical and electrical machine, the probability of failure is much higher than other systems, improve the mechanical and electrical machine is the core component of the hoisting system, according to the literature [2] of mine fault motor type, choose the representative from different fault types of three kinds of fault types as the research object, including motor overload, motor current fault bearing failure. The samples with large noise volume and more noise areas are eliminated to construct the sample library of effective signals. In addition, the effective parts of bird song and noise reduction are retained, and the samples with a long silent area are clipped, which is conducive to extracting effective MFCC feature information from the hoist signals. Taking the overload fault signal samples of the motor as an example, FIG. 1 shows the comparison before and after clipping.

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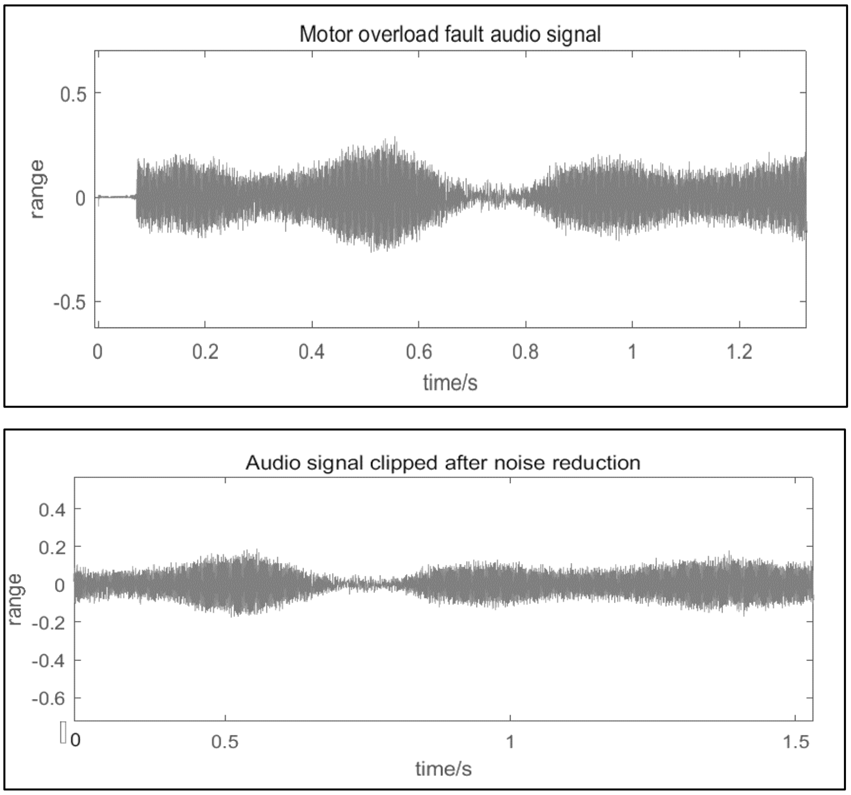

Fig .1 Motor overload fault signalMotor overload fault signal

2.2. MFCC feature extraction

By imitating human speech recognition technology, the MFCC parameters of elevator audio are extracted by using MEL frequency filter banks, and different fault types can be classified and identified by combining classification model. The calculation procedure of MFCC is shown in the figure2.

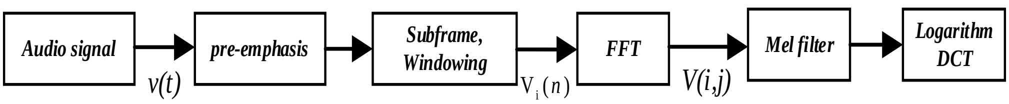

Figure .2 Calculation steps of MFCC

Step 1: Pre-weight the input signal $\mathrm{v}(t)$ to improve the high-frequency part of the audio signal of the elevator $\mathrm{v}'(t)$. The formula is as follows:

$$\mathrm{v}'(t) = \mathrm{v}(t) - a\mathrm{v}(t-1) \tag{1}$$

In Equation, a is the strengthening coefficient, $a = 0.96$.

Step 2: For $\mathrm{v}'(t)$ framing, the audio signal of the hoist has the characteristics of non-stationary time-varying and short-time stationarity.For this reason,the method of overlapping segmentation is adopted to reduce the influence of non-steady-state and time-varying.The principle of overlapping segmentation is to partially overlap between two adjacent frames.The overlapping part is called frame shift, which is conducive to smooth transition between two frames.

