

Retraction

Retracted: Remote Control and Fault Diagnosis of Port Mechanical Equipment Based on Wireless Communication Technology

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation. The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

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Research Article

Remote Control and Fault Diagnosis of Port Mechanical Equipment Based on Wireless Communication Technology

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In order to solve the problem that there is a huge amount of port machinery operating state data, the traditional fault diagnosis method is difficult to effectively obtain the mechanical fault information from the massive data and also cannot accurately diagnose the fault. This paper presents a fault diagnosis method for port machinery based on the FastAP algorithm. By analyzing the characteristics of the FastAP algorithm, the algorithm is introduced into port machinery fault diagnosis, and a port machinery fault diagnosis model based on FastAP is proposed. Through simulation experiments, the algorithm and its application in port machinery fault diagnosis are verified. The experimental results show that compared with the standard AP algorithm, the FastAP algorithm performs well in the sum of similarity, clustering accuracy, and clustering calculation time and has better performance, which is more suitable for fault diagnosis. The fault diagnosis method based on the FastAP algorithm has a high diagnosis accuracy of port machinery fault, reaching more than 92%, and can accurately diagnose the normal state, inner and outer ring fault state, and rolling element fault state of the actual port mechanical belt conveyor. The research on remote control and fault diagnosis of port machinery equipment based on wireless communication technology can effectively solve the problem that there is a huge amount of port machinery operating state data, and the traditional fault diagnosis methods are difficult to effectively obtain mechanical fault information from the massive data and thus cannot accurately diagnose the fault.

1. Introduction

With the continuous improvement of the level of scientific and technological development and the continuous enhancement of economic strength, high-tech concepts and measures have been widely popularized, providing positive help for the improvement of people's living standards and the further strengthening of industrial development. Strengthening the rational application of electrical automation technology in port operation can greatly improve the cargo throughput of the port, improve the quality and efficiency of port trade, and provide a continuous impetus for the development of port trade towards automation and intelligence [1]. With the rapid development of science and technology, the degree of automation of port machinery is becoming higher and higher [2]. With the increase of the tonnage and quantity of port cargo, the requirements for the quantity and tonnage of machinery are becoming higher and

higher. In order to achieve a certain cargo handling capacity in the port, the remote control of machinery must be improved [3]. In recent years, there are more and more research studies on the remote control of port machinery, and wireless monitoring has become a necessary breakthrough topic to achieve the economic development of the port [4]. In port production and operation, the technical level of various lifting and transportation machinery as loading and unloading equipment plays a decisive role [5]. However, the maintenance and management of various loading and unloading equipment mainly depend on the experience of equipment-related technicians. Various operation status, fault status, and other data of loading and unloading equipment cannot be obtained in real time, resulting in low equipment production efficiency and management level [6]. Therefore, it is necessary to establish a set of remote monitoring system to connect various discrete mechanical equipment, share various data and information, and realize

remote maintenance and networked management of equipment.

This paper presents a new monitoring system architecture, which enables users to monitor multiple remote field devices at the same time in the terminal office building (or use the Internet at any place and at any time), and on this basis, the controller of the device can be remotely controlled, maintained, and managed.

2. Literature Review

At present, in the port automation control work, the bulk cargo handling automation technology and mechanical and electrical automation technology are most widely used [7]. This is mainly because this type of controller has relatively stable operation efficiency. It is not only the core development component of the electrical automation technology of port equipment but also simple to operate. It can further improve the comprehensive performance of port facilities and equipment from the root cause. It is the core technology and effective measure to promote the comprehensive development of the port in the future. Therefore, strengthening the in-depth study on the technical characteristics and control measures of port mechanical and electrical automation can provide positive help for the development of port construction towards intelligence, large-scale, and automation and make outstanding contributions to the harmonious and stable development of society [8].

