Method for Recognizing Mechanical Status of Container Crane Motor Based on SOM Neural Network

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Abstract. The recognition of mechanical state of container crane motor is a complex nonlinear mode classification problem. In this paper, a deep learning method based on self-organizing feature map (SOM) neural network was developed for the cluster analysis of motor vibration signals to characterize the mechanical state of the lifting motor. Through Python software simulation, the vibration intensity signal of the lifting motor can be divided into five different categories, and the interval range of each type of vibration intensity signal is statistically obtained, which corresponds to the five mechanical states of the motor. The SOM neural network can realize the effective and rapid self-adaptive classification of the motor vibration signal, realize the recognition of the mechanical status of the crane motor, and provide a certain basis for the maintenance of the motor.

1. Introduction

The Container crane is huge and complex in structure, and the Container crane fault diagnosis is a complex nonlinear classification problem. The nonlinear classification of SOM neural network is very suitable for the research of the Container crane complex system[1]. The author in [2] based on SOM neural network bearing fault detection and diagnosis, the results show that using SOM neural network clustering to improve the classification performance of fault detection process has a good effect; The author in [3] use improved Hidden Markov model and self-organizing map data drive to identify bearing faults, it has a very significant effect that the recognition rate of up to 99.58%. In addition, the SOM neural network has the advantages of simple structure, high self-organization and self-learning ability [4]. In this paper applies the SOM neural network to the state cluster analysis of the Container crane lifting motor.

2. Signal acquisition and processing

2.1. Vibration signal acquisition

Acceleration sensors are installed on the output terminals of the right and left lifting motors of the Container crane. The sampling period is set to collect a vibration signal every 10 seconds and the signals are collected by the signal conditioning collector. The installation position of motor sensor as shown in Figure 1. The sensor collects about 8000 vibration signals every day. In this paper, select the vibration signal from 0 o'clock on January 10 to 12 o'clock on January 16 for research.
2.2. Vibration signal time-domain diagram
In order to observe the trend of the vibration signal, we can use MATLAB to draw a time domain diagram of the motor vibration signal for a week, as is shown in Figure 2. The amplitude of the vibration can be seen directly from the figure 2. When the lifting motor works for a long time with a large vibration amplitude, the motor or even the Container crane may be damaged. Therefore, it is necessary to identify the state of the motor through the collected vibration signal to ensure that the motor operates in a relatively safe state.

![Image](figure1.png)

**Figure 1.** Lift motor sensor installation diagram.

3. Vibration signal feature extraction
Statistical feature extraction is an important basis for judging the operating status of Container crane motor. The characteristic parameters of the motor reflect its mechanical properties and the abnormal data contains information on the degree of vibration hazard. The degree of danger is proportional to the degree of deviation from the average value of the data. Then we can formulate reference standards for analysis. When analyzing the status of the lift motor, it can be divided into five states: good, normal, early warning, warning and danger [5]. The physical concept of vibration of the motor is used in the diagnosis process, the clustering analysis was performed by extracting the effective values \( X_{RMS} \) of the vibration intensity of the motor as the eigenvalues [6]-[8].

\[
X_{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} X_i^2}
\]

4. SOM neural network clustering principle and steps
4.1. SOM neural network clustering principle
The SOM neural network consists of an input layer and a competition layer, the input layer corresponds to a high-dimensional input vector and the competition layer consists of ordered nodes on a two-dimensional grid, they are connected by weight vectors[9]. The basic structure as shown in Figure 3. Through network training established a network layout, which can make each weight vector of the competition layer is located in the center of the input vector cluster [10][11].
Figure 3. SOM neural network topology.

4.2. SOM neural network clustering steps

The SOM network can selectively respond to input data and automatically configure similar input data on the network according to similarity between input vectors [12]. The network training steps are as follows.

4.2.1. Step 1 (Initialization and normalization of weights) Initialization of weights is such that the initial position of the weights and the distribution area of the input samples sufficiently overlap. By selecting part of the data from the vibration intensity data of the motor as a training sample for the SOM neural network, then randomly selected \( m \) input sample from all training sample sets as initial weights and normalized.

\[
\hat{w}_{ji} = \frac{w_{ji}}{\|w_{ji}\|}, (1 \leq i \leq m)
\]

(2)

Note: \( w_{ji} \) is the initial weight, \( \|w_{ji}\| \) is the Euclidean norm of the weight vector and \( \hat{w}_{ji} \) is the normalized weight.

