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Machine Learning-Based Automatic Fault Diagnosis Method for Operating Systems

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Abstract: ***In order to improve the stability, security and service quality of the operating system, an automatic fault diagnosis method based on machine learning is proposed in this paper. Firstly, using the fault detection of Tesla system as the background, AR model coefficient is taken as the feature of the fault system, and the influence of different state number and different mixed Gaussian number on the classification of hidden Markov model is explored. Secondly, the maximum likelihood estimation method is used to update the model parameters step by step, and the probability density function of the observed values is calculated to realize fault detection and diagnosis. Furthermore, a self-organizing competitive neural network is introduced to simplify the system into a running index and event substitution graph by using similarity graph, and faults are described as event sequence according to event time correlation. Finally, the ranking method is used to identify the key events and clear the fault mode, so as to realize the automatic fault diagnosis of the operating system. The method proposed in this study provides a new idea and method for the effective diagnosis of operating system faults.***

Keywords: Machine learning; Operating systems; Fault diagnosis; Hidden Markov models; Self-organizing competitive neural networks.

1. INTRODUCTION

The development of sensor networks has revolutionized various fields by enabling large-scale data collection and analysis in real-time. However, the effectiveness of these networks is heavily reliant on the robustness and efficiency of the underlying operating systems that govern the behavior of individual sensor nodes. Given the limited capacity and energy constraints of each sensor node, coupled with the highly dynamic nature of network topologies in adverse environments, creating a reliable sensor network poses significant challenges.

The operating system within each sensor node serves as the backbone for higher-layer applications and protocols, managing both software and hardware resources critical for network operation. Hence, the fault diagnosis of these operating systems becomes imperative to ensure the overall network's performance and reliability.

Previous studies [1-3] have proposed trend recognition methods for sequence data, integrating expert knowledge to enhance fault diagnosis accuracy. However, these methods rely heavily on expert-defined trend characteristics and may lack adaptability in dynamic environments. Another approach [4] leverages optical grayscale image recognition for fault diagnosis, yet it may not be directly applicable to operating system faults.

In response, this paper presents an automatic fault diagnosis method for operating systems based on machine learning. By utilizing an AR-continuous HMM-based fault diagnosis model, the accuracy of diagnosis is significantly improved. The paper analyzes the mechanisms and advantages of machine learning, constructing a self-organizing competitive neural network. Through the utilization of similarity graph methods, the proposed approach achieves automatic fault diagnosis with high efficiency and accuracy, thereby enhancing operating system performance and delivering superior network services to users.

2. RELATED WORK

2.1 Machine learning fault detection

The traditional operation and maintenance mode has obvious shortcomings in monitoring, problem discovery, alarm, fault handling and other links, and needs to rely heavily on human experience. The efficiency of data collection, abnormal diagnosis and analysis, and fault handling needs to be improved.

Intelligent fault diagnosis (IFD) refers to the application of machine learning theory to machine fault diagnosis. This is a promising way of liberating human labor and automatically identifying the health of machines, so it has gained a lot of attention in the past two or three decades. [5]While IFD has had considerable success, there are still gaps in systematically covering the development of IFD from cradle to flowering, with few possible guidelines for future development. In order to bridge this gap, this paper gives an overview and roadmap of the development of IFD based on the progress of machine learning theory, and gives a prospect of the future. In the past, traditional machine learning theories began to weaken human labor, bringing the era of artificial intelligence into machine fault diagnosis. In recent years, IFD has been revolutionized by the emergence of deep learning theory, and since the 2010s, IFD has further liberated human labor and encouraged the construction of end-to-end diagnostic processes. It means directly connecting the relationship between the growing amount of monitoring data and the health state of the machine.

