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FAULT DETECTION OF ELECTRICAL SYSTEM IN TREE BARRIER CLEANING EQUIPMENT BASED ON COMPRESSED PERCEPTION MODEL

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ABSTRACT. A detection method based on compressed sensing model is proposed for the fault diagnosis of electrical systems in tree obstacle cleaning equipment. Firstly, the electrical system faults of the tree obstacle cleaning equipment are divided into three categories: circuit faults, control faults, and aging faults. Secondly, balance the imbalance of various fault data. Again, based on the compressed sensing model, sparse representation and reconstruction of fault data are performed, followed by clustering analysis of fault types using the KNN algorithm. The experimental results show that our proposed method has higher detection accuracy for 9 types of faults in the electrical system of tree obstacle cleaning equipment.

1. Introduction

Tree obstacle cleaning equipment is a specialized electromechanical equipment. To ensure the safe and stable operation of tree obstacle cleaning equipment to the greatest extent possible, it is necessary to detect and diagnose electrical equipment faults as early as possible [5, 10, 14]. Electrical equipment fault diagnosis is an important research branch in the field of electrical technology, with research methods including traditional physical model analysis, statistical analysis, machine learning, and intelligent diagnostic techniques [3, 6, 12].

With the development of intelligence and digitization, many research focuses on intelligent diagnosis, deep learning, and big data analysis. These methods identify the characteristics and patterns of electrical equipment faults by analyzing a large amount of historical data, thereby achieving rapid diagnosis of faults [4, 13]. The numerical data comes from infrared detection, ultraviolet detection, ultrasonic detection, oil chromatography monitoring, and partial discharge monitoring, including dissolved gas content in oil, discharge amount, temperature and other data, providing quantitative basis for fault diagnosis [2]. The power text information comes from fault case reports, inspection records, test records, etc., including equipment ledger data, fault phenomena, fault types, diagnostic criteria, etc., providing qualitative basis for fault diagnosis and playing an important guiding role [7]. Expert systems simulate the knowledge, skills, and processing experience of domain experts, usually using a series of rules and reasoning techniques to analyze data and make

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decisions, improving diagnostic efficiency and accuracy. They are a manifestation of early artificial intelligence, but there are problems such as insufficient reasoning ability and difficulty in development [11]. Traditional machine learning based diagnostic methods include support vector machines, K-nearest neighbor algorithm KNN, etc. [1]. The principle of SVM text classification is to extract text feature vectors through word bag models or TF-IDF models, and then classify them. It requires manual construction of rule templates or dictionaries, which has problems such as incomplete feature coverage and limited sentence meaning extraction ability [9]. There are diagnostic methods based on deep learning, such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), BERT, etc. Choudhary proposed a CNN based transformer fault diagnosis method based on characteristic gases, which has strong feature extraction ability, and the CNN itself has a simple structure and short model training time [8, 15, 16].

On the basis of previous research results, this article fully considers the issue of imbalanced electrical fault data and conducts fault diagnosis analysis based on compressed sensing models after balancing processing, in order to improve the safety of the electrical system of tree obstacle cleaning equipment.

2. Proposed method

2.1. **Fault classification of electrical systems for tree obstacle cleaning equipment.** Tree obstacle cleaning equipment is a large-scale electromechanical equipment with a very complex internal structure and system composition. Various functional units such as mechanical, electrical, control, and sensing are interlocked and combined together, making it very difficult to identify the cause of faults once they occur.

The common faults in the electrical system of tree obstacle cleaning equipment can be divided into two categories: one is mechanical faults, which are purely caused by mechanical parts, mechanisms, etc; Another type is electrical faults, which include faults in the electrical, control, and sensing parts. In this article, the main focus is on the category of electrical faults. The common classification of electrical faults in tree obstacle cleaning equipment is shown in Figure 1.

