ISSN: 2414-1895 DOI: 10.6919/ICJE.202012_6(12).0029

Recognition and Visualization of Working State of Quay Crane Based on K-means

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Abstract

The working efficiency of the port is affected by the working sustainability of the quay crane equipment, so it is necessary to ensure the healthy state of the quay crane. By analyzing the daily operation data of the quay crane, it can help to formulate a reasonable equipment maintenance and repair plan. In this paper, the operation data of a certain type of quay crane during continuous operation in a certain period of time are extracted. Each working day is taken as a cycle, and the integral of stress value with time at the section where the middle tie rod is 2 m away from the hinge is taken as the working strength of the quay crane. The distribution characteristics of the working conditions are observed by frequency statistics, and the number of working conditions is determined. This paper presents a method based on K-means and weighted PCA to obtain the visual state characteristics of the quay crane, and reasonably arrange the lifting capacity of the quay crane. The results show that this method can not only classify the load state of vibration signal reasonably, but also realize the diagnosis and recognition of each operation state of the quay crane.

Keywords

Unsupervised clustering; K-Means; Quay crane; Condition monitoring; Predictive maintenance.

1. Introduction

With the rapid increase of China's port trade volume and the improvement of Industrial Science and technology level, the port lifting equipment system is developing towards highly integrated and intelligent with the improvement of industry 4.0 level. Therefore, it is particularly important to carry out real-time online monitoring and condition assessment of some key system parts of port lifting equipment. With the continuous improvement and improvement of computer level and sensor technology in the 21st century, a large number of diversified data related to operating characteristic parameters can be obtained by monitoring quayside crane equipment[1].

Quayside container bridge crane (hereinafter referred to as quay crane) is a kind of equipment which is installed on the shore of port terminal for loading and unloading containers. With the development of international trade, more and more goods are hoisted between the wharf and the transport ship in the form of containers. The quay crane usually works continuously to ensure the cargo handling efficiency of the port. Therefore, the implementation of operation status analysis and fault diagnosis of the quay crane can find the characteristics and evolution rules of the health mode of the quay crane under different working conditions, which can help to formulate the appropriate predictive maintenance plan, avoid the occurrence of serious faults and accidents, and at the same time, it can also obtain the influence of working conditions on the state of the quay crane, which provides a basis for maximizing the use of the quay crane equipment.

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At present, the difficulty of condition monitoring and fault diagnosis of quayside crane mainly lies in the fact that the quay crane usually works under variable working conditions. Different working conditions have great influence on the state of quay crane, and the signals generated are mostly non-stationary processes, so it is difficult to get the exact analytical model by mathematical modeling method. In addition, even if the analytic model is established[2], it still faces great challenges in practical application due to its lack of self-renewal ability.

In this paper, the operation data of a certain type of quay crane during continuous operation in a certain period of time are extracted. Each working day is taken as a cycle, and the integral of stress value with time at the section where the middle tie rod is 2 m away from the hinge is taken as the working strength of the quay crane. The distribution characteristics of the working conditions are observed by frequency statistics, and the number of working conditions is determined. A method based on K-means and weighted PCA is proposed to obtain the visual state characteristics of the quay crane.

2. Data preprocessing and analysis of quay crane

The working process of the mechanism can be regarded as the input and output process of energy. In the transition stage of mechanism, the dynamic load and its change of transmission system are closely related to the electric drive characteristics.

In most quayside cranes, the crane motor is usually started and braked in working cycle, so the current is not constant[3]. During starting and braking, the peak current has an important impact on the heating and vibration of the hoist motor. In the working cycle of the crane motor, the stop time always occurs at the intersection with the movement time.

Due to the influence of noise, sensor installation, measurement method, and other uncertain factors, field data usually include noise, outliers, and false data, which do not truly represent the working state of the machine, and have a considerable adverse impact on the subsequent analysis and research. Therefore, visualizing the original data in advance is helpful to intuitively obtain the numerical characteristics of variables, and inspire the next step to take appropriate data processing and analysis methods. First, all the data are visualized and identified as sensor1, sensor2, sensor3……. From the visualization results, we can know that there is a strong linear relationship between several variables.

