Group Intelligence Perception Applied in the Electromechanical Equipment Fault Intelligent Diagnosis Support System

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Abstract. The paper designs a fault diagnosis and monitoring system for electromechanical equipment based on group intelligence perception technology. The system uses the Internet of Things technology to establish a fault feature selection and fault diagnosis model for electromechanical equipment. At the same time, the system uses micro-electromechanical system sensors to realize real-time monitoring of electromechanical equipment, and realizes the collection and upload of status data and fault data of base electromechanical equipment. The design of this system allows all parties involved in electromechanical equipment such as users, manufacturers, maintainers, and industry experts to break through the constraints of time and space. All relevant parties can communicate in real time on the problems of the equipment, so that the electromechanical equipment can be more efficiently automated and intelligently maintained.

Keywords: Group intelligent perception, Internet of Things, fault diagnosis of electromechanical equipment, Internet 5g, wife6 technology, efficient and intelligent.

1. Introduction
Nowadays, the composition structure and working principle of the electrical control system of electromechanical equipment are very complicated, and traditional detection methods cannot quickly detect, locate and diagnose the various electrical equipment and system modules. In order to meet the needs of relevant units’ support capacity building, this paper proposes a research design of a fault detection support system based on group intelligence perception technology based on in-depth research and analysis of the composition, working mechanism, fault characteristics and interface signal attributes of the equipment electrical control system Program [1]. The system uses the high level of confidentiality and reliability of the Internet of Things technology to establish a fault information transmission network, and based on virtual reality technology to reproduce the failure of electromechanical equipment and the battlefield environment, use the large professional team at the rear to diagnose and support the fault, and to a certain extent the configuration and scheduling of guarantee resources are realized.
2. Electromechanical equipment fault feature selection and fault diagnosis algorithm model

2.1. Feature selection method

The article assumes that there are C types of failure types of electromechanical equipment. Use time-frequency analysis and spectrum analysis to analyze the vibration signals of all electromechanical equipment states, obtain a total of N signal sample sequences corresponding to each fault type, and calculate a variety of statistical features to construct the original feature set \( \{OF^1, OF^2, \ldots, OF^M\} \), then all \( N \) The matrix composed of the \( m \) feature of the sample signal is shown in (1).

\[
OF^m = \begin{bmatrix}
F_{11}^m & F_{12}^m & \cdots & F_{1N}^m \\
F_{21}^m & F_{22}^m & \cdots & F_{2N}^m \\
\vdots & \vdots & \ddots & \vdots \\
F_{C1}^m & F_{C2}^m & \cdots & F_{CN}^m 
\end{bmatrix}
\] (1)

In the formula, \( F_{cn}^m \) represents the collection of the \( n \) first characteristic in the \( m \) first signal sample when the fault type is \( c \). The number of cluster centers is the same as the number of the above-mentioned fault types, set as \( C \), cluster analysis is performed on the original feature set \( \{OF^1, OF^2, \ldots, OF^M\} \) through FCM, and the corresponding AMI value sequence \( AMI = \{AMI(1), AMI(2), \ldots, AMI(M)\} \) is calculated. The row elements in matrix \( OF^m \) represent the state of the same kind of electromechanical equipment, and the standard deviation of the first characteristic can be expressed as:

\[
SD_e^m = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (S_{ci}^m - \overline{S}_c^m)^2}
\]

\[
\overline{S}_c^m = \frac{1}{N} \sum_{i=1}^{N} S_{ci}^m
\] (2)

Then after calculation, the standard deviations of all \( C \) types of electromechanical equipment states are constructed in sequence, and the standard deviation set of the \( m \) feature is \( \{SD_1^m, SD_2^m, \ldots, SD_C^m\} \), and the sum of them is obtained:

\[
SSD(m) = \sum_{j=1}^{M} SD_j^m
\] (3)

After calculating the AMI values and standard deviations of all \( M \) statistical characteristics, the calculation formula of AMISR is defined to obtain the AMISR value sequence, and the calculation method is shown in formula (4).

\[
AMISR(m) = \frac{AMI(m)}{SD(m)} \quad m = 1, 2, \ldots, M
\] (4)
The paper uses AMISR to evaluate the original feature set, and screens out high-relevant features, which is beneficial to improve the effect of electromechanical equipment fault diagnosis.