As a gateway to international trade, the port is a distribution center for material import and export. With the rapid development of modern industrial technology, the degree of port automation and mechanization has gradually increased [9]. However, due to the complex working environment and huge workload of port machinery, the parts of machinery are prone to failure. In order to avoid the economic loss caused by mechanical failure, it is necessary to carry out real-time and accurate diagnosis of mechanical failure and timely repair the failure to ensure the safety of port production and transportation. At present, the fault diagnosis methods for port machinery mainly include the methods based on statistical analysis and signal processing. Luo et al. proposed a diagnosis method for rolling bearing fault based on the principle of optimization index consistency, which can effectively detect the fault location [10]. Bril and others proposed a signal processing method based on sound feature and improved sparse representation, which effectively realized mechanical fault diagnosis [11]. However, the above methods often have the problem of low diagnostic accuracy. In recent years, the rapid development of artificial intelligence technology has brought new opportunities for mechanical fault diagnosis. Therefore, this study uses artificial intelligence technology to mine and identify effective fault information in mechanical data through the FastAP clustering algorithm, which realizes port mechanical fault diagnosis and improves the accuracy of fault diagnosis [12].

On the basis of current research, this paper presents a research method of remote control and fault diagnosis of port mechanical equipment based on wireless communication technology. By analyzing the characteristics of the FastAP algorithm, the algorithm is introduced into port machinery fault diagnosis, and a port machinery fault diagnosis model based on FastAP is proposed. Through simulation experiments, the algorithm and its application in port machinery fault diagnosis are verified.

3. Research Methods

3.1. Overall Scheme of the Monitoring System. The main function of the monitoring system is to realize the real-time monitoring, management, and online information service of the operation status of the port machinery group. The whole system consists of field equipment, wireless LAN, monitoring station, web server, and Internet users [13].

3.1.1. Key Technologies in the Monitoring System. On the port and wharf, the mechanical equipment works in the open air and often meets extremely harsh environments, such as wind, rain, snow, lightning, thunder, and other spatial electromagnetic interference. Therefore, the port wireless network data communication system must have good anti-interference ability and stable transmission ability. The system adopts spread spectrum technology to meet the needs of port production environment. Spread spectrum technology expands the signal to a very wide frequency band, performs correlation processing on the spread spectrum signal at the receiving end, i.e., bandwidth compression, and restores it to a narrow-band signal [14, 15]. As far as the jamming signal is concerned, because it is not related to the spread spectrum pseudorandom code, it is extended to a very wide frequency band, which greatly reduces the jamming power entering the signal passband and correspondingly increases the output signal jamming ratio. Its power density decreases with the broadening of the spectrum and can even submerge the signal in the noise. Therefore, it has strong anti-interference ability. Its antiinterference ability is directly proportional to the expansion ratio of its frequency band. The wider the spectrum is expanded, the stronger the anti-interference ability is.

The bandwidth allocation strategy is to make two different types of data (periodic data and aperiodic data, including emergency data and nonemergency data) and reuse bandwidth reasonably under the condition of meeting the real-time performance of the system and network stability [16, 17]. In this system, the periodic data are mainly the monitoring data generated by the sensors and controllers in the network control system, occupying a fixed bandwidth. The emergency data in aperiodic data are mainly alarm signals and operation command signals. Their generation is sudden, the typical distribution is unknown, the probability of occurrence is very low, the data traffic is small, and the transmission has strict time limit, so their bandwidth is reserved. Nonemergency data are mainly used for statistical data report files, historical database information, etc. Their generation is random and generally conforms to Poisson distribution. Data transmission is non-real-time, and the traffic is large. Therefore, nonemergency data occupy the remaining bandwidth of the first two types of data. This



FIGURE 1: FastAP algorithm flow.

system proposes a bandwidth allocation strategy of sharing dynamic time with aperiodic data divided by nodes. Its essence is to make all nodes dynamically time-sharing the bandwidth to ensure the requirements of real-time performance and network stability. After a node obtains the transmission right, it transmits emergency data, periodic data, and nonemergency data in turn.