From Figure 1, it can be seen that in order to facilitate the sorting of faults in the electrical system of the tree obstacle cleaning equipment, they are further divided into three categories: the first category is electrical line faults, the second category is control faults, and the third category is aging faults. In electrical circuit faults, they can be further divided into open circuit faults of electrical circuits, open circuit faults of electrical circuits, and misconnection faults of electrical circuits; In control failures, they can be further divided into system controller failures, system critical component failures, and various sensor failures; In aging faults, they can be divided into circuit paint aging faults, circuit core aging faults, component aging faults, etc. The specific category of a fault can vary depending on the situation. For example, if there is a malfunction in the CPU or RAM of the electronic control system, it is considered as a system controller malfunction and a critical component malfunction, respectively; If there is a malfunction in the indicator light, travel switch, etc., it is considered a sensor failure; If the circuit is short circuited due to aging of the paint,

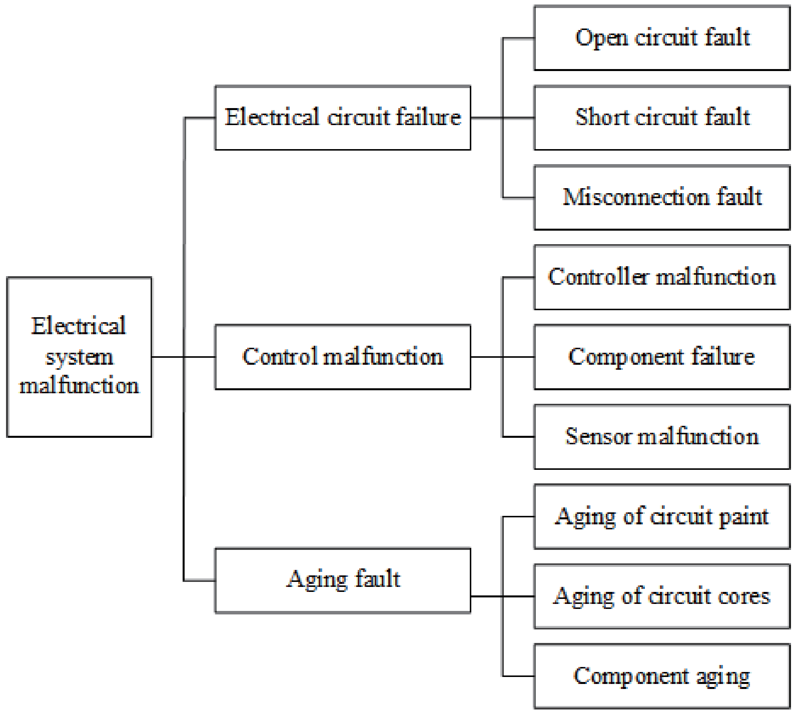

FIGURE 1. Classification of Electrical System Faults in Tree Barrier Cleaning Equipment

it is considered a fault of aging of the paint; If there is an open circuit due to aging of the inner core, it belongs to an aging fault of the inner core of the circuit.

2.2. **Balanced processing of electrical system fault data for tree obstacle cleaning equipment.** In order to achieve accurate diagnosis of electrical system faults in tree obstacle cleaning equipment, it is necessary to iteratively train the diagnostic model based on a large amount of raw fault data. The probabilities of various types of faults shown in Figure 1 are different, and a small number of data samples for a certain type of fault can lead to an imbalance in the training process. Therefore, this article uses interpolation algorithm to balance the data of electrical system faults in tree obstacle cleaning equipment, as shown in Figure 2.

As shown in Figure 1, the tree obstacle cleaning equipment's electrical system fault data balance processing steps are as follows:

The first step, set the set consisting of a small number of data as X, which contains a total of n samples.

The second step, select sample $x_i (i \in [1, n])$ from a small dataset as the root sample for synthesizing new samples.

