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ANALYSIS OF FROZEN DATA ANOMALY AND UPDATE METHOD OF ELECTROMECHANICAL ENERGY METER TERMINAL BASED ON DEEP LEARNING

FANG YAO* AND LIBIN TAN†

Abstract. In view of the lack of advanced and mature substation fault detection and facility detection technology, combined with the characteristics of the actual application environment of substation, a substation operating equipment autonomous monitoring and fault diagnosis detection system based on deep learning intelligent detection robot is proposed. That is, the deep learning algorithm, Big data analysis technology and patrol robot with HD camera are organically combined. The image information collected by the high-definition camera is fused with the data information collected by a variety of sensors, and then the fault tree and Big data analysis algorithm are used to carry out real-time intelligent detection and analysis of all equipment in the substation, and the early warning can be sent to the relevant equipment maintenance personnel in a timely manner. The experimental results indicate that, the number of input nodes in the fault tree is 7, the number of output nodes is 2, the number of center vectors is 14, the number of nodes in the basis function layer is 7, and the threshold of the basis function is set to 0.8257. In actual training, after 31 iterations, the training results can quickly converge to the target value, the training error meets the requirements, and the fault diagnosis accuracy reaches over 90%. It has been proven that the diagnostic performance of the system is good, achieving the expected design effect.

Key words: Substation, Inspection robot, Fault diagnosis, Intelligent algorithms

1. Introduction. Ensuring operation and maintenance production, as well as maintaining the safety of the power grid, is the top priority in power production work. Equipment inspection is an important part of operation and maintenance production. Conducting regular equipment inspections and inspections of substations, mastering equipment status, and promptly identifying and eliminating equipment hazards are important tasks for achieving safe, stable, and fault free operation of substations [1]. In recent years, intelligent inspection robots for substations have been widely installed in ultra-high voltage and intelligent stations. Robots are used to cooperate with or even replace operation and maintenance personnel in daily inspection work, constantly detecting the status of substation equipment. Taking ultra-high voltage substations as an example, two outdoor mobile intelligent inspection robots are equipped, responsible for the inspection of 1000kV GIS, main transformers, and high impedance equipment, as well as the inspection of 500kV GIS and 110kV equipment [2]. They can perform daily work such as red ginseng 'I-N temperature, meter reading, oil level, etc, and through preset threshold comparison, timely indicate the general, serious, and critical defects of the equipment. However, the current intelligent inspection robot system cannot automatically search for and analyze the types of faults in hidden equipment, and can only generate reports on devices whose data has exceeded the threshold. Moreover, it is currently difficult for robots to identify equipment appearance defects, in the process of equipment status evaluation, many equipment appearance damage, oil leakage and other defect information can only be obtained through manual inspection and entered into the production system [3]. In order to make greater use of intelligent inspection robots as a powerful tool, deepen the application of robot backend, and improve the efficiency of intelligent inspection robots in substation operation and maintenance work, a data processing and feedback system is designed, integrating data from the production system, online monitoring, and robot control backend, and analyzing and processing the data, automatically evaluating the status of equipment, determining the type and location of fault hazards, searching for inspection points related to faults, developing the best inspection strategy, and achieving intelligent inspection robots to independently strengthen special inspections of hidden equipment, is very challenging and feasible [4].

*Chuzhou Polytechnic, Anhui, 239000, China(Corresponding author's e-mail:FangYao37@163.com)
†Anhui University of Technology, Anhui, 243000, China (LibinTan6@126.com)

2. References. At present, the development of power equipment towards high power, high reliability, and high intelligence has increased the difficulty of daily operation, maintenance, and testing. In the trend of unmanned substations, traditional inspection methods and fault diagnosis technologies are increasingly difficult to meet the needs of complex equipment diagnosis. The traditional inspection work of substation equipment mainly relies on regular inspections by operation and maintenance personnel and infrared temperature measurement. However, due to the influence of the experience and technical level of the inspection personnel, there is often a phenomenon of missed testing [5]. At the same time, using existing testing instruments makes it difficult for testing personnel to centrally manage data, resulting in low efficiency in deep mining of historical data, which greatly restricts the development of live detection technology. The research and application of intelligent inspection robots in substations have brought new solutions to the above-mentioned problems, providing a foundation for timely, effective, comprehensive, and intelligent diagnosis and maintenance of power equipment. Many scholars at home and abroad have conducted research on intelligent inspection robots for substations [6,7].