Step 3: After framing, add hamming window to signal to change to $\mathrm{V_i}(n)$,i is the corresponding frame.The frame length and frame shift are shown in Figure 3。

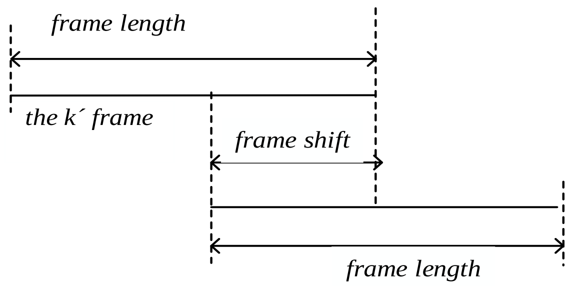

Figure .3 Frame length and frame shift diagram

Step 4: Fast Fourier Transform (FFT) was performed on the sound signal V(n) of the hoist after frame splitting and window addition, and the spectral data of each frame of the sound signal of the hoist was calculated, as shown in Formula (2).

$$V(i, j) = FFT[v_i(n)] \tag{2}$$

In the formula, ***i*** is frame ***i*;*j*** is the ***j-th*** spectral line in the frequency domain $V(i, j)$ is the sound signal of the elevator in the frequency domain。

Step 4: Calculate the power spectrum of each frame according to the frequency domain value of the signal.The power spectrum calculation formula of sound signal is shown in Equation (3).

$$E(i, j) = [V(i, j)]^2 \tag{3}$$

The energy value of the filtered sound obtained by the designed Meir filter bank is:

$$S(i,m) = \sum_{j=0}^{N-1} E(i, j) H_m(k), \quad 0 \le m < M \tag{4}$$

In the formula, $S(i,m)$ is the frequency spectrum energy of each frame after passing the Mel filter; ***M*** is the total number of filters, $H_m(k)$ is the frequency domain response of Mel filter.

Step 5: The discrete cosine transform cepstrum value can be calculated by the energy spectrum obtained by the sound signals of the machine, and the corresponding calculation formula is:

$$mfcc(i,n) = \sqrt{\frac{2}{M}} \sum_{m=0}^{N-1} \log[S(i,m)] \cos[\frac{\pi n(2m-1)}{2M}] \tag{5}$$

In the formula, ***n*** is the corresponding spectral line after the discrete cosine transform.

According to the above calculation process, the MFCC coefficient of the sound signal of the elevator motor can be obtained. Figure 4 shows the MFCC characteristic parameter diagram of the sound signal of the normal sound of the elevator machine, motor overload, motor current fault, and motor mechanical fault. X axis, Y axis and Z axis respectively represent the sample number (80 samples are selected from each sound signal type), dimension (to avoid errors, 12 dimensions are removed from the first and last frames) and characteristic parameter values. The dimension of characteristic parameters in the figure are all 12 dimensions.