3. Cluster analysis of the original data

3.1 Data acquisition

NetCMAS has been effectively applied to large enterprises such as container companies at home and abroad, realizing the programming of equipment status analysis and management ideas. NetCMAS provides equipment engineers with advanced practical methods and tools for automatic data acquisition, effective analysis and management[4]. The characteristic of NetCMAS data processing is to collect and process signals at the same time. Since the data collected by the system is real-time, the signal includes the signal of working state and non working state as well as interference signal.

All the data analyzed in this paper are from the radial and axial real-time vibration signals of a hoist motor measurement point in NetCMAS. The selected time is from May 18, 2019 to June 18, 2019.

3.2 Cluster the working condition data

Generally speaking, clustering is to find clusters with similar observation results, and divide the sample data into several categories by using similarity. In other words, the observation distance in one cluster is smaller than that in other clusters. In the process of clustering, we should first determine the number of classes, that is, the given data set is divided into some K classes, and define K centers. Because different initial centers will produce different clustering results, the key to clustering is to select the appropriate center. The distance between each sample and K cluster centers is calculated to find the minimum distance, and the samples are classified into the nearest cluster centers. When all the data points are assigned to the range of the central point, the initial clustering is formed. After the

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adjustment, K new cluster centers are calculated for the new category by average method, and then the given data is reassigned to the nearest new center point. The results show that K centers change gradually until their positions remain unchanged, that is, the clustering centers do not move. The strategy of K-means clustering method is that the distance between clusters is as large as possible, and the distance within the cluster is as small as possible. The field data were divided according to the collection time, and the field data of 30 working days were obtained. The working strength of each working day $W=\int PdT$, where p is the stress size and t is the time[5]. The frequency statistics of working intensity is shown in Fig. 1, and it can be determined that the optimal number of working conditions is 5.

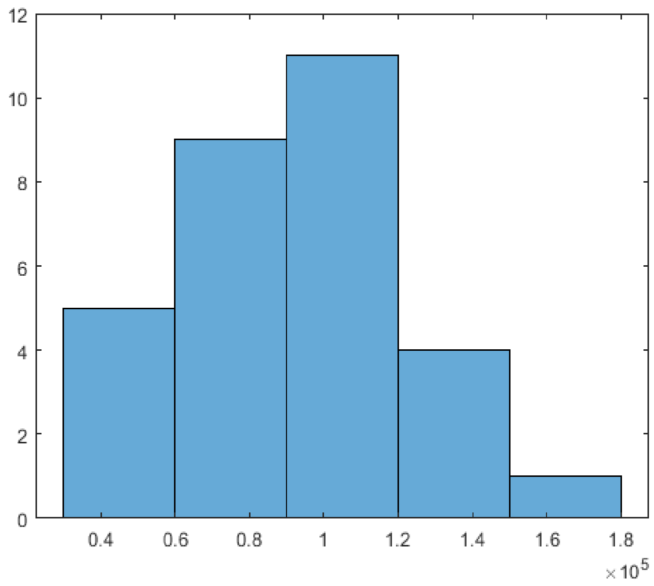

Fig.1 Frequency statistics of working condition data in 30 working days

Use Euclidean distance to cluster the working condition data by K-means, and the result is shown in Figure 2. After six iterations, the minimum sum of squares of distance is 1.26057e + 09, and the centers of clustering are 102511.24, 56995.27, 78577.15, 31381.59, 132804.25, and then label the original data with cluster 1, cluster2, cluster3.