Liao, X will use OCR technology to improve the anomaly recognition system for detecting robot equipment. Based on the collection of video information, DSP comprehensive information processing is carried out, and the detection information is analyzed using frequency domain filtering methods through the human-computer interaction interface. At the same time, pattern recognition methods were used to extract the main component features of substation detection components, and a resolution model for similar features in video surveillance images was constructed [8]. Traditional cage inspections require divers to complete, which is inefficient and dangerous. Underwater robot detection is a method to solve this problem. When the robot is in motion, the camera captures the mesh cage, replacing manual inspection. Wei, Y proposed a hybrid control strategy based on neural networks (NN) and proportional integral differential (PID) for underwater three-dimensional path tracking, overcoming the drawback of traditional feedback regulation that can only work after deviations occur [9]. The purpose of Jiang, C is to demonstrate a multi-purpose detection robot that can walk on the ground and climb on power poles. The structure design, size optimization, Kinematics analysis, experiment and algorithm of the robot are introduced. The robot consists of three adjustable modules and a series connected two degree of freedom parallel mechanism. The wheel finger mechanism of each module can open and close the wheel finger to achieve rapid movement and obstacle crossing [10].

From the above analysis, it can be seen that the current research on intelligent inspection robots for substations has certain advantages compared to traditional manual inspection methods, but they still cannot meet the requirements of automatic removal of faulty parts and foreign object removal of equipment. Their performance in autonomous tracking and intelligent diagnosis analysis also needs to be improved. In addition, most of the intelligent inspection robots mentioned above use a single grid charging method, which is not conducive to the long-term inspection work of the intelligent inspection robots, especially when monitoring key equipment point-to-point for a long time, it cannot ensure sufficient electricity.

3. Application of Robot Intelligent Inspection Technology in Fault and Defect Detection of Substation.

3.1. Intelligent inspection robot. Robot technology is a strategic technology industry in China, related to a series of cutting-edge technologies such as automatic control, image recognition, and intelligent learning. According to the "Made in China 2025" plan, industrial robots will be selected as one of the ten key fields to promote epoch-making development, promote robot standardization and modularization, expand market applications, and effectively promote the growth of the emerging robot market [11]. With the development of the times, the lack of human resources and the requirements of refined operation and maintenance of electrical equipment, intelligent inspection robots in substations are increasingly valued. This will be widely used for intelligent inspection of transmission equipment, real-time evaluation and auxiliary decision-making of power grid operation status, informatization, automation, and the establishment of interactive intelligent networks.

The intelligent intelligent inspection robot is equipped with intelligent detection equipment such as high-quality visual light cameras, infrared imaging devices, high-definition photography heads, environmental monitoring sensors, and intelligent analysis algorithm software [12]. It completes the management and control circuit of fast data collection and real-time information transmission, intelligent analysis and early warning decision feedback, replacing manual detection, achieving automatic detection and intelligent analysis of the status of power equipment, and improving the quality of power equipment, research on the reliability of power grid and power equipment operation, and the use of power intelligent inspection robots is an important means of realizing the intelligence of power grid, and also an important direction for the development of future smart grids.

3.2. Intelligent algorithms. With the rapid development of the era of artificial intelligence and Big data, many industries are also following the development form of ”machines replacing people”. It is mainly divided into two application fields: Machine vision intelligent algorithm for fault tree and Big data analysis algorithm for multidimensional heterogeneous data [13].

(1) Intelligent Algorithm for Machine Vision. In recent years, with the deepening of industrial restructuring and the structural transformation and upgrading of modern manufacturing, more and more enterprises have implemented the ”robot strategy”. The application of robots in fields such as automobiles, logistics, aerospace, and even food has become increasingly widespread, driving the development of related industries.