Faced with the three major pain points of traditional operation and maintenance, such as low fault handling efficiency, inaccurate problem positioning and labor cost, this key technology combines artificial intelligence and operation and maintenance, and gradually replaces human decision-making by [6] AI. Through machine learning methods, decision-making suggestions are quickly given or faults are avoided in advance, and intelligent analysis and optimization of network cloud services are realized, thus greatly improving operation and maintenance productivity. In general, intelligent operation and maintenance is more efficient than traditional operation and maintenance, and data collection is more accurate and intelligent.

The machine learning based anomaly detection and intelligent analysis technology is based on multi-modal data such as resources, alarms, performance, dial-test, and logs. By using artificial intelligence technology, the source and noise reduction of abnormal business events are carried out, and the root cause and location analysis of anomalies are displayed to O&M personnel in the first time, improving the troubleshooting efficiency of O & M personnel and reducing O&M costs.

Generally, the output of anomaly detection includes exception indicators, major alarms, and exception logs, providing a reference for intelligent analysis of cloud service health.

This key technology includes indicator anomaly detection, alarm compression and noise reduction, log anomaly detection, intelligent analysis and other technologies. Indicator anomaly detection technology, access operation and maintenance monitoring indicators through the anomaly detection algorithm to obtain the abnormal points of indicators; The alarm compression and noise reduction technology mining the correlation between massive alarm events, reducing the number of alarm messages while ensuring the core alarm content, and providing effective alarm information for operation and maintenance personnel. The log anomaly detection technology analyzes the change trend of log modes in real time from massive logs to discover service exceptions in time. Intelligent analysis technology: Based on the detected anomaly indicators, major alarms, and anomaly logs, and combined with the fault propagation relationship, decision tree, and knowledge graph technologies, the intelligent analysis technology can analyze the network cloud service faults and hidden dangers, and output the root cause, location, and recommended measures to improve the troubleshooting efficiency of [7] O & M personnel and reduce O & M costs.

Therefore, Markov fault detection is a common method in machine learning, which is based on Markov models to identify faults in a system. Markov model uses state transition probability to describe the state evolution of the system and infer the current state of the system from the observed data. In fault detection, Markov model can identify possible faults by monitoring abnormal behavior of state transition, and then realize automatic fault detection and diagnosis. This method can be effectively applied to various systems, including sensor networks, operating systems, etc., and provides important technical support for improving system stability and reliability.

2.2 Application of mechanical fault detection and diagnosis

Depending on the inference engine, The diagnosis model based on expert system can be divided into rule-based reasoning, fuzzy logic-based reasoning and neural network-based reasoning reasoning) and case-based reasoning (case-based reasoning). Each section is summarized below.

The rule-based reasoning method is adopted to operate the diagnostic knowledge and make decisions according to the designed rules [15]. In the field of IFD, Krishnamurthi et al. [8-9] designed a rule-based reasoning expert system for a Cincinnati Milacron 786 robot, one of the earliest studies in this field. The designed diagnostic framework greatly reduces the development time and workload of diagnostic model in the aspects of knowledge acquisition, application system generation, learning and interpretation. Gelgele et al. [10] used IF-THEN rules to build an automotive engine diagnosis model based on expert system. The rule-based reasoning method is applied to the fault diagnosis of hydraulic system [20], rolling bearing [11] and centrifugal pump [12]. Although rule-based reasoning can build a nonlinear mapping from selected features to health states, for complex machines, reasoning efficiency decreases as the number of rule designs increases.

Based on fuzzy logic inference, fuzzy set theory is introduced into inference engine to describe imprecise non-numerical information . In IFD, Lee et al. [13] designed a fuzzy reasoning system for power systems, which is one of the earliest works in the application of fuzzy logic reasoning. the system consists of a meta-inference system, an expert system for hybrid diagnosis and an expert system for the diagnosis It is composed of four parts: the expert system for the diagnosis of transmission network and the Expert System for the diagnosis of transmission network, which improves the efficiency and reliability of the fault diagnosis process. Liu et al. [14] used fuzzy multi-attribute group decision making group to build a diagnosis model based on expert system. Wu et al. used fuzzy logic reasoning to identify the health of scooter engines. Berredjem et al. applied fuzzy expert system to bearing fault diagnosis and achieved high diagnostic accuracy. The inference performance based on fuzzy logic is related to fuzzy data set, but fuzzy data set is difficult to capture. As a result, this reasoning is often less learnable and may reduce diagnostic accuracy.