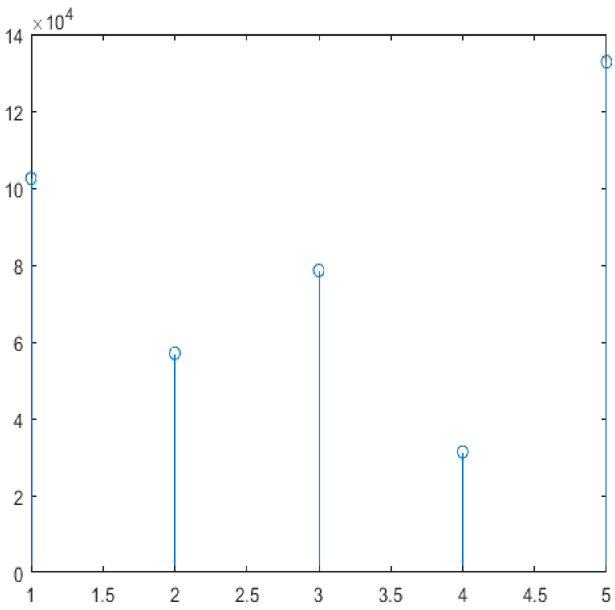

Fig. 2 K-means clustering results of working condition data

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3.3 Correlation analysis of raw data

The visualization of the original data shows that there may be strong linear relationship between variables, but the strength of correlation can not be obtained directly $\rho_{XY}=\frac{cov(X,Y)}{\sigma_X\sigma_Y}$, where $\text{cov}(X,Y)=\frac{\sum_{i=1}^{N}(x_i-\mu_X)(y_i-\mu_Y)}{N-1}$,σX,and σY are the standard deviations of X and y, and μX and μY are the mean values of X and Y. Because of $\rho_{XY}=\rho_{YX}$,Therefore, a 32 × 32 symmetric matrix C of correlation coefficient coefficient is obtained[6]. From the result C, it can be seen that the absolute value of the correlation coefficient of some variables is close to 1, which indicates that there is a strong linear relationship between these variables. The visualization of C is shown in Fig. 3.

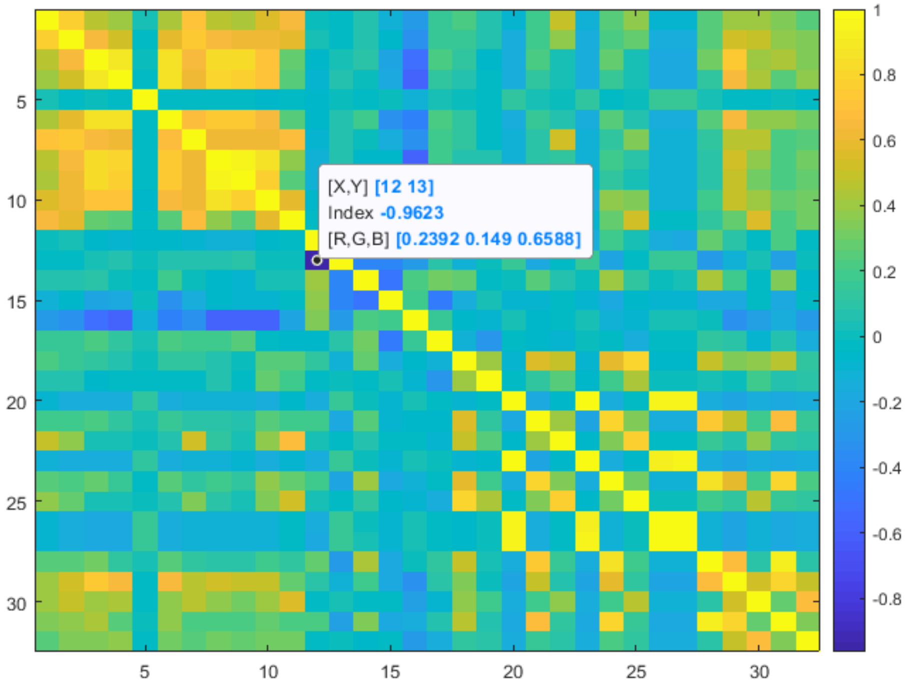

Fig. 3 Correlation coefficient matrix between variables

3.4 The original data is reduced by weighted PCA

Because the units of the variables in the original data are not unified and the variance of the variables is large, the weighted linear dimensionality reduction method is used to reduce the dimension of the original data, so as to observe the distribution characteristics visually.

Principal component analysis (PCA) is a data analysis method based on Karhunen Loeve (K-L) transformation [7]. It projects high-dimensional data into low-dimensional space through transformation. The main idea is to calculate a set of new features from a set of features, which are arranged in the order of importance from large to small, and these features are not related to each other, and then the data are represented by less principal components.

