IOP Conf. Series: Materials Science and Engineering **220** (2017) 012034 doi:10.1088/1757-899X/220/1/012034

Load Weight Classification of The Quayside Container Crane Based On K-Means Clustering Algorithm

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Abstract. The precise knowledge of the load weight of each operation of the quayside container crane is important for accurately assessing the service life of the crane. The load weight is directly related to the vibration intensity. Through the study on the vibration of the hoist motor of the crane in radial and axial directions, we can classify the load using K-means clustering algorithm and quantitative statistical analysis. Vibration in radial direction is significantly and positively correlated with that in axial direction by correlation analysis, which means that we can use the data only in one of the directions to carry out the study improving then the efficiency without degrading the accuracy of load classification. The proposed method can well represent the real-time working condition of the crane.

1. Introduction

Nowadays, the demand for crane is growing. Due to the lack of scientific basis, there are still problems in the evaluation of service life of the crane. [1] There is a strong association between the service life of the crane and the actual load of each operation. The traditional life assessment methods usually pay attention to the methodological research and lack actual data and experiment verification [2-4].

Even we can figure out the total load during a period through the record book, the load weight for each individual operation is hard to know. The vibration signal of the hoist motor has a nonlinear relationship with the actual load of each operation of the crane. [5] The analysis of the real-time vibration of the motor allows estimating the load weight of each operation which provides reliable data for the further evaluation of crane service life and improves the accuracy of the assessment.

Data analysis methods are essential for analyzing the ever-growing massive quantity of data. [6] One of the most popular and efficient clustering methods is the K-means method [7,8]. This paper proposes a container crane load classification method based on K-means clustering algorithm. The proposed technique allows discriminating and classifying a set of vibration signals of the hoist motor corresponding to different classes of the loads.

The paper is organized as follows. Section 1 describes the data acquisition and raw data pre-processing. Section 2 analyzes the acquired data and presents the crane's load classification. Section 3 validates the classification method with real-time data. Section 4 concludes the paper.

2. Data processing

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2.1. Data acquisition

NetCMAS (network condition monitoring and assessment system) has been effectively used for equipment state analysis and management in big container companies. [9] NetCMAS acquires and processes real-time signals of different equipment. It can also save the data. As the data acquisition is in real-time, the signal contains two kinds of states including working and non-working in addition of interference signals.

As mentioned previously, the load is directly related to the vibration signals which can be required directly. The data analyzed in this paper are acquired by NetCMAS from real-time vibration signals in radial and axial directions of a measuring point of hoist motor of the crane (refer with: Figure 1, equipment installed on the crane in a Shanghai port). We select the data from 2pm January 18, 2010 to11pm February 7, 2010 for a period of three weeks which are comparatively representative.



Figure 1. left : crane; right : hoist motor.

2.2. Data preprocessing

The real-time data collected by the system, which usually contain abnormal data, repeated data or missing data, cannot be used directly to their classification and they should be preprocessed.

2.3. Data normalization preprocessing

The data are limited to the range of 0~1 through their normalization which is a convenient way for the future data processing and reducing the operation time.

First of all, we get the data, representing the radial and axial vibration signals of the hoist motor, of each hour and take the average hourly. There are 490 sets of data totally. The maximum value of the radial direction is 3.14, and the maximum value along the axial direction is 4.93. They are used for the data normalization (the data are normalized by dividing each value with the maximum value). The range (the max value minus the min value of the data) for radial data is 3.08, and the range for the axial data is 4.87 which means that the magnitude of change of vibration signals is not big. So it meets the conditions for the K-means clustering analysis. The standard deviations along the axial and radial directions are 0.61 and 0.87 respectively which indicate that the dispersion of the data is relatively small.

3. Load classification

3.1. Crane load and motor vibration

The motor of crane is generally a three-phase asynchronous model. The load of quayside crane is proportional to the input power of the motor according to the mechanical characteristics of three-phase asynchronous motor. What's more, the input power is proportional to the electromagnetic torque. The input power is inversely proportional to the slip.