Machine vision is a system that automatically obtains target images, analyzes and processes image features, analyzes results, obtains target knowledge, and makes decisions. Moving object testing technology is one of the functions of machine vision systems, this is the process of serializing image change regions and extracting moving targets from background images. The main purpose of machine vision research is to provide convincing data sources for subsequent object extraction and tracking in image arrangement compared to camera moving targets. Machine vision algorithms generally target specific application scenarios, there is currently no universal algorithm applicable to any situation. That is to say, all machine vision algorithms have their own applicability [14].

(2) Big data analysis and processing intelligence. The field of algorithm Big data involves a wide range. It deepens the Big data that occurs in the industrial field. With the deep integration of informatization and industrialization, information technology has penetrated into all parts of the industrial chain of various industries. For example, bar codes, two-dimensional codes, communication and identification, industrial sensors, industrial automatic control systems, industrial networks, etc., enterprise resource planning, Computer-aided design, Computer-aided manufacturing, Computer-aided engineering, etc. are widely used in enterprises. The application of next-generation information technologies such as the Internet, mobile Internet, and Internet of Things in the industrial field has brought enterprises into a new stage of development, and data is becoming increasingly abundant, especially in manufacturing enterprises where production lines are running at high speeds and a large amount of data is generated in industrial equipment. Models and algorithms are the two core issues of Big data analysis. The research on Big data analysis models can be divided into three levels [15]. Descriptive analysis, predictive analysis, and normative analysis. Descriptive analysis is the analysis and exploration of historical data, explaining what has happened. This stage includes discovering a set of data rules, mining related rules, describing model discovery, and visual analysis of data rules. Predictive analysis is used to predict future probabilities and trends.

3.3. Intelligent inspection fault diagnosis system. The intelligent patrol fault detection system uses fault tree vision algorithm, Big data analysis technology and intelligent patrol robot with high-definition camera. Through the fault tree, the image information collected by the HD camera carried by the intelligent patrol robot is fused with the data information collected by various sensors, and then through the Big data analysis algorithm, the real-time intelligent fault detection and analysis of all equipment in the substation is carried out. The overall diagram of the intelligent inspection fault detection system is shown in Figure 3.1.

(1) Using Fault Tree Machine Vision Algorithm to Determine Fault Information. Machine vision involves related technologies such as optical imaging, visual information processing, artificial intelligence, and mechatronics. It is a necessary technology for many highly automated industries to achieve intelligence. Machine vision technology has a series of advantages such as high accuracy and strong real-time efficiency, and is one of the important driving forces for intelligent robots. With the continuous improvement of various technologies and the increasing demand for high-quality products in the manufacturing industry, image processing has been mainly used for industrial electronic assembly error detection and is gradually applied in manufacturing, monitoring, visual navigation, communication and other applications. Therefore, studying imaging technology is of great significance for promoting the industrial development of intelligent industrial robots [16].

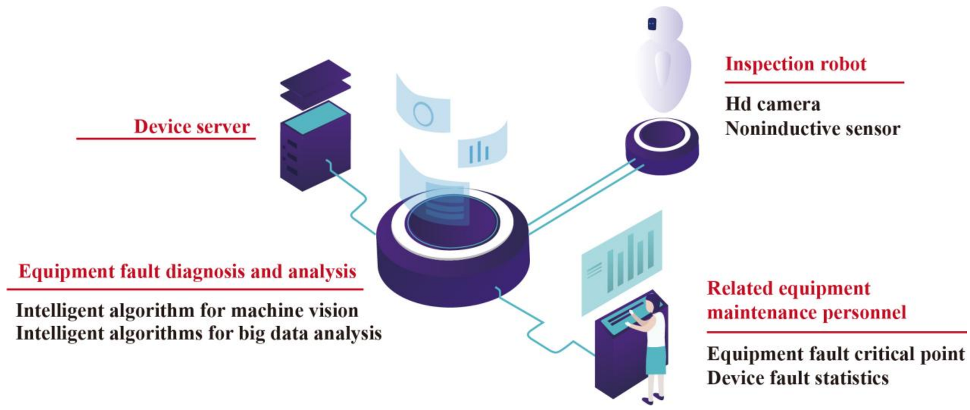

Fig. 3.1: Block diagram of fault detection system of intelligent inspection robot