From the reading literature, the weight $w=\frac{1}{var(X_i)}$, that is, the reciprocal of the variance of the variable Xi. Using w as the weight of PCA to reduce the dimension of the original data, the characteristics of each variable in the new coordinate system can be obtained[8]. The explanatory degree of the variance of the variables is drawn into a Pareto Diagram. The results are shown in Figure 4. It can be found that the first principal component explains 41.55% of the variance, and the second principal component explains 12.95% of the variance. From Figure 5, it can be found that the contribution of some data to the first two principal components is almost zero. To sum up, it is typical to select the first two principal components for analysis and processing.

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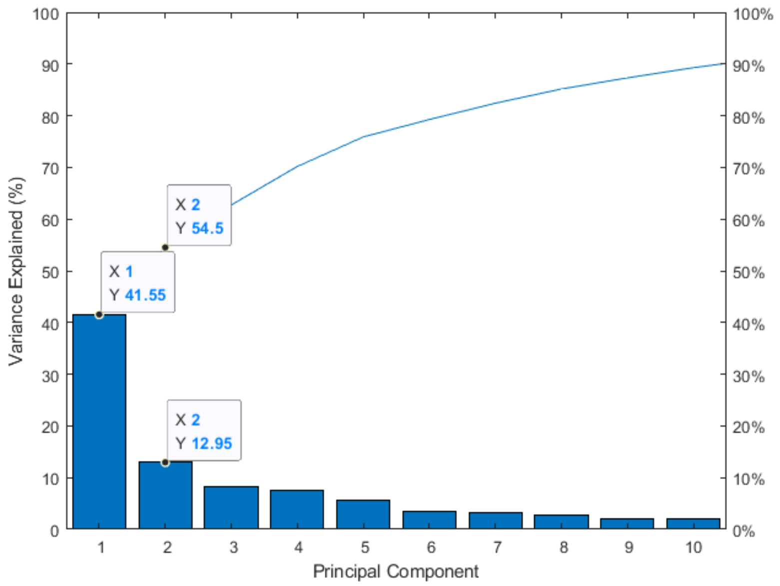