After the motor stator being connected to the power supply network, the fundamental wave of magnetic motive force produces the rotating magnetic field with same speed and same directions. The amplitude is proportional to the stator current which is proportional to the input power.

Generally, with the increase of the load of the hoist motor, the vibration of the hoist motor will also increase [10]. Therefore, in order to investigate the load category, the radial and axial vibration intensity data can be used. However, they are not two independent signals. To investigate their relationship, the correlation analysis is carried out.

3.2. Correlation analysis

We use R language and SPSS (Statistical Product and Service Solutions) to analyze the correlation between the axial and radial vibration intensities. SPSS is a series of software products and related services for statistical analysis, data mining, predictive analysis and decision support tasks promoted by IBM. In this study, the axial vibration intensity, denoted by xi, is taken as independent variable and the radial one, denoted by yi as dependent variable. There is a significant positive correlation (refer with: Figure 2) between the axial and radial vibration signals for a measuring point as shown in figure 2. Let X represent the radial direction, and Y the axial direction. In figure 2, a point represents the data of one hour and different colors correspond to different days. This correlation can be quantified by the following correlation coefficient (refer with: (1)):

$$r = \frac{N\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{N\sum x^2{}_i - (\sum x_i)^2}\sqrt{N\sum y^2{}_i - (\sum y_i)^2}} \tag{1}$$

where r is the Pearson correlation value whose absolute value is limited by one; N is the number of the data samples; xi is the ith radial vibration intensity; yi is the ith axial vibration intensity.

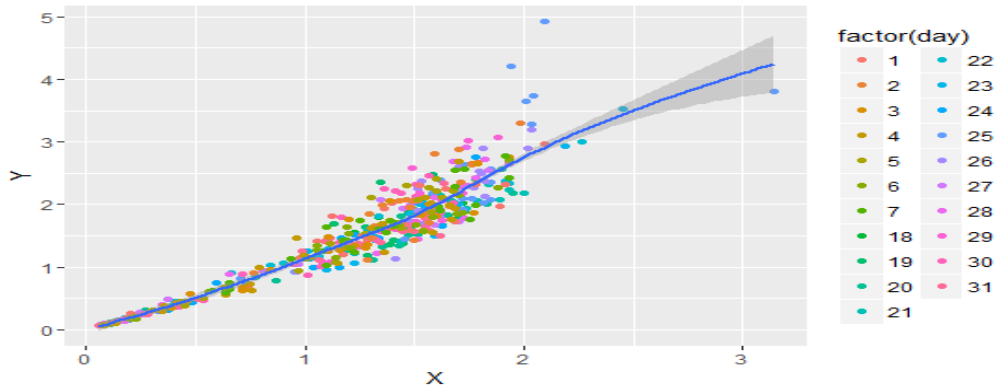


Figure 2. Axial vibration intensity in terms of radial vibration intensity

After calculating, the Pearson correlation value between the radial and axial vibration intensities is 0.964. So, there is a significant positive correlation between the radial and axial intensities. In order to get a quantitative model of the axial vibration intensity (y) and radial vibration intensity (x), we establish the following linear regression model (refer with: (2)) between them:

$$y = ax + b \tag{2}$$

By applying the least squares method to the data, we get a = 0.895 and b = 0.151. Finally, the mathematical model (refer with: (3)) of the relation between the radial and axial vibration intensities can be written as:

$$y = 0.895x + 0.151 \tag{3}$$

This model shows that we can predict the radial vibration intensity values from the axial value through Equation 3. Consequently, the data of one of the two directions can be used for the load classification, which will reduce the memory requirement and calculation complexity.