The monitoring interface is the interface between the user and the field equipment. It is responsible for receiving the user's commands and handing them to the real-time processing part for processing and displaying the equipment information and query results through the graphical interface to realize the remote control, maintenance, and management of the equipment. The main monitoring interface mainly realizes the overall condition monitoring of all mechanical equipment of the whole system. The main information includes the workload statistics, energy consumption statistics, equipment operation status, and equipment fault status of the equipment, so as to fully realize the network management of the equipment. *3.1.2. Introduction to FastAP Algorithm.* FastAP algorithm is an improved clustering algorithm based on the AP clustering algorithm, which improves the clustering effect of the algorithm by introducing incomplete similarity [18]. The specific implementation process is as follows:

Step 1: calculate the sample similarity matrix S [19].

Step 2: calculate the compressed similarity matrix S' according to the compressed similarity matrix algorithm, as

$$S' = \{e_{\text{new1}}, e_{\text{new2}}, e_{\text{new3}}, \dots e_{\text{nenu}}\},\$$
$$e_{\text{new}} = \max_{i \in C_{\text{new}}} \sum_{j \in C_{\text{new}}} s(i, j),$$
(1)

where, e_{new} represents the clustering example; C_{new} stands for new clustering; and NE represents the instance in each iteration.

Step 3: S' is thinned to obtain the sparsity *similarity matrix S^* .



FIGURE 2: Fault diagnosis model of port machinery based on FastAP.

Step 4: iteratively calculate the attractiveness matrix R = (r(i, j)) and the attribution matrix A = (a(i, j)).

Step 5: judge whether the algorithm has reached the iteration times. If the maximum iteration times is reached, the cluster information will be returned and the algorithm will be ended. If the algorithm does not reach the number of iterations, judge whether the algorithm iteration process converges. If it converges, return the cluster information and end the algorithm. Otherwise, return to step 4. The above process can be illustrated in Figure 1.

3.1.3. Fault Diagnosis Model of Port Machinery Based on FastAP. According to the above analysis of the FastAP algorithm, the cluster of FastAP algorithm does not need to be set in advance, and the implementation process is relatively simple. Therefore, this algorithm is selected as the fault diagnosis algorithm, and the port machinery fault diagnosis model shown in Figure 2 is constructed. The model includes three modules: fault feature extraction, cluster analysis, and fault diagnosis:

The first module is fault feature extraction. Fault feature extraction is to obtain sample features more quickly and accurately, so as to improve the accuracy of fault clustering and then improve the accuracy of fault diagnosis. Firstly, EEMD is used to decompose the time-domain vibration signal of port machinery to obtain IMFs components, and then approximate entropy analysis method is used to calculate the approximate entropy of IMFs components and convert them into fault feature vectors.

Assuming that each original fault sample of port machinery contains a time-domain signal $x = (x_1, x_2, ..., x_m)$ with a length of N, EEMD decomposes *m* IMFs components into $I = (I_1, I_2, ..., I_m)$, calculates the approximate entropy of IMFs components using the approximate entropy method, and forms a feature vector $V = (v_1, v_2, ..., v_m)$, where *V* is the fault feature of port machinery.

The second module is cluster analysis. The clustering analysis results directly affect the accuracy of port machinery fault diagnosis. This study determines the clustering effect of the algorithm by calculating whether the clustering accuracy of the clustering results of the FastAP algorithm reaches the set threshold [20]. If the clustering accuracy reaches the set threshold, the clustering results are saved and the clustering analysis is ended. If the clustering accuracy does not reach the set threshold, it indicates that the algorithm does not achieve the best clustering effect. At this time, adjust the algorithm parameters and cluster the adjusted algorithm again until the clustering accuracy reaches the set threshold.

The third module is fault diagnosis. Fault diagnosis is to identify fault samples, which is the ultimate goal of the whole model. The specific diagnosis steps are as follows:

Step 1: EEMD decomposes fault sample signal $x = (x_1, x_2, ..., x_m)$ to obtain IMFs component $I = (I_1, I_2, ..., I_m)$.

Step 2: calculate the approximate entropy of $I = (I_1, I_2, ..., I_m)$ and form the eigenvector $V = (v_1, v_2, ..., v_m)$.