Fig. 4 Interpretation results of principal component variance

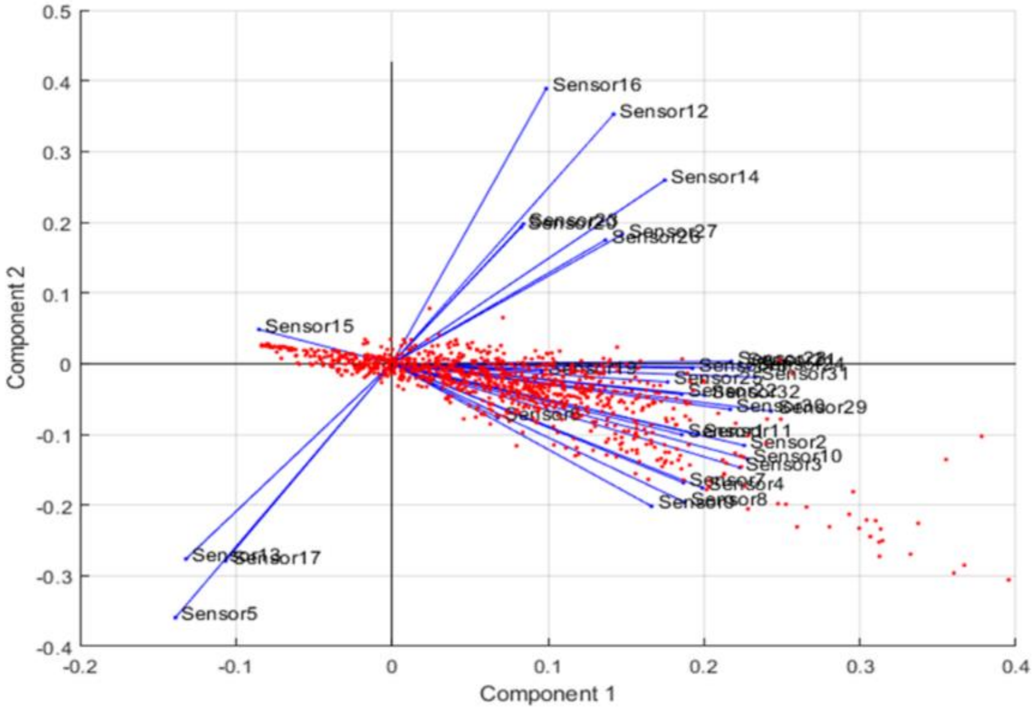

Fig. 5 The effect of each dimension on the first two principal components

4. Visualization of state change of quay crane

4.1 Analysis of quay crane status according to continuous time

The results of state mode change with time under different working conditions are shown in Fig. 6, in which different colors represent different working conditions.