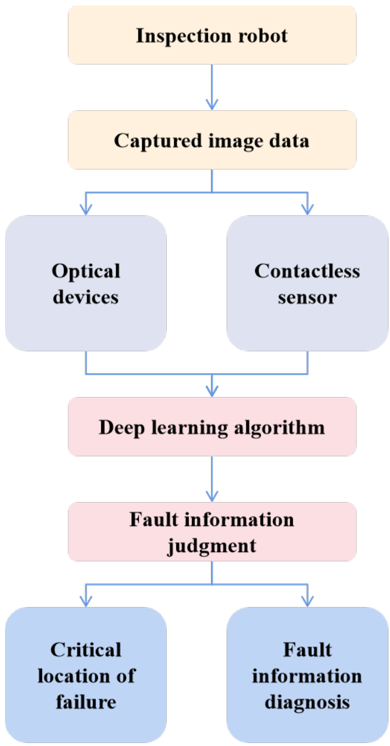

Fig. 3.2: Schematic diagram of fault position determination by intelligent inspection system

The organic combination of fault tree machine vision algorithm and intelligent inspection robot can enable the intelligent inspection robot to flexibly and intelligently locate the key positions of all equipment faults during substation inspection, ensuring that maintenance personnel can timely maintain and handle the key positions where faults occur (Figure 3.2).

(2) Use Big data to analyze fault information. With the rapid development of the era of Big data and artificial intelligence, the organic integration of industrial automation and Big data and other technologies can promote the industry to move towards digitalization, intelligent transformation and integration with the era of Big data. The power generation system of all equipment in the substation is complex and highly centralized [17].

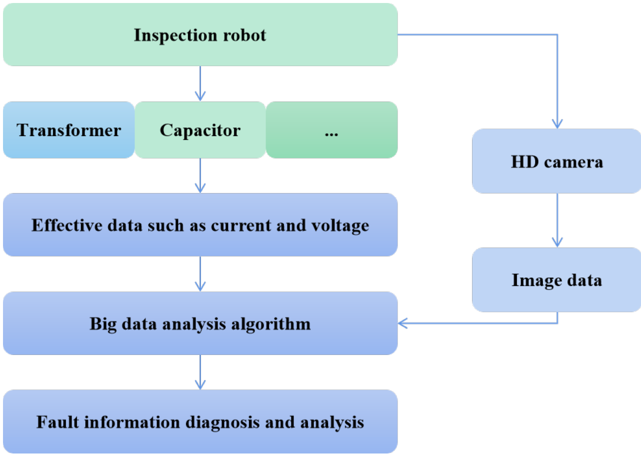

Fig. 3.3: Schematic diagram of fault information diagnosis of intelligent inspection system

Collect data transmitted by sensors on devices through intelligent inspection robots, and combine the results processed by machine vision. Through Big data analysis technology, targeted algorithms are adopted to establish various data mining models and equipment analysis models for substations, and real-time early warning and diagnosis of substation equipment faults and operation modes (Figure 3.3). The intelligent patrol robot combines the image data collected by machine vision technology with the operation data (such as real-time current and voltage data) of transformers, high-voltage circuit breakers, disconnectors, capacitors, reactors and other equipment in the substation to generate a large number of real-time effective data. After Big data analysis algorithm, it can accurately analyze whether there is fault information of the equipment at the moment. If there is any fault information, relevant equipment maintenance personnel can be notified in a timely manner through the early warning system of the intelligent inspection robot [18].

3.4. Fault Tree Diagnosis Principle. The model consists of three layers: input layer, intermediate layer, and output layer. During fault diagnosis, the data decision table is first trained as the training sample of the fault tree to obtain their respective connection weights and thresholds, and then the corresponding connection weights are stored to form a knowledge base. Finally, the trained fault Tree model model is used for fault location and diagnosis. Before working on the fault tree, the first step is to establish a fault knowledge base based on experimental data and expert experience. In order to obtain initial data, the system uses hardware circuits to obtain radar detection signals, and then uses fault trees for shallow empirical reasoning [19]. Then, fault diagnosis is carried out by combining fault trees with expert systems. The network inputs the fault phenomena of the diagnosed object, and the network outputs the probability of the diagnosed object's failure. When constructing the model, the number of nodes in each layer of the fault tree is mainly set based on the empirical formula of previous radar faults, and adjusted based on the training results.