The third step, based on the upsampling rate n , select an odd number k (for example, $k = 3$), and use k neighboring samples x_{ij} as auxiliary samples for synthesizing new samples, where $x_{ij} \in X$, $j = 1, 2, \ldots, k$.

The fourth step, generate a new sample by interpolation between the root sample x_i and the auxiliary sample x_{ij}. The execution Equation for interpolation processing

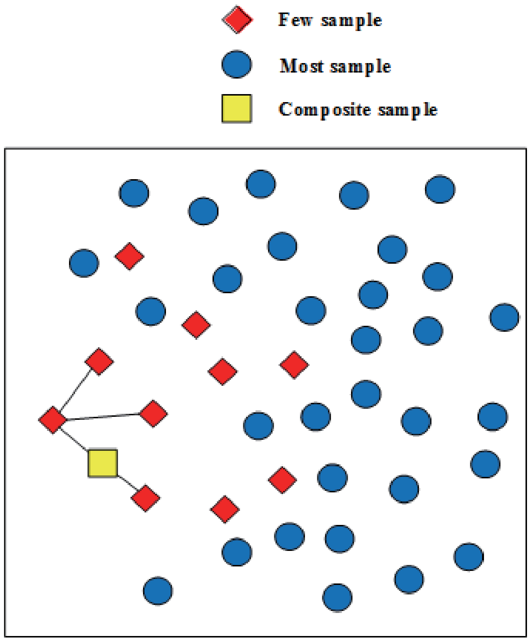

FIGURE 2. Balance processing of electrical system fault data for tree obstacle cleaning equipment

is shown in Equation (2.1):

$$x_{new} = x_i + \gamma^* |x_{ij} - x_i| . \tag{2.1}$$

Here, x_{new} represents the new sample, γ A random number that represents a value in the $0 - 1$ interval.

2.3. **Fault data analysis based on compressive sensing model.** In the field of signal transmission, the Shannon Nyquist sampling theorem is a universal theorem. According to this theorem, the frequency of the sampled signal must reach twice or even higher times the frequency of the original signal in order to obtain meaningful sampling, and the resulting sampled signal can reproduce the original signal.

However, the Shannon Nyquist sampling theorem also brings a prominent problem, as the amount of data obtained by sampling at high frequencies is relatively large. For the fault diagnosis of the electrical system of tree obstacle cleaning equipment, it is not only necessary to monitor multiple types of information at the same time, but also to monitor for a long time, and then sample and extract signals according to the Shannon Nyquist sampling theorem, which will result in a very large amount of information. The collection of electrical fault related information for tree obstacle cleaning equipment is too large, which not only leads to information redundancy, but also brings huge computational burden to the fault diagnosis algorithm and the generation of diagnostic results, resulting in a decrease in diagnostic efficiency. Therefore, this article adopts the Compressed Sensing Model (CS model for short), which uses a smaller amount of data to represent the original electrical signals of tree obstacle cleaning equipment.

Compared to the Shannon Nyquist sampling theorem, the biggest advantage of the CS model is that it samples at a lower frequency. After obtaining relatively sparse data information, the CS model is reconstructed according to certain rules and can also reproduce the original signal, greatly reducing the storage of data and subsequent calculations, diagnosis, and other processing.

It can be seen that sparse representation is the prerequisite and foundation for CS models to process large-scale data. The condition that sparse representation can be achieved is that if there are only a few non-zero values observed along the time axis of the electrical system state, then the observed signal can be compressed, that is, sparse representation. However, this sparse representation cannot be performed in the normal signal domain. CS models generally need to change the signal or observation data to other expression domains, such as the Fourier transform domain, frequency domain, wavelet transform domain, and so on. In the transformation domain, the redundancy of signals or observation data can be removed on a large scale, achieving compression and sparse representation of signals or observations.