From the visualization results, we can see that the state patterns of the first 18 days and the 21st to 26th days are similar, and the state patterns of the 19th, 20th, 27th, 28th, 29th days are similar. Moreover, the state mode changes suddenly along with the change of working conditions on the 19th, 27th and 30th days, which may be the time point of fault occurrence. Therefore, it is necessary to carry out deep fault mode analysis and failure mechanism analysis based on the actual situation.

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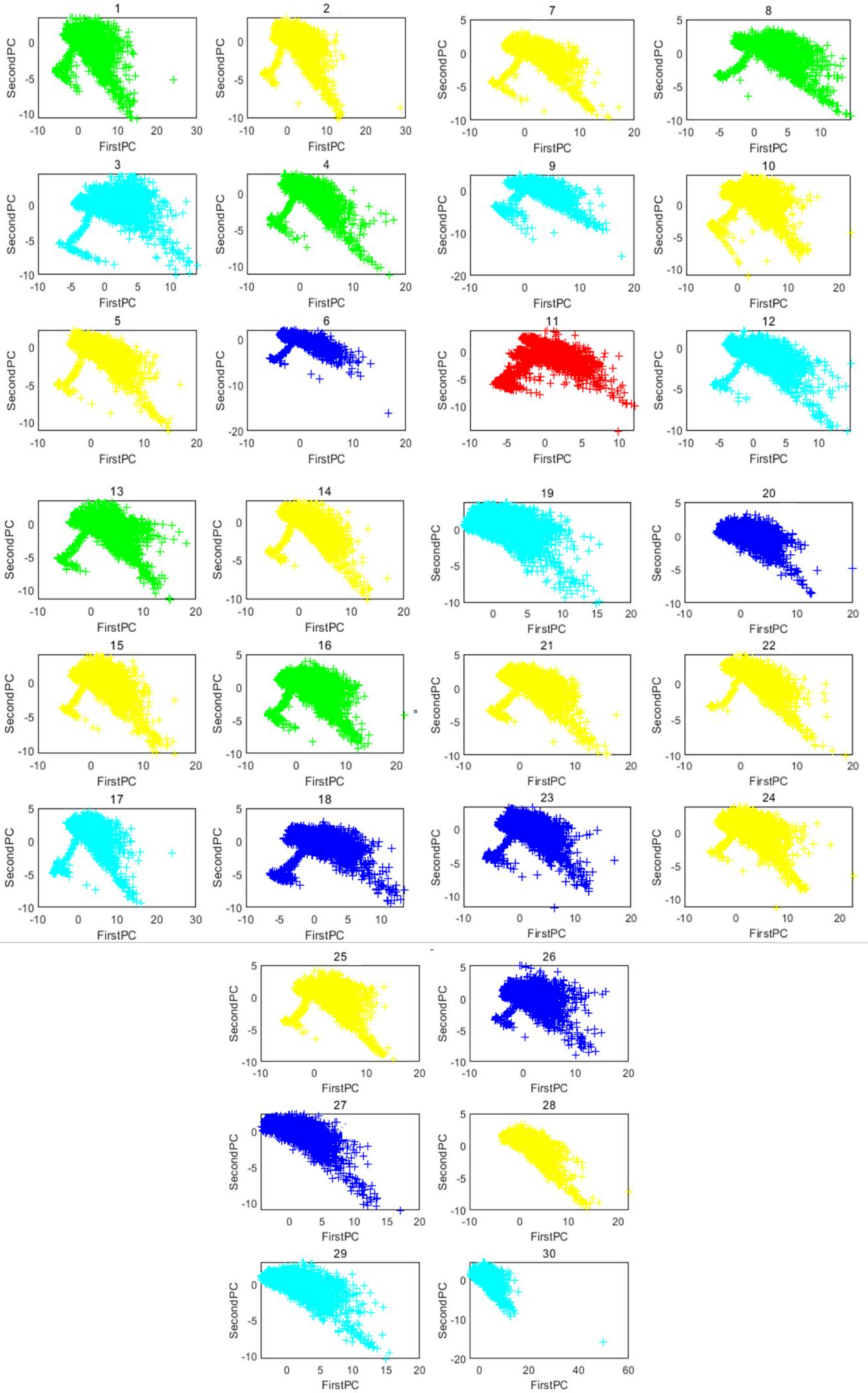