Step 3: calculate the distance between v and cluster center according to

$$s(i, j) = -||x_i - x_j||^2, \quad i \neq j,$$
 (2)

where s(i, j) represents the similarity value of data points x_i and x_j .

Step 4: select the cluster with the minimum distance from the feature vector (d_{\min}) and calculate the maximum distance within the cluster (d_{\max}) ;

Step 5: compare the size of d_{\min} and d_{\max} . If $d_{\min} > d_{\max}$, classify the fault samples into unknown categories and go to step 7. Otherwise, go to step 6.

Step 6: count the actual categories and select the category with the most occurrences as the fault sample category.

Step 7: output the diagnostic results. The above steps can be illustrated in Figure 3.

3.2. Simulation Experiment

3.2.1. Experimental Environment. The simulation is carried out on MATLAB software, Windows7 is selected as the operating system, the hardware condition is Intel corei3-2328M, the CPU is 2, 20 GHz, and the RAM is 4096 MB.

3.2.2. Data Source and Preprocessing. The algorithm verification data sets include two types: one is the four-composite data sets randomly generated by MATLAB that obey the Gaussian distribution, as shown in Table 1. The first



FIGURE 3: Fault diagnosis process.

TABLE 1: Four composite data sets.

Data set	Data volume	Variance
1	400	0.2
2	600	0.2
3	800	0.2
4	1800	0.2

category is 7 real data sets in UCI machine learning library, as shown in Table 2.

Considering that the attribute values of different data sets in the seven real data sets vary widely, which will affect the clustering accuracy of the algorithm, in order to reduce the impact of attribute values between different data sets, the seven data sets are normalized, then the processed data sets are converted, and the mat file can be input into the algorithm.

The fault diagnosis verification selects the fault data at the driving end of a rolling bearing of a university as the experimental data set, including two data sets with the bearing operating speed of 1797 rpm and 1772 rpm, as shown in Table 3.

TABLE 2: 7 real data sets.

Data set	Attribute	Category	Data volume
Iris	4	3	150
Seale	4	3	625
Yeast	8	10	1484
Wine	13	3	178
WDBC	30	2	569
Semeion	256	10	1593
MFHN	649	10	2000

3.2.3. Evaluation Index. The sum of similarity (SS), clustering accuracy (accu), and clustering calculation time are selected as the indicators to evaluate the performance of the FastAP algorithm. The calculation methods are

$$SS = \sum_{i=1}^{N} S(i, c_i),$$
 (3)

$$\operatorname{accu} = \frac{\sum_{i=1}^{N} \delta(c, c^{*})}{N},$$
(4)

1797RPM			0 1
1/2/101 101	0	80	39
1772RPM		157	79
1797RPM			
1772RPM			
1797RPM	0.0990 mm	40	10
1772RPM	0.0889 11111	40	19
1797RPM			
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	1772RPM 1797RPM 1772RPM 1797RPM 1772RPM 1797RPM 1772RPM	1772RPM 0 1797RPM 1772RPM 1797RPM 0.0889 mm 1772RPM 1797RPM 1797RPM 1797RPM 1797RPM 1772RPM	1772RPM 0 157 1797RPM 1772RPM 1797RPM 1797RPM 0.0889 mm 40 1797RPM 1797RPM 1797RPM 1797RPM 1797RPM 40





where *N* represents the total number of data points x_i ; $s(i, c_i)$ indicates the similarity between x_i and its example x_{ci} ; c_i , c^* represents the algorithm clustering result and the actual clustering label, respectively. When $c = c_i$, $\delta(c_i, c_i^*) = 1$; when $c_i \neq c_i^*$, $\delta(c_i, c_i^*) = 0$. The iteration times of the AP algorithm and FastAP algorithm are set to 50 and 500, respectively, the damping coefficient is set to 0.5, the preference parameters are set to the median of similarity matrix, and the compression ratio and sparsity ratio of the FastAP algorithm are set to 0.2 and 0.5, respectively.