Neural network-based reasoning inherits the learning, association and memory abilities of neural networks. Wu et al. used probability neural network and generalized regression neural network respectively to construct a diagnosis model of internal combustion engine based on expert system. Hajnayeb et al. [15] built an inference engine using multi-layer perceptron neural network to infer the relationship between collected data and bearing health status. Jayaswal et al. [16] combined neural network and fuzzy rules to build a bearing diagnosis model based on expert system. Inference based on neural networks requires the acquisition of diagnostic knowledge from sufficient training data, which is difficult to satisfy in engineering scenarios. In addition, due to the black box of neural networks, this reasoning cannot clearly explain the reasoning process and the physical meaning of the stored knowledge.

Case-based reasoning attempts to solve specialized problems based on solutions to similar existential problems. Vingerhoeds et al. use case-based reasoning to combine the knowledge and experience of train manufacturers and railway companies for online fault diagnosis. Varma et al. proposed a fault diagnosis system for locomotive based on case-based reasoning using on-board fault information. Wu et al. developed a modern commercial aircraft fault diagnosis expert system, which is designed based on case-based reasoning and fuzzy logic. Vong et al. built a computer-aided diagnosis system based on case-based reasoning and nuclear k-means for automotive engine ignition systems.

2.3 Model-based fault diagnosis method

Model-based fault diagnosis was proposed by Beard in 1971 to replace hardware redundancy with analytical redundancy. In a model-based approach, models of industrial processes or actual systems are required to be available and to be accessible through the use of physical principles or system identification techniques. On the basis of this model, a fault diagnosis algorithm is developed to monitor the consistency between the measured values [17]. The output of the actual system and the output predicted by the model. In this paper, model-based fault diagnosis methods are divided into four categories: deterministic fault diagnosis methods, random fault diagnosis methods, discrete event and hybrid system fault diagnosis methods, and network and distributed system fault diagnosis methods, classified according to the type of model used.

(1) Deterministic fault diagnosis method

For the monitored system/process with deterministic model characteristics, the observer plays a key role in model-based fault diagnosis. Obstreper-based fault diagnosis principles, as shown in the figure, include fault detection, fault isolation, and fault identification (Otherwise known as fault reconstruction or fault estimation).