3.3. Classification for the crane's load

In practice, the load of the hoist motor can be divided into 5 categories representing the 5 typical working conditions, and the working cycle of the hoist motor in this paper is defined as:

1. non-load: idle;
2. small-load: lifting few rated load and generally lifting small load;
3. medium-load: occasionally lifting rated load and generally lifting medium load;
4. high-load: usually lifting rated load;
5. over-load: continually lifting rated load.

4. Load classification based on K- means cluster

By comparing the hierarchical clustering and K-means clustering, the most common classification methods, it is shown that the K-means clustering is more suitable for this study due to the large amount of data. The output results by K-means are easier to understand than the results by hierarchical clustering.

This paper classifies 21 sets of data by K-means clustering and sets time as categorical variables and vibration signals in radial and axial directions as the independent variables. Six categories are shown in Table 1.

Table 1. Hoist motor vibration intensity K-means clustering

Categories	**1**	**2**	**3**	**4**	**5**	**6**
Time	0127	0125	0119、0120	0121	0122、0128	0118、0123
			0124、0130	0131	0129、0203	0126、0201
			0205、0206		0204	0202、0207

From Table1, we observe that the load state of the hoist motor can be defined to five different categories which is summarized in Table 2.

Table 2. Classification standard of hoist motor load

Load Condition	**Y**	**X**
Non-Load	$0<y\leq0.4356$	$0<x\leq0.3763$
Fractional-Load	$0.4356<y\leq0.5199$	$0.3763<x\leq0.4197$
Medium-Load	$0.5199<y\leq0.6101$	$0.4197<x\leq0.5293$
High-Load	$0.6101<y\leq0.7069$	$0.5293<x\leq0.5963$
Over-Load	$0.7069<y\leq1$	$0.5963<x\leq1$

In order to verify the reliability of this classification result, we classify the vibration intensity of the radial and axial directions separately. The results, in Table3, show that the categorized results in axial direction are almost matched to those in radial direction. Hence, we can only use the data in one of the directions to carry out the study.

Table 3. Categorized results in radial and axial directions separately

Categories	1	2	3	4	5	6
Percentage Of Matching Degree [%]	100	85	85	100	100	90

The axial vibration and radial vibration intensities are positively correlated, and their classification results are almost the same, therefore we only need to measure the vibration intensity in one direction

in practical application, which will greatly reduce the amount of calculation and improve the calculation speed.

In the following, we calculate the number of times of each working state of the quayside container crane in one day by coding through Java. We can learn from the real-data in NetCMAS that the data interval is about 15s. The statistical results are shown in Table 4. The data displayed in this table can be used to accurately evaluate the service life of the crane which is such a great improve. As we all know, the over-load working states usually cause the damage to the crane.

Table 4. Proportion of load time in January 26th

Load Condition	Time Percentage [%]	Operation Times
Non-Load	16	115
Small-Load	44	316
Medium-Load	4	29
High-Load	17	123
Over-Load	19	137

According to the statistical results, the hoist motor is occasionally in the condition of lifting rated load and usually in the state of small and medium load.

5. Conclusion

From the above analysis, this paper made the following conclusions:

1. This paper analyzes the real-time vibration data of the hoist motor of the crane in order to classifying the load of crane. This method has many advantages such as: selecting few characteristic parameters, simple operation, high accuracy and strong practicality.
2. The classification results are well adapted to the engineering application. According to the classification results, this paper calculates the number of times and proportion of operation of each type of the load of the crane in one day. That method provides helpful data for the evaluation of service life of the crane in application.
3. We have come to the conclusion that there is significant positive correlation between radial and axial vibration signals. This conclusion has practical significance for engineering application, which can simplify the monitoring work and release memory.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (No. 31300783), China Postdoctoral Science Foundation (No. 2014M561458), Doctoral Fund of the Ministry of Education Jointly Funded Project (No. 20123121120004), the Shanghai Maritime University Research Project (No. 20130474), the Shanghai Top Academic Discipline Project- management science & engineering, and the high-tech research and development program of China (No. 2013A2041106).

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