4.2.2. Step 2 (Training sample normalization)

\[
\hat{x} = \frac{x - \langle x \rangle}{\sqrt{\sum_{j=1}^{n} x_j^2 / \sum_{j=1}^{n} x_j}}
\]

(3)

Note: \( \hat{x} \) is the training sample, \( \|\hat{x}\| \) is the Euclidean norm of the training sample vector and \( x_j \) is the \( j \) characteristic component value of the training sample vector.

4.2.3. Step 3 (Get winning neurons) The normalized vibration intensity sample data of the motor is put into the input layer of the SOM network, the Euclidean distance of the training sample data and the weight vector is calculated, and the neuron with the smallest distance is defined as the winning neuron \( d_j \).

\[
d_j = \|X - W_j\| = \sqrt{\sum_{t=1}^{m} (x_t(t) - \omega_{jt}(t))^2}
\]

(4)

4.2.4. Step 4 (Defining a winning neighborhood) The winning neighborhood determines the weight adjustment domain at time \( t \) with the winning neuron \( j^* \) as the center. The initial neighborhood \( N_{j^*}(0) \) is larger, and \( N_{j^*}(t) \) gradually shrinks with the training time. The size of the winning neighborhood is expressed by the radius of the neighborhood.

\[
r(t) = C_0 e^{-\beta t / T}
\]

(5)
Note: $C_i$ is a constant greater than zero related to the number of nodes in the output layer, $B_i$ is a constant greater than one and $T$ is the preset maximum number of times of training.

4.2.5. Step5 (Adjustment weight) Adjust the weights of all neurons in the winning neighborhood.

$$w_{ij}(t + 1) = w_{ij}(t) + \eta(t, N) |x_i^p - w_{ij}(t)|(i = 1,2,\cdot\cdot\cdot, n, j \in N_j(t))$$ (6)

Note: $W_{ij}(t + 1)$ is the adjusted weight, $\eta(t, N)$ is a function of the training time $t$ and the topological distance $N$ between neurons in the neighborhood.

4.2.6. Step6 (training requirements) The $\eta(t)$ is the functional value of the topological distance between the $j$ neuron and the winning neuron after training, $\eta_{\text{min}}$ is the set minimum topology distance function value. If $\eta(t) < \eta_{\text{min}}$, the network training is ended. Otherwise, come back 4.2.3 to continue.

5. Python simulation
The system adopts Python 3.6 as the simulation test platform. The SOM network training sample set is obtained after the experimental data was normalized. The cluster center of the vibration intensity data of the lifting motor is obtained After training, as is shown in Table 1.

Table 1. Lifting motor vibration intensity data clustering center.

| date       | Center 1 | Center 2 | Center 3 | Center 4 | Center 5 |
|------------|----------|----------|----------|----------|----------|
| January 10 | 0.73132647 | 0.52094046 | 0.88128821 | 0.20799421 | 0.98397678 |
| January 11 | 0.6819084  | 0.85353541 | 0.47250587 | 0.97799975 | 0.7786049  |
| January 12 | 0.70053833 | 0.54252202 | 0.83406307 | 0.23099253 | 0.96693977 |
| January 13 | 0.7135338  | 0.83996019 | 0.55152768 | 0.97295295 | 0.25481011 |
| January 14 | 0.70336614 | 0.54701719 | 0.83178712 | 0.23983624 | 0.96237557 |
| January 15 | 0.71072541 | 0.83709021 | 0.5549968 | 0.97080239 | 0.27162745 |
| January 16 | 0.70474831 | 0.53329382 | 0.83521524 | 0.218813  | 0.96852065 |
| January 17 | 0.70938256 | 0.84585213 | 0.54987844 | 0.97570655 | 0.24867736 |
| January 18 | 0.70835896 | 0.53834956 | 0.84790267 | 0.22074443 | 0.97738899 |
| January 19 | 0.70574111 | 0.8426558 | 0.53011293 | 0.97529536 | 0.21113709 |
| January 20 | 0.72004292 | 0.5386122 | 0.8448222 | 0.22185959 | 0.97447465 |
| January 21 | 0.69385631 | 0.84248636 | 0.53483934 | 0.97502712 | 0.22415564 |
| January 22 | 0.68699258 | 0.48156783 | 0.85929699 | 0.22554832 | 0.97644026 |
| January 23 | 0.72657318 | 0.87636944 | 0.51139136 | 0.97413152 | 0.21563879 |