2.2. Dimensionality reduction and pattern support vector machine recognition algorithm
In order to achieve this goal, a linearly separable training set $T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$ is given, where $x_i \in \mathbb{R}^n$, $y_i \in \{+1, -1\}$, $i = 1, 2, \ldots, N$, $x_i$ represents the i-th feature vector, and $y_i$ is the sample category label, including two categories of positive and negative examples [2]. The division of the hyperplane is described by the linear equation $\omega \cdot x + b = 0$, where $\omega$ is the normal vector and $b$ is the displacement. The geometric interval from any sample point in the sample feature space to the hyperplane can be expressed as:

$$\gamma_i = y_i \left( \frac{\omega \cdot x_i + b}{\| \omega \|} \right)$$  \hspace{1cm} (5)

The minimum value of the geometric interval of all sample points in the hyperplane with respect to the data set is:

$$\gamma = \min_{i=1,2,\ldots,N} \gamma_i$$  \hspace{1cm} (6)

If the hyperplane can achieve the correct division of samples, the following constraints must be met for any sample point $(x_i, y_i)$:

$$\begin{cases} 
\omega^T x_i + b \geq +1, & y_i = +1 \\
\omega^T x_i + b \leq -1, & y_i = -1 
\end{cases}$$  \hspace{1cm} (7)

For the sake of simplicity, the constraints are optimized and transformed, and the simplified result is shown in equation (8).

$$\min_{\omega, b} \frac{1}{2} \| \omega \|^2 \hspace{1cm} \text{s.t.} \hspace{1cm} y_i (\omega \cdot x_i + b) \geq 1, i = 1, 2, \ldots, N$$  \hspace{1cm} (8)

The above optimization problem contains inequality constraints and is a convex quadratic programming problem [3]. To solve this problem, it is usually necessary to use the Lagrangian multiplier method to transform the original optimization objective function to obtain an easy-to-solve unconstrained Lagrangian Objective function.

$$L(\omega, b, \alpha) = \frac{1}{2} \| \omega \|^2 - \sum_{i=1}^{N} \alpha_i (y_i (\omega \cdot x_i + b) - 1)$$  \hspace{1cm} (9)

In the formula, $\alpha_i \geq 0$ is the Lagrange multiplier. In order to find the maximum value of the function, $\omega$ and $b$ need to be differentiated respectively:
\[ \omega = \sum_{i=1}^{m} \alpha_i y_i x_i \]
\[ 0 = \sum_{i=1}^{m} \alpha_i y_i \tag{10} \]

Bring the above two equations into the Lagrangian objective function, eliminate \( \omega \) and \( b \), and convert the maximum value of the solution to the minimum value of the solution function by adding a minus sign to the objective function, then the transformed the optimization problem can be expressed as:

\[
\begin{align*}
\min_a & \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) - \sum_{i=1}^{N} \alpha_i \\
\text{s.t.} & \sum_{i=1}^{N} \alpha_i y_i = 0 \quad \alpha_i \geq 0, i = 1, 2, \ldots, N
\end{align*}
\tag{11} \]

From the above analysis, it can be seen that there is at least one support vector \( \alpha^*_j > 0 \) in \( \alpha^* \) and \( y_j (\omega^* \cdot x_j + b^*) - 1 = 0 \) for this \( j \). \( \omega^* \) and \( b^* \) can be obtained by further solving to determine the optimal hyperplane. The solution formula and classification decision function of the optimal hyperplane are shown in formula X.

\[
\begin{align*}
\omega^* &= \sum_{i=1}^{N} \alpha^*_i y_i x_i \\
b^* &= y_i - \sum_{i=1}^{N} \alpha^*_i y_i (x_i \cdot x_j) \\
f(x) &= \text{sign}(\omega^* \cdot x + b^*) \tag{12}
\end{align*}
\]

3. Key technology of fault monitoring and diagnosis system for electromechanical equipment

3.1. Group intelligence perception

The purpose of the Qunzhi Perception System is to collect effective and high-quality data. The existing mobile group intelligence perception platform, such as Medusa, is mainly used for task release and data collection, and can release different tasks and processing of different data collection. Participants in the platform decide to complete certain tasks according to different rewards and task difficulty. The optimization goal is not considered (such as minimizing the moving distance in the case of minimizing user information). The mobile group intelligence perception system consists of three parts: task release, task allocation and data collection. When the cloud server receives the information request of the data user, it sends the perception task to the task participant, processes the collected perception task and performs other management tasks. After the participants receive the perception task, they perform the perception of the required data, and then return the data to the server. The server processes the data and returns it to the data user. Through the entire process, functions such as data perception, data collection, and information service are realized. Task assignment and task execution need to consider many factors [4]. The willingness of participants for different tasks and the impact of collecting data on the normal activities of participants are not the same. Different participants have the reliability of collected data due to their hardware equipment and their own professionalism. It is also different... and other factors cause uncontrollable data collection on the platform. In the perception...
system, participants often use spatial invisibility to obscure their location and realize location privacy protection. This method has been widely used in location-based services.