The input layer implements nonlinear mapping from $x \to \phi_i(x)$, and the output layer implements Linear map from $\phi_i(x) \to y_k$, namely:

$$y_k = \sum_{j}^{k} \omega_{kj}\phi_j(X) + \theta \qquad j = 1, 2, ..., h \tag{3.1}$$

In the formula, k is the number of output nodes; ω_{kj} is the output weight value; θ is the threshold value; $(x_1, x_2, ..., x_n)^T$. The kernel function of the hidden layer node will produce a certain response to the input signal locally. When the input signal is close to the central range of the kernel function, the hidden layer node will produce a larger output. The kernel function often used is the Gaussian function. Fault tree analysis (FTA) is a method to describe the causal relationship. It qualitatively describes the causal relationship between the layers of fault propagation. It can use the Minimum cut set to find possible fault sources, and is effectively applied to various complex analysis and diagnosis situations. This method applies certain decision conditions to conduct in-depth analysis of specific conditional states, revealing the relationship and correlation between conditions and events, and expressing them through graphical means. The fault tree graph can clearly list the association and logical relationship between the major faults and specific Glitch of the system [20].

The fault tree is established through the following steps:

1. Determine the top event. In the backend analysis system, it generally refers to the type of fault, which can be a large category of faults or specific faults.
2. Analyze the top event, screen the various reasons that trigger the top event, and associate these identified reasons with the top event through logical gates, forming the upper input of the top event.
3. Analyze the causes of the top events, decompose these events again, and identify their input events.
4. Repeat the calculation layer by layer until it can not progress again, that is, get the bottom event, and build and complete the fault Tree model.

Fault tree is a powerful tool for establishing correlations between data and mining causal relationships, but it is difficult to automatically search for relevant knowledge through a large and complex substation operation and maintenance database, the workload of building fault trees through manual experience is too huge. So it is necessary to introduce rough set technology to obtain knowledge of data classification and attribute association for constructing fault trees, which can be used to conveniently construct fault trees.

If there is a bottom event $B_i(i = 1, 2, ..., n)$ and its state is $x_i(t)$ at a certain time, then:

$$x_i = \begin{cases} 1, \text{The bottom event occurs at time t} \\ 0, \text{The bottom event did not occur at time t} \end{cases} \tag{3.2}$$

The probability of triggering the bottom event at this time is:

$$p_i(t) = E[x_i(t)] = p[x_i(t) = 1] \tag{3.3}$$

If the top event in the fault tree is triggered as M, and its state is M [X (t)] at a certain time, then

$$M[X(t)]_i \begin{cases} 1, \text{The bottom event occurs at time t} \\ 0, \text{The bottom event did not occur at time t} \end{cases} \tag{3.4}$$

And the probability of M at t is

$$p_1 = E\{M[X(T)]\} = p[\{M[X(T)] = 1\}] \tag{3.5}$$

Converting the fault tree into a structural function can facilitate data calculation and correlation analysis. If the gates and the three OR gates in the fault tree are T1T2T3T4, respectively,then

$$T_4 = B_5 + B_6 \tag{3.6}$$

$$T_3 = B_3 + B_4 \tag{3.7}$$

$$T_2 = B_1 + B_2 \tag{3.8}$$

$$T_1 = T_2T_3T_4 \tag{3.9}$$

Indicates the likelihood of an event occurring, including:

$$p_{and} = \prod_{i=1}^{n} p_i \tag{3.10}$$

Table 4.1: Typical Fault State Model of P100 Unit

State model	Sample number
P101 board fault	001001
P102 board fault	010010
P103 board fault	101101
Azimuth drive fault	011011
High and low drive failure	110110
15 MHz clock failure	001011
PRF signal failure	100011
Equipment is normal	000000