According to Table 1, we can get the cluster center of the vibration intensity of the Container crane lifting motor and draw the change trend of the cluster center through SPSS, as is shown in Figure 4.

![Cluster center distribution](image)

Figure 4. Cluster center distribution.

From January 10th to January 16th, the cluster center of the Container crane lifting motor vibration data is approximately equal. Therefore, the average value of the cluster center at each day can be equivalent to the data of all the vibration intensities within a week. We can obtains the classification intervals for each cluster center by MATLAB, as shown in Table 2.
Table 2. Lifting motor vibration intensity data classification interval.

| Date       | Interval 1      | Interval 2      | Interval 3      | Interval 4      | Interval 5      |
|------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| January 10 | (0.719803106)   | (0.719803106,6.604036273) | (6.604036273,11.48826944) | (11.48826944,16.37250261) | (16.37250261,∞) |
| January 11 | (0.783360843)   | (0.783360843,6.813725508) | (6.813725508,11.84409017) | (11.84409017,16.87454848) | (16.87454848,∞) |
| January 12 | (0.337818312)   | (0.337818312,5.196238951) | (5.196238951,9.054695951) | (9.054695951,12.91308023) | (12.91308023,∞) |
| January 13 | (0.133435932)   | (0.133435932,4.937436915) | (4.937436915,8.741437897) | (8.741437897,12.54538888) | (12.54538888,∞) |
| January 14 | (0.475390459)   | (0.475390459,5.683604877) | (5.683604877,9.89181929)  | (9.89181929,14.10003371)  | (14.10003371,∞) |
| January 15 | (0.348258668)   | (0.348258668,5.360417335) | (5.360417335,9.372575981) | (9.372575981,13.38437463) | (13.38437463,∞) |
| January 16 | (0.157578106)   | (0.157578106,6.03307690)  | (6.03307690,10.49037275) | (10.49037275,14.9476686) | (14.9476686,∞) |

Table 2 shows the interval critical value and classification interval of the vibration intensity data. The classification threshold of each day is very close and the existence of a slight difference may be due to measurement error and other factors. Therefore, we can reduce the error by calculating the average of the critical values within a week. The calculated critical values for the intervals are: 1.51298707, 5.67584588, 9.83673070, and 13.9986025. The classification intervals 1 to 5 are (0, 1.51298707), (1.51298707, 5.67584588), (5.67584588, 9.83673070), (9.83673070, 13.9986025), (13.9986025,∞).

According to the lifting motor vibration severity data classification interval, the motor status is divided into five categories: good, normal, early warning, warning and danger. Interval 1 represents the motor's in good state, interval 2 represents the motor's in normal state, interval 3 represents the motor's in warning state, interval 4 Indicates motor in warning status and interval 5 represents motor in dangerous status.

In this paper, SOM neural network is used to excavate the corresponding relationship between the vibration intensity data of lifting motor and the working state of the motor. By comparing the collected vibration intensity data with the classification interval, the working status of the lifting motor can be judged.

6. Conclusion

This method can accurately identify the working status of the Container crane lifting motor, so as to feedback to the Container crane operator to identify and reduce the economic loss. The SOM neural network has the advantages of simple structure, high degree of self-organization and self-learning ability, high efficiency and strong anti-interference ability. It also can be used in the other Container crane motor state recognition. In addition, because there are few sample data in this training, the classification thresholds and classification intervals obtained through SOM neural network training are not accurate enough. When the collected vibration signal database is large enough, the comparison between motor state and vibration intensity data can be established accurate relationship.

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