3.2. Micro-Electro-Mechanical System (MEMS)
MEMS (Micro-Electro-Mechanical System) is the core interactive device in the intelligent era, integrating micro-sensors, actuators, as well as signal processing and control circuits, interface circuits, communications and power supplies. MEMS technology is a typical multidisciplinary cutting-edge technology, involving many fields of natural science. MEMS sensors have also become the core of intelligent terminals in the field of industrial Internet of Things. The MEMS sensor uses an etching process to encapsulate mechanical and electronic components on a small chip. It is small in size, hardly affected by the earth's gravity, and is less affected by the external environment, without calibration; the output is a fully digital signal, which is easy to analyse and process. Based on this, the use of MEMS sensors can effectively ensure the low-power operation of the system, ensure that non-destructive installation is achieved, and the original structure of the electromechanical equipment will not be damaged.

3.3. IoT communication technology
Narrowband Internet of Things has the characteristics of long distance, multiple nodes, low power consumption, self-organizing network, low maintenance cost, strong privacy, and suitable for battery power supply. The electromechanical equipment and important communication equipment of the depot base are widely distributed, large in number, and monitoring points are large, and the monitoring data has time intervals [5]. Therefore, high performance, long distance, low power consumption and large-scale support are proposed for the collection equipment and data. Requirements such as the number of nodes. The fault monitoring and diagnosis system for electromechanical equipment based on the Industrial Internet of Things is the first application of narrowband Internet of Things technology in the depot base environment, aiming to upload monitoring data of electromechanical equipment and important communication equipment through the narrowband Internet of Things. The data communication process of the narrowband Internet of Things is shown in Figure 1.

![Figure 1. Narrowband IoT data communication process](image)

4. System Design
4.1. Hardware design

The fault detection system can complete the detection of the output signal of the electrical control system installed on the equipment. The hardware design of the equipment detection system adopts a modular design scheme, which divides the system into several hardware and software functional modules, simplifies the design process and shortens the design cycle, at the same time facilitates expansion and update, has a flexible structure, and enhances the adaptability of the system [6]. The design of the hardware system mainly includes industrial computer module selection, button module design, CAN communication module design, acquisition module design, conditioning board design, and detection cable design. The composition of the fault detection system is shown in Figure 2.

![Figure 2. The overall composition of the electronic control system fault instrument](image)

4.2. Software design

4.2.1. Detection software structure. The main control program of the detection system is mainly responsible for the management and scheduling of the entire system, and cooperates with the system self-inspection program to complete the initial detection. The fault detection system is a collection of programs that complete the fault detection of each detected component, which is called and executed by the main control program in the format of an application program. According to the needs of component testing, output related excitation or debugging signals to the tested component, and at the same time receive the response signal or other characteristic signals output by the tested component, and process and store it. The database system contains various data resources required for testing, including: testing and diagnosis database, testing result database, instrument resource database, guarantee object database, testing process database, process variable database and interface information database, etc.

4.2.2. Fault detection module. The development of the fault detection module is based on the following workflow: Based on the analysis of the fault phenomenon, the fault detection module is selected, the equipment is connected to the detector through the communication cable, and the detector applies the excitation signal to the tested component and collects the corresponding detection feedback signal. The tester then calls the internal data processing module to complete the data analysis. The fault diagnosis module determines the fault location and the cause of the fault based on the provided
analysis data, and then the tester gives the display results and the maintenance guidance module in the knowledge-based expert system provides maintenance suggestions.

4.2.3. The program structure of the fault detection system. The electrical control system fault detection software includes more than 20 internal modules. The software module program structure diagram of the detection system is shown in Figure 3 on the following page. Under the coordination of the fault information database, it completes functions such as plug-in program call, monitoring data management, fault detection process execution and fault detection diagnosis, and realizes the control of the main control box, automatic control centre unit cabinet, magnetic induction protection intelligent node, and plough in the electrical control system. Intelligent fault detection and diagnosis of body intelligent node 1, plough body intelligent node 2, blocking intelligent node, ignition control box, explosion sweep relay box, relay box, valve box, CAN bus interface, and various sensors and proximity switches.

Figure 3. Program structure diagram of the fault detection system

5. Conclusion
On the one hand, the fault monitoring and diagnosis system of electromechanical equipment can accurately and effectively predict the occurrence, development and transfer of potential faults of electromechanical equipment. The electromechanical equipment fault monitoring and diagnosis system can intelligently diagnose the cause and severity of equipment faults, and predict and classify the faults. Maintenance personnel can carry out the next maintenance work based on the early warning of the equipment failure and the remaining life. It improves the safety of equipment operation, thereby saving maintenance costs and avoiding major accidents. On the other hand, it can provide historical data for future design, evaluation and system analysis, and optimize the design of the system by analysing and summarizing the equipment that is prone to failure in the system or the specific location where the equipment is prone to failure.

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