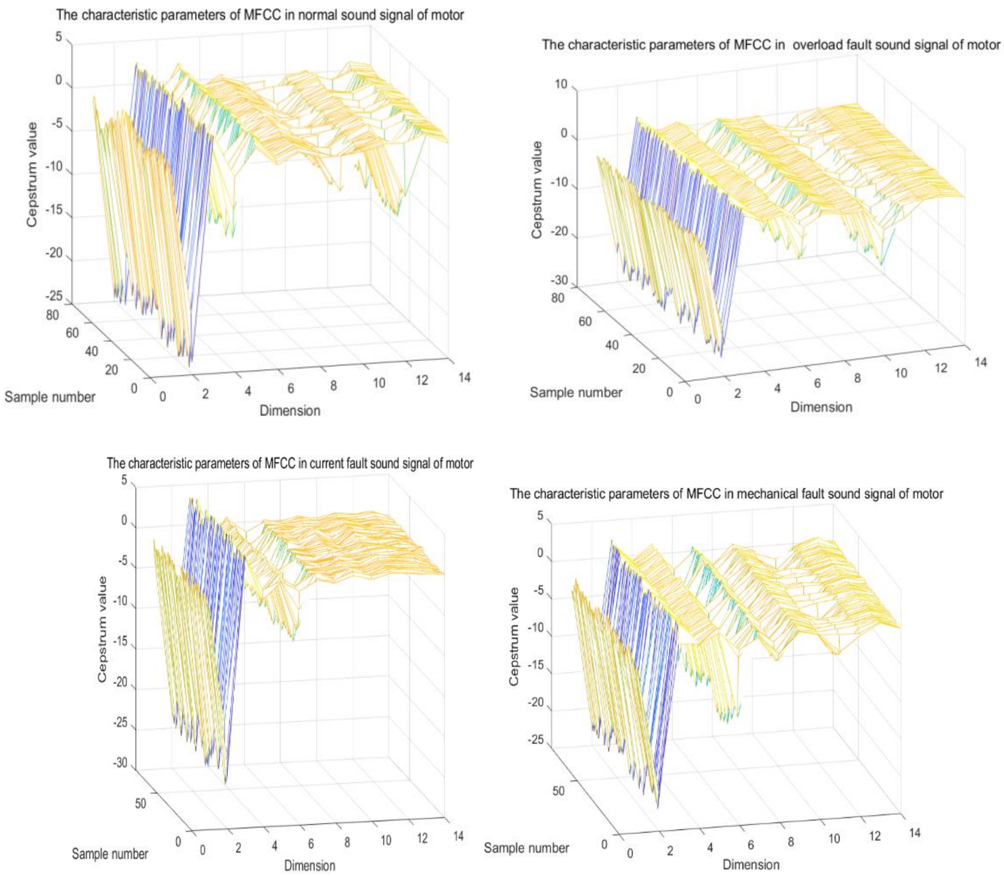

Figure .4 MFCC characteristic parameter diagram of sound signal of hoist

As can be seen from Figure 5, MFCC characteristics of fault signals of the four typical types related to hoist faults are quite different from normal sound signals. 12-dimensional MFCC parameters can be used to characterize the information contained in fault sound signals of hoist faults, which can be used to distinguish different types of faults.

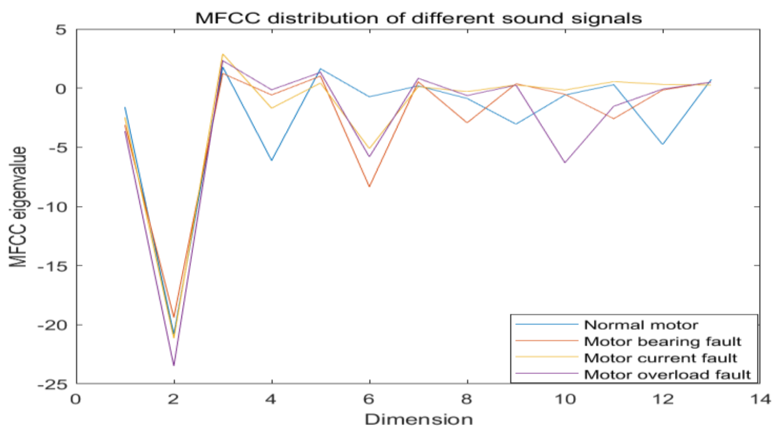

Figure .5 MFCC features of different signals

3. Elevator fault classification identification

After extracting the MFCC characteristic parameters of the four kinds of elevator sound samples, SVDD constructs the hypersphere of the sound recognition model, and uses randomly selected marker samples for training, and then classifiers and recognizes the test sample set.

3.1. Support vector data description (SVDD)

The core idea of SVDD algorithm is to seek a hypersphere with the smallest volume and the center of the sphere is ***a*** and the radius is ***r***. The hypersphere requires ***a*** maximum number of samples containing the elevator abnormal sound data. The non-target class sample points are located outside the hypersphere. So, it can be obtained by minimizing r, as shown in the formula.

$$\begin{aligned} &L=\sum_{i=1}^{N}\alpha_i(x_i\cdot x_i)-\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j(x_i\cdot x_j) \\ &\text{s.}t.\sum_{i=1}^{N}\alpha_i=1, 0\le\alpha_i\le C, i=1,\cdots,N \end{aligned} \tag{6}$$

In the formula, $x_i \cdot x_j$ represents the inner product between the elevator sound samples, which can be replaced by the Gaussian kernel function, which is

$$K(x\cdot y)=exp(\frac{-\|x-y\|^2}{2\sigma^2}) \tag{7}$$

The support vector of the classifier boundary is obtained by solving the optimal set of quadratic programming method $\alpha=(\alpha_1,\alpha_2,\cdots,\alpha_n)$,The corresponding variable x_i in the equation is determined by the equality sign in the inequality.