Fig. 6 Evolution results of quay crane health mode over time

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4.2 State mode change analysis of quay crane according to working condition category

Since the complexity of the problem is increased under the changing working conditions, which is not conducive to the analysis of the state mode evolution, the analysis is carried out under the fixed working conditions, and the state data corresponding to each working condition are visualized. The results are shown in Fig. 7, Fig.. 8, Fig.. 9, Fig. 11 and Fig.. 12.

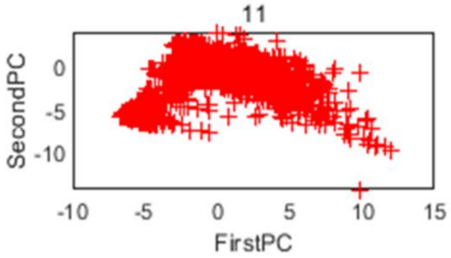

Fig. 7 State mode corresponding to condition 1

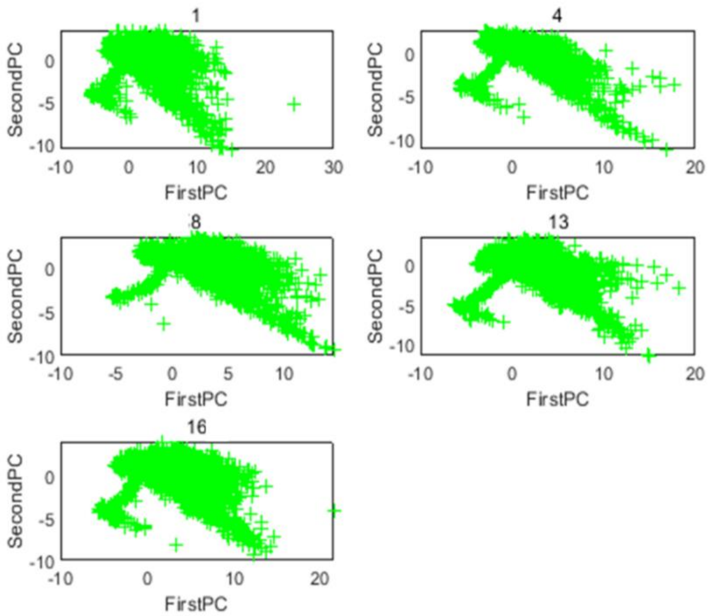

Fig. 8 State mode corresponding to condition 2

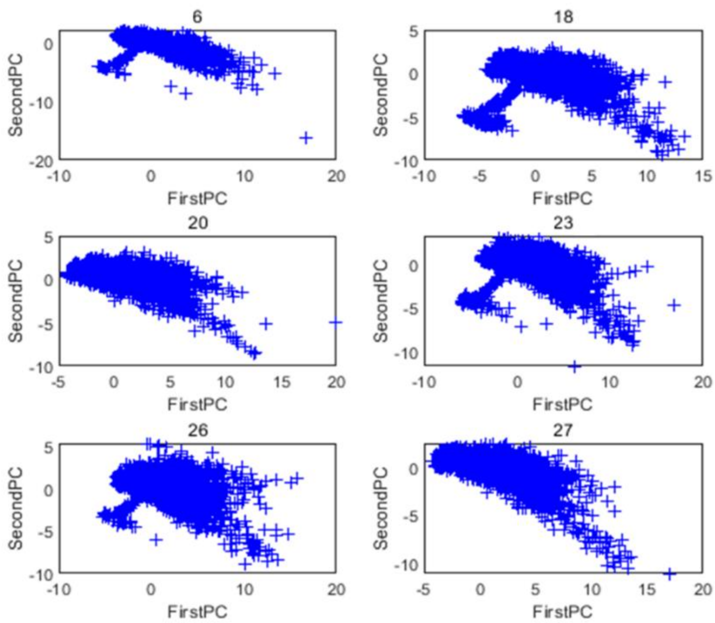

Fig. 9 State mode corresponding to condition 3

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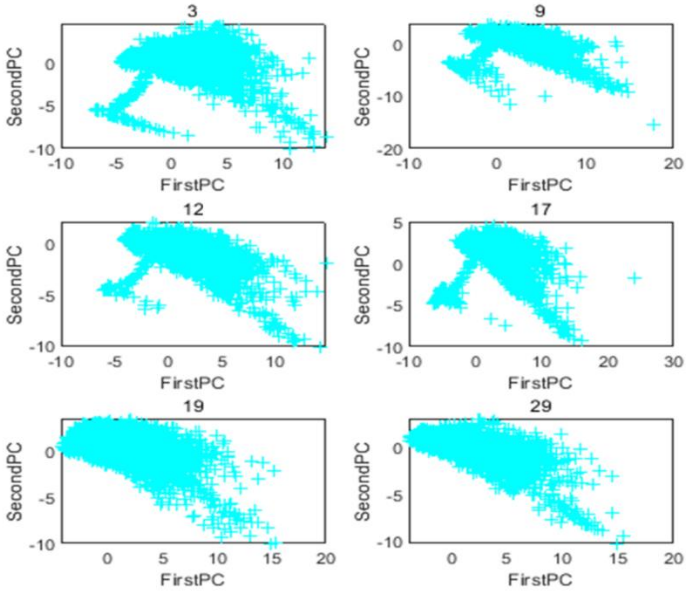