Table 4.2: Typical fault state model of the P 200 unit

State model	Sample number
24 V power failure	000011
P201 board fault	000110
P202 board fault	001101
P203 board fault	011010
High voltage power supply 200 V fault	000111
Serial communication failure	100111
Equipment is normal	000000

$$p_{or} = 1 - \prod_{i=1}^{n}(1 - p_i) \tag{3.11}$$

In summary, the event probability can be conveniently calculated through the structure of the fault tree. The system can determine the probability of each bottom event based on the obtained event probability, and make fault judgments and equipment evaluation and maintenance strategies for the most likely bottom events. However, some faults have high importance and high risk factors, and the probability of them appearing in the bottom event is often very small. Therefore, the fault coefficient is set as $F_i(u) = I_i P_i$.

4. System Experiment Results and Analysis. The radar is composed of three independent unit modules: P100, P200, and P300. In order to verify the effectiveness of fault tree for fault diagnosis, the typical faults of the radar P100 unit are taken to establish a sample training model, and the samples are initialized. The typical fault state model of the P100 unit is shown in Table 4.1.

In actual training, after 29 iterations, the training results can quickly converge to the target value, the training error meets the requirements, and the fault diagnosis accuracy reaches over 90%. In order to verify the fault diagnosis effect of the system on other units, the typical faults of the radar P200 unit are taken to establish a sample training model, and the samples are initialized. The typical fault state model of the P200 unit is shown in Table 4.2.

The number of input nodes in the fault tree is 7, the number of output nodes is 2, the number of center vectors is 14, the number of nodes in the basis function layer is 7, and the threshold of the basis function is set to 0.8257. In actual training, after 31 iterations, the training results can quickly converge to the target value, the training error meets the requirements, and the fault diagnosis accuracy reaches over 90% [21]. Each radar unit was divided into 25 sets of fault and non fault samples, with a total of 225 fault samples to test the diagnostic performance of the system. The diagnostic results are shown in Figure 4.1.

From the diagnostic results data, it can be seen that the fault diagnosis accuracy of all three units is above 90%, indicating that the diagnostic performance of the system is good and meets the expected design effect [22].

5. Conclusion. This article is based on the fact that current technologies such as fault detection and diagnosis for substation equipment have not yet entered full intelligence. By combining the practical application

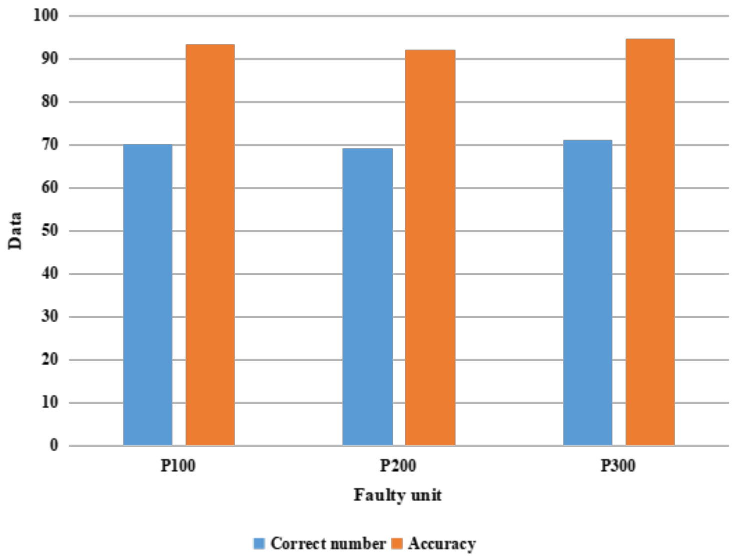

Fig. 4.1: Troubleshooting results

environment characteristics of substations, an intelligent intelligent inspection robot autonomous monitoring and fault diagnosis detection system is proposed. The fault tree, Big data information analysis technology and carrying high-definition camera are organically combined, the fault tree model model is used to diagnose the fault, and a large amount of simulation data is used to provide experimental samples for the fault tree.

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