In order to verify the effectiveness of the algorithm, this algorithm and the standard AP algorithm are used to cluster the experimental data set. On the four synthetic datasets, the difference between the standard AP algorithm and FastAP algorithm in the sum of similarity and clustering accuracy indicators is small, but the clustering calculation time of FastAP algorithm is shorter, the advantage of clustering calculation time is more obvious with the increase of data volume, and the difference between the standard AP algorithm and FastAP algorithm is small on the sum of similarity indicators of the four real datasets; In terms of clustering accuracy, the standard AP algorithm is close to the FastAP algorithm. In terms of the clustering calculation time index, the FastAP algorithm performs best and the standard AP algorithm performs worst. On the whole, although the clustering accuracy of FastAP algorithm is slightly lower than that of standard AP algorithm, its overall performance is better. In order to verify the effect of fault diagnosis based on the FastAP algorithm, the port machinery fault data set is used for fault diagnosis. It can be seen that the fault diagnosis

accuracy of the FastAP algorithm proposed in this study is higher than 92%, and the fault diagnosis accuracy increases gradually with the increase of fault samples. In order to further prove the superiority of this algorithm for fault diagnosis, K-means algorithm and FastAP algorithm are used for fault diagnosis of apen1~apen3. When the working speed is 1797 rpm, the accuracy of K-means algorithm and FastAP algorithm for fault diagnosis is significantly different. The accuracy of the FastAP algorithm is significantly higher than that of the K-means algorithm, and the FastAP algorithm has more obvious advantages in the accuracy of fault diagnosis when there are fewer clustering centers of the K-means algorithm. When the operating speed is 1772 rpm, the difference between the fault diagnosis accuracy of the K-means algorithm and FastAP algorithm is small. The reason is that there are many fault samples at the operating speed, so the diagnosis accuracy of the two algorithms is high. On the whole, the fault diagnosis method based on the FastAP algorithm proposed in this study can be accurately diagnosed regardless of the number of fault samples, so the performance of this research algorithm is better than K-means algorithm.

4. Result Analysis

In order to verify the practical application effect, some historical data of a bulk cargo port belt conveyor system are selected as fault samples for fault diagnosis, and the results shown in Figure 4 are obtained. From Figure 4, it can be seen that the accuracy of the FastAP algorithm proposed in this study for normal state, inner and outer ring fault, and rolling element fault diagnosis reaches 100%; The diagnostic accuracy of crack fault is 80% and that of bearing looseness fault is 0. The reason is that there are few samples of crack fault and bearing looseness fault, especially there are only 6 samples of bearing looseness fault, which makes it difficult for the algorithm to extract effective information in cluster analysis, resulting in low diagnostic accuracy.

To sum up, the fault diagnosis method based on the FastAP algorithm can effectively identify different types of mechanical faults. Compared with the standard AP algorithm and K-centers algorithm, the performance of this research algorithm is better, and it performs better in the sum of similarity, standardized mutual information, clustering accuracy, and clustering calculation time. Compared with the K-means algorithm, the fault diagnosis accuracy of this algorithm is higher, reaching more than 92%. The feasibility and effectiveness of the algorithm are verified by the application in the fault diagnosis of port machinery. It can accurately diagnose the normal state, inner and outer ring fault state, and rolling element fault state of port belt conveyor, and the diagnosis accuracy reaches 100%.

5. Conclusion

This paper presents a research method of remote control and fault diagnosis of port machinery based on wireless communication technology. By analyzing the characteristics of the FastAP algorithm, the algorithm is introduced into port machinery fault diagnosis, and a port machinery fault diagnosis model based on FastAP is proposed. Through simulation experiments, the algorithm and its application in port machinery fault diagnosis are verified. Port remote monitoring system is an inevitable product of the improvement of port cargo throughput. It not only needs advanced network technology support but also needs a perfect structural system to meet the needs of users. In order to realize the automation development of port freight transport in the future, it is necessary to research and make breakthroughs in its key technologies such as network, communication, and hardware.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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