The radius r of the elevator abnormal sound hypersphere can be calculated by calculating the distance between the center of the sphere and the weight factor less than C ($0<\alpha_1<C$) abnormal sound x_i .The radius of the sphere is calculated by the following formula (8).

$$r^2=\|x_k-\alpha\|^2=K(x_k\cdot x_k)-2\sum_{i=1}^{m}\alpha_i K(x_i\cdot x_k)+\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i K(x_i\cdot x_i) \tag{8}$$

Calculate the distance d^2 from the elevator fault sound test data to the ball center ***a***. The formula is shown in (9)

$$d^2=K(z\cdot z)-2\sum_{i=1}^{n}\alpha_i K(x_i\cdot z)+\sum_{i=1}^{n}\sum_{i=1}^{n}\alpha_i, K(x_i\cdot x_i) \tag{9}$$

According to the size relationship between d^2 and r^2, it is determined whether the fault test data of the hoist is inside the hypersphere, and the criterion is:

$$\begin{cases} d^2\ge r^2 & \text{normal elevator sound signal} \\ d^2<r^2 & \text{faulty elevator sound signal} \end{cases} \tag{10}$$

3.2. Case analysis

In order to verify the accuracy and feasibility of the fault diagnosis method of mine hoist based on MFCC-SVVD proposed in this paper, the experimental simulation of the motor temperature of mine hoist is carried out in this paper.

A total of 600 sample sets of 4 types of elevator sound signals were established, among which 150 samples were for each type. The training set and test set were constructed in a 2:1 ratio. The MFCC characteristic parameters of the training set were used to train the SVDD model, and the matching model of four kinds of elevator sound signals was established. Then 300 test samples were tested by classification. To avoid chance, divide the test into three groups

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Table 1. Fault type recognition and classification of elevator based on SVDD

Elevator sound signal type	Classification and recognition accuracy /%			
	Test 1	Test 2	Test 3	Average
Normal motor	86.4	83.1	89.2	86.2
Motor overload fault	89.5	87.7	85.9	88.7
Motor current fault	90.6	92.1	93.2	91.9
Motor bearing fault	93.1	94,7	90.1	92.6

The identification results show that the MFCC parameter of the elevator sound signal is taken as the input characteristic quantity and the multi-classification model is established by using SVDD, which can effectively identify the fault categories of the elevator sound signal. On the basis of the research results of this paper, the elevator sound fault signal sample library can be further expanded to find more representative elevator fault feature quantity and feature selection, while trying other classification and recognition models to improve the accuracy of elevator fault classification and recognition.

4. Summary

a. The MFCC parameters of the elevator sound signal differ greatly, which can be used to characterize the fault characteristics of the elevator and as the input of the elevator fault classification model. The SVDD model was established for training and testing, and four typical elevator fault sound signals were identified. The average classification recognition accuracy of three random tests was 89.85%, and the recognition accuracy of each bird species was in the range of 86.0% ~ 92.6%.

b. Based on MFCC features and SVDD, the intelligent identification of fault related types of the elevator machine can be realized. The further expansion of the elevator sound fault signal sample library can search for more representative elevator fault features and carry out feature selection. At the same time, other classification and recognition models are tried to improve the accuracy of elevator fault classification and recognition.

References

[1] Di Nayan,Sharif Muhammad Zahid,Hu Zongwen,Xue Renjie,Yu Baizhong. Applicability of VGGish embedding in bee colony monitoring: comparison with MFCC in colony sound classification. [J]. PeerJ,2023,11.

[2] Yan Hao,Bai Huajun,Zhan Xianbiao,Wu Zhenghao,Wen Liang,Jia Xisheng. Combination of VMD Mapping MFCC and LSTM: A New Acoustic Fault Diagnosis Method of Diesel Engine[J]. Sensors,2022,22(21).