Fig. 10 Corresponding to condition 4

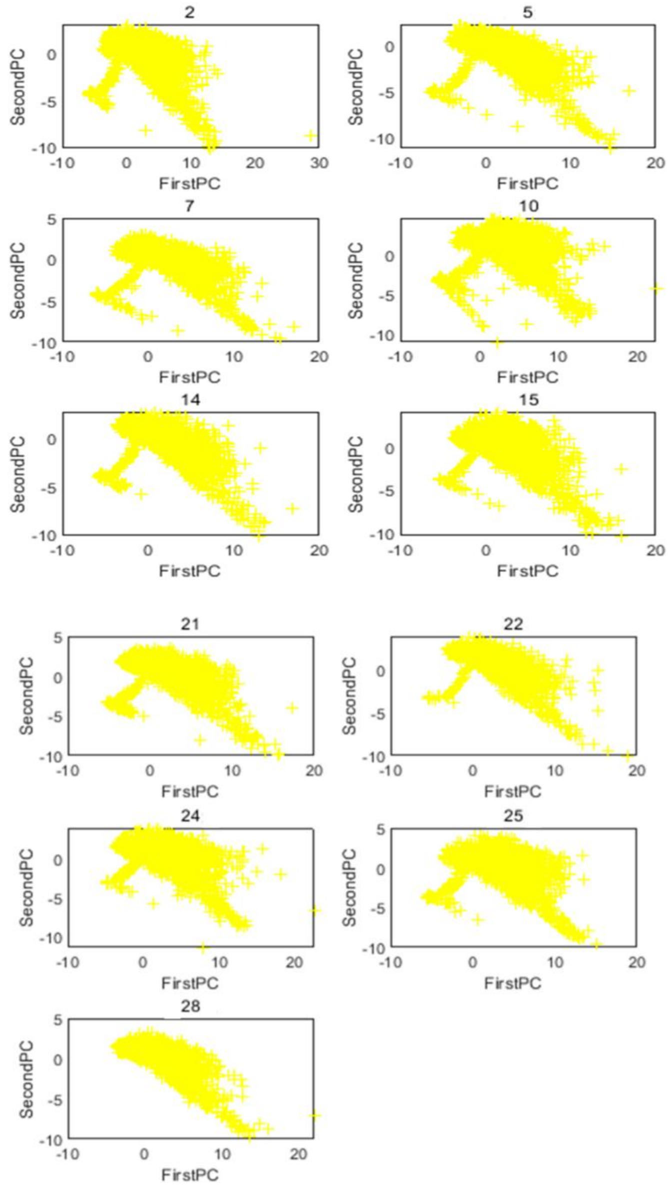

Fig. 11 State mode corresponding to condition 5

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Compared with the results of the above figures, it can be seen that there is only one sample in Figure 7, so condition 1 may be a dangerous condition. From Figure 12, it can be seen that condition 1 is a safe condition because the indicators of working conditions on the 11th day are smaller than others. It can be seen from the clustering results that the class center value of condition 2 is higher than others, that is, the working intensity of condition 2 is the largest, so fatigue analysis of condition 2 should be carried out. It can be seen from Figure 11 that the number of samples in the corresponding condition 4 is the largest. Therefore, the strength of condition 4 should be evaluated to determine whether it is the ideal working strength.

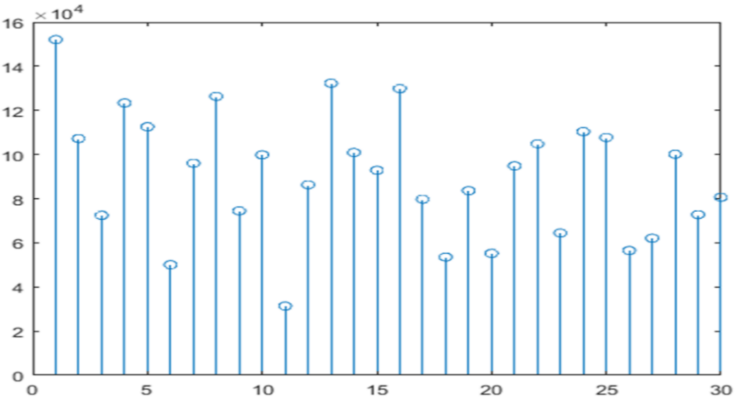

Fig.12 Distribution of working condition indexes in 30 working days

5. Conclusion

The working state data of quay crane are collected, and the characteristics of data are intuitively obtained by using visualization method, and the linear dimensionality reduction method is inspired to process the data. The characteristic parameters of quay crane working conditions are determined, and the optimal number of categories is obtained after statistical analysis of the working condition data. Secondly, weighted PCA is used to reduce the dimension of the original data with different units[9]. The reciprocal of variance of each variable is used as the weight. Then, the condition category label is added to the low dimensional data, and the state mode of the quay crane is represented by visualization method. The characteristics of the state change with time and the state evolution characteristics under each mode are obtained. By observing the state portraits of the quay crane under different working conditions, the topological characteristics and time of the state mutation of the quay crane are intuitively obtained, from which the further identification of the state that needs to focus on the analysis can be obtained. By observing the state portraits of the quay crane under the same working conditions, the state characteristics of the quay crane under the same working conditions are obtained. The greater the difference is, it shows that the influence of the working condition on the quayside crane is unfavorable. It is necessary to further check whether the working condition is healthy, and finally put forward the adjustment suggestions to feed back to the daily use, so as to extend or maximize the use efficiency of the quayside crane.

Combined with unsupervised clustering and dimensionality reduction visualization method, it overcomes the problem that it is difficult to express the state of quay crane visually, and overcomes the limitation between the goal and method of supervised method. It is helpful to help the equipment managers to make more reasonable use of the quay crane.

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