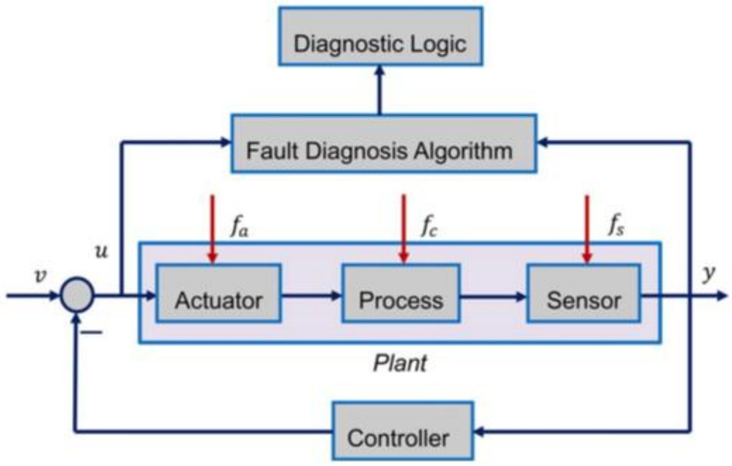

Figure 1: Fault diagnosis principle of intelligent operating system observer

(2) Random fault diagnosis method

With the development of deterministic system fault diagnosis methods, random methods were also used in fault diagnosis in the early 1970s. A general fault detection and diagnosis program is proposed for the first time, which uses residuals (or innovations) generated by Kalman filters with sim- similar to observer structures to diagnose faults by statistical tests of whiteness, mean and covariance of residuals. Various statistical tools such as generalized likelihood, $\chi 2$ test [18], cumulative sum algorithm, and multiple hypothesis testing were further developed to test the residual based on Kalman filtering to check the likelihood of a particular fault occurring. Further research has led to some improved Kalman filtering techniques for fault diagnosis, such as Extended Kalman filter (ekf), etc

(3) Discrete event and hybrid system fault diagnosis methods

In industrial processes, the signals of some dynamic systems switch from one value to another, rather than continuously changing their values. Such a system is called a discrete event system. In the 1990s [19], the fault diagnosis of discrete event systems was initialized and the basic theory of fault diagnosis of discrete event systems was proposed. The basic problem of event-driven fault diagnosis is model-based reasoning at run time, using the sequence of observable events to determine whether a given unobservable fault event has occurred in the past. According to the model used, the fault diagnosis methods of discrete event systems can be roughly divided into automaton-based fault methods and petri-net based fault methods [20]. In order to overcome the complexity of tasks, automaton-based fault diagnosis methods are developed, which are divided into decentralized method, symbolic method, and the combination of decentralized and symbolic method. On the other hand, Petri nets have inherent distributed characteristics, in which the concepts of state and behavior are local, which is an asset fault diagnosis problem to reduce the computational complexity of the solution.

(4) Network and distributed system fault diagnosis methods

The rapid development of network technology has greatly promoted real-time control and monitoring through communication channels, that is, network control and monitoring, with valuable advantages such as high cost effectiveness, low weight and power requirements, easy installation and maintenance, and resource sharing. It is worth noting that the introduction of limited capacity network cables or wireless sensors in the control and monitoring loop inevitably brings some unexpected problems, such as random communication delays, data loss, scheduling confusion, etc., which makes network-based monitoring and fault diagnosis more challenging than traditional point-to-point control and monitoring systems [21]. Therefore, in network-based fault diagnosis, residuals or fault estimation errors must be robust not only to modeling errors, process interference, and measurement noise, but also to transmission delays, data output, and complete measurements caused by communication channel capacity limitations. In recent years, a variety of fault diagnosis techniques have been developed for various network systems. For example, fault detection filters have been developed in the United States for systems that suffer from communication delays and data loss, where the network state is assumed to vary in a Markov manner. In [13], least-squares filters and Kalman filters are integrated into fault detection, isolation, and network target sensing systems.

3. METHODOLOGY

3.1 Principle of automatic fault diagnosis

Based on reliability assessment (SRA) and improved convolutional neural network (ICNN), a new sample data-driven method is proposed to solve the problem of non-ideal fault diagnosis data. The data processing process of the proposed fault diagnosis method can be divided into four parts, as shown in Figure 2:

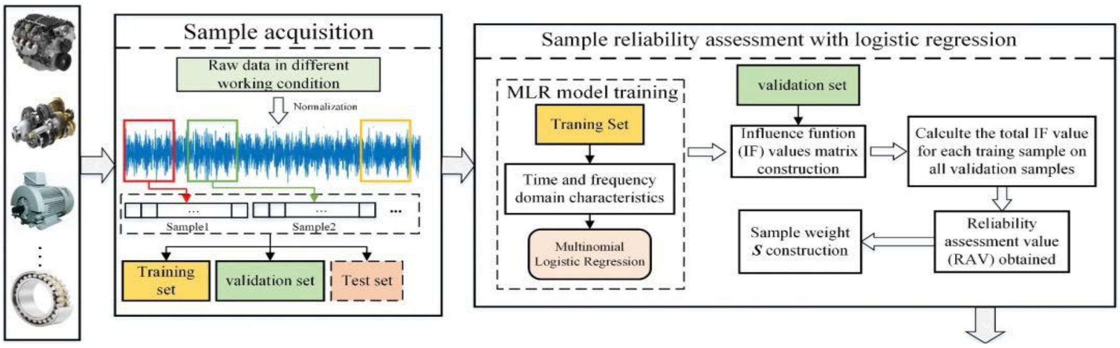

Figure 2: Working principle of fault diagnosis method

(1) Sample collection: The sample is constructed from the original signal with a certain sampling length, and the sample is divided into training set, verification set and test set.

(2) Sample reliability evaluation: In order to achieve the reliability evaluation of sample quality, the MLR algorithm is used to build an evaluation model by analyzing the time-frequency input of the original sample. The system is simple in structure and can effectively analyze the influence of sample quality on the determination accuracy. The statistical method of influence function is introduced to further accelerate the process of sample evaluation.

(3) Network construction and training: In order to make better use of the feature mining performance of CNN, continuous wavelet transform (CWT) [22]is used to convert one-dimensional samples into time-frequency images and further compress them. In the loss function, sample weight and class weight strategies are introduced to help the model focus on high-quality samples and ignore low-quality samples, and to solve the problem of model precision decline in the case of class imbalance.

(4) Fault classification: Compared with traditional CNN, the trained ICNN model can make better use of fault features in non-ideal data, thus improving the reliability of mechanical fault diagnosis model identification.

3.2 Experimental design

To assess the superiority of the sample reliability assessment (SRA) process, two importance-sampling based sample weighting methods, upper-bound and LOW, were employed and compared with the baseline method (2DCNN, without sample weighting). We conducted 5 tests on the sample set S0-S5, and obtained the average test accuracy, as shown in Figure 3. The results show that ICNN has the highest fault identification accuracy on all six sample sets. At the same time, with the increase of the unreliability of the sample set, the ICNN method shows a more significant improvement effect. This shows that ICNN method can deal with non-ideal samples more efficiently than other methods.

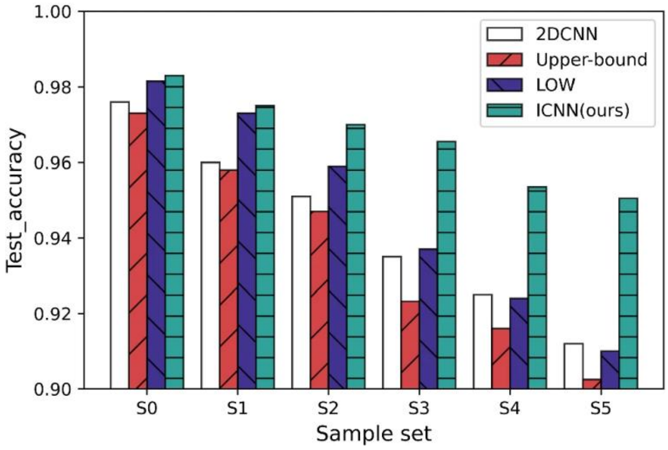

Figure 3: Comparison with other sample weighting methods

In addition, we further investigate the effects of strategies such as sample weight (SW), classification weight (CW), and early stop (ES). We separately removed these policies from the ICNN model to determine their impact on model performance. The results are shown in Figure 3, showing that the SW policy contributes the most to ICNN performance because the model without SW policy has the lowest accuracy. The ES strategy also has a significant effect on the performance, even equivalent to the SW strategy in sample sets S6 and S7 in some cases [23]. The CW strategy also plays a role in improving the recognition performance of the model on most sample sets, although the improvement is not obvious. Therefore, it can be concluded that all three improvement strategies in the ICNN method are valid and necessary.