[3] M Azim Naz,R Sarath. Combined classification models for bearing fault diagnosis with improved ICA and MFCC feature set [J]. Advances in Engineering Software,2022,173.

[4] Hawi Sara,Alhozami Jana,AlQahtani Raneem,AlSafran Dannah,Alqarni Maram,Sahmarany Lola El. Automatic Parkinson's disease detection based on the combination of long-term acoustic features and Mel frequency cepstral coefficients (MFCC)[J]. Biomedical Signal Processing and Control,2022,78.

[5] Yildirim Muhammed. Automatic classification and diagnosis of heart valve diseases using heart sounds with MFCC and proposed deep model[J]. Concurrency and Computation: Practice and Experience,2022,34(24).

[6] Shi Yi,Liu Xinyu,Wei Chuliang. An event recognition method based on MFCC, superposition algorithm and deep learning for buried distributed optical fiber sensors[J]. Optics Communications,2022,522.

[7] Yang Jingdong,Chen Lei,Cai Shuchen,Xie Tianxiao,Yan Haixia. Prediction of H-type Hypertension Based on Pulse Wave MFCC Features Using Mixed Attention Mechanism[J]. Journal of Medical and Biological Engineering,2022,42(5).

[8] Choudakkanavar Gangavva,Mangai J. Alamelu,Bansal Mohit. MFCC based ensemble learning method for multiple fault diagnosis of roller bearing[J]. International Journal of Information Technology,2022,14(5).

[9] Tirronen Saska,Kadiri Sudarsana Reddy,Alku Paavo. The Effect of the MFCC Frame Length in Automatic Voice Pathology Detection. [J]. Journal of voice: official journal of the Voice Foundation,2022.

[10] Zakariah Mohammed,B Reshma,Ajmi Alotaibi Yousef,Guo Yanhui,Tran Trung Kiet,Elahi Mohammad Mamun. An Analytical Study of Speech Pathology Detection Based on MFCC and Deep Neural Networks[J]. Computational and Mathematical Methods in Medicine,2022,2022.

[11] Zhai Wenya,Lu Shaowu,Wenjing Cai,Canjun Yuan,Yunxuan Zhang,Yuge Zheng. An Improved SVDD Algorithm for Fast Real-time Response[C] 2021: 268-272.DOI: 10.26914/c.cnkihy.2021.031917.

[12] SeyyedMohammad JavadiMoghaddam, Reyhane Rateghi. A one-class classification approach based on SVDD for imbalanced and overlapping classes[J]. International Journal of Data Analysis Techniques and Strategies,2021,13(4).

[13] Guiyun Xu,Di Song,Di Zhang,Xiaoguang Zhang,Shikang Sha. A novel mechanical design of disc brakes for fault diagnosis and monitoring positive braking pressure in mine hoist[J]. Advances in Mechanical Engineering,2019,11(4).

[14] Laurent Giraud,Bertrand Galy. Fault tree analysis and risk mitigation strategies for mine hoists[J]. Safety Science,2018,110.

[15] Engineering - Safety Engineering; Research Conducted by L. Giraud and Co-Researchers Has Updated Our Knowledge about Safety Engineering (Fault tree analysis and risk mitigation strategies for mine hoists) [J]. Journal of Engineering,2018.

[16] Ting-ting Dai. Personal credit assessment based on improved SVDD algorithm[J]. IOP Conference Series: Materials Science and Engineering,2018,439(4).

[17] Ting-ting Dai. Personal credit assessment based on improved SVDD algorithm[C],2018:1217-1222.

[18] Li Juanli,Xie Jiacheng,Yang Zhaojian,Li Junjie. Fault Diagnosis Method for a Mine Hoist in the Internet of Things Environment. [J]. Sensors (Basel, Switzerland),2018,18(6).

[19] Liyan Zhang,Zhilin Liang,Xianling Zeng,Dandan Fu. SVDD ALGORITHM BASED ON NOISE COST FOR ANOMALY DETECTION IN HYPERSPECTRAL IMAGERY[J]. Applied Computer Letters,2017,1(2).

[20] Birch B,Griffiths CA,Morgan A. Environmental effects on reliability and accuracy of MFCC based voice recognition for industrial human-robot-interaction[J]. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture,2021,235(12).