3.3 Experimental conclusion

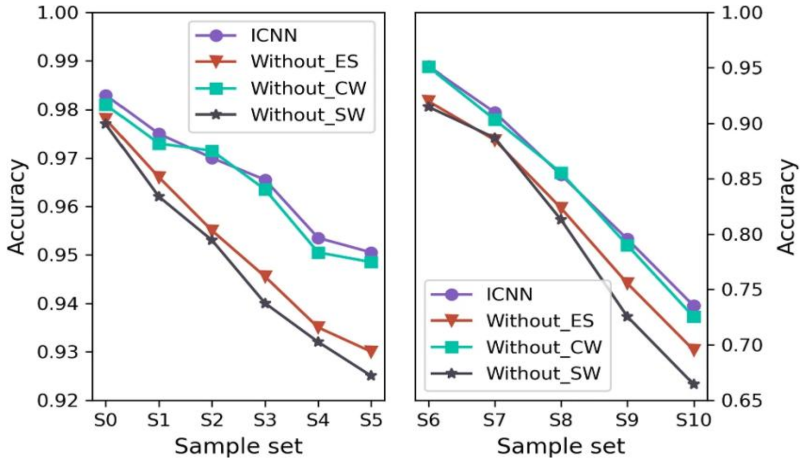

Figure 4: Comparison of the impact of three improvements of CNN on test accuracy

In this study, a data-driven approach based on sample reliability assessment process and improved ICNN is proposed to improve the fault diagnosis performance of the model in the case of non-ideal data [24]. By using the MLR evaluation model to evaluate the original training samples, and using the influence function to simplify the calculation, the RAVs of all the training samples are obtained. Then, the network structure is improved by introducing three strategies based on RAVs: sample weight, class weight and early stop. The trained ICNN can automatically extract features and achieve fault diagnosis in the case of input compression of time-frequency images. Experimental results show that the proposed method can effectively optimize the model training process and improve the performance of fault recognition, and provide a feasible solution to the problem of fault diagnosis under non-ideal data.

4. CONCLUSION

In this study, we propose a data-driven approach based on a sample reliability assessment process and an improved ICNN to improve the fault diagnosis performance of the model in the case of non-ideal data. By using the MLR evaluation model to evaluate the original training samples, and using the influence function to simplify the calculation, the RAVs of all the training samples are obtained. Then, the network structure is improved by introducing three strategies: sample weight, class weight and early stop based on [25-27] RAVs. The trained ICNN can automatically extract features and achieve fault diagnosis in the case of input compression of time-frequency images. Experimental results show that the proposed method can effectively optimize the model training process and improve the performance of fault recognition, and provide a feasible solution to the problem of fault diagnosis under non-ideal data.

In the future, with the continuous development and popularization of emerging technologies such as the Internet of Things, cloud computing and edge computing, the field of fault detection of operating systems will face more challenges and opportunities. First of all, with the popularity of Internet of Things devices and the diversification of application scenarios, the application of operating systems in embedded devices, smart homes, industrial automation and other fields will be more extensive, which will lead to more complex and diversified operating system fault detection. Therefore, future research needs to focus on how to deal with the needs of operating system fault detection in different fields and scenarios, and propose more intelligent, flexible and efficient detection methods and technologies.

Secondly, with the continuous development and application of technologies such as artificial intelligence and deep learning, the field of operating system fault detection will also usher in new opportunities. The use of machine learning, deep learning and other technologies can better mine and use large-scale data to improve the accuracy and efficiency of fault detection [28-30]. Future research can explore how to combine traditional fault detection methods with machine learning, deep learning and other technologies to build a more intelligent and efficient operating system fault detection system to provide users with more stable and reliable services.

In addition, with the increasing popularity of technologies such as edge computing and cloud computing, the application of operating systems in distributed systems, big data processing and real-time computing will also continue to increase. In this context, operating system fault detection will face more complex and diversified challenges. Future research could explore how to design and optimize operating system fault detection algorithms and models for distributed systems, big data processing, and real-time computing scenarios to improve system stability, security, and reliability.

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