After sparse representation of signals or observation data, how to reconstruct the original signal from this sparse signal is the core task of the CS model. This involves the transformation from sparse data to dense data, and from low dimensional space to high-dimensional space. This paper adopts an approximation solution method of two norm processing to achieve the reconstruction of sparse signals by the CS model. The core Equation for reconstruction is shown in Equation (2.2):

$$\begin{array}{c}\hat{x} = \arg\min \|x\|_0 \\ \text{s.t. } y = \varphi x\end{array}. \tag{2.2}$$

Here, x represents the electrical system signal of the tree obstacle cleaning equipment (represented by the sparse expression of the CS model), $\hat{x}$ represents the electrical system signal that is approximated and solved according to the 0 norm, $\arg\min \|\|_0$ represents the approximation and solution operation of the 0 norm on the data inside, y represents the observation values of the electrical system signal, and φ represents the observation matrix.

The core Equation for reconstruction based on norm 1 is shown in Equation (2.3):

$$\begin{array}{c}\hat{x} = \arg\min \|x\|_1 \\ \text{s.t. } y = \varphi x\end{array}. \tag{2.3}$$

Here, x represents the electrical system signal of the tree obstacle cleaning equipment (represented by the sparse expression of the CS model), $\hat{x}$ represents the electrical system signal reproduced by approximating and solving according to the norm $0, \arg\min \|\|_1$ represents the approximation and solving operation of the norm 1 on the data inside, y represents the observation values of the electrical system signal, and φ represents the observation matrix.

According to the approximation processing of norm 1, sparsely express the original signal and then reconstruct it. Compared to the original signal, although the reconstructed signal is based on sparse data, most of the effective waveforms in the original signal are preserved and reproduced.

After compression processing of the CS model, a sparse representation of the electrical system signal of the tree obstacle cleaning equipment can be obtained.

In this way, the amount of data obtained through continuous observation will not be very large, which can improve the efficiency of fault diagnosis. In further fault diagnosis, perform KNN clustering diagnosis on the CS signals that have already been obtained.

The execution strategy of the KNN method is very clear. By setting the data values that are determined as faults, prior information that can be used as criteria for fault type judgment is obtained. Afterwards, for the reconstructed CS signal, the distance is calculated and compared with various fault standard values, and the closest distance is the most reliable fault type discrimination result. It can be seen that the key to the CS-KNN fault diagnosis method lies in the calculation of the distance between the reconstructed signal value and the fault standard value. The following methods are generally used here:

(1) Reconstruct the Euclidean distance between the signal value and the fault standard value Euclidean distance is a commonly used distance calculation method in the field of mathematics, which is also applicable to the fault diagnosis of the electrical system of the tree obstacle cleaning equipment to be solved in this article. Its form is shown in Equation (2.4):

$$d(a,b) = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2}. \tag{2.4}$$

Here, a represents the reconstructed signal value, b represents the fault standard value, a_i represents the i-th coordinate of the reconstructed signal value in Euclidean space, b_i represents the i-th coordinate of the fault standard value in Euclidean space, and $d(a,b)$ represents the Euclidean distance between the reconstructed signal value and the fault standard value.

(2) Manhattan distance between reconstructed signal value and fault standard value

The calculation method of Manhattan distance is somewhat different from the calculation method of Euclidean distance, one is to use the absolute difference value, and the other is to use the difference square and then open the root sign, but its connotation is basically the same.

3. Experimental results and analysis

During the experiment, 10000 sets of actual data on electrical system faults of tree obstacle cleaning equipment were selected as the experimental objects. These 10000 sets of data contain over 300 fault data, which are used to train the method proposed in this article. During the training process, first observe the iterative training effect before and after using data balance, as shown in Figure 3.

From Figure 4, it can be seen that without using data balancing, the peak and valley fluctuations during the iterative training process are severe and strong. After using data balancing, the iteration process becomes smooth. This is because there is no negative impact caused by data with significant differences.

The following experiment will examine the performance comparison of the training process before and after CS-KNN fusion, as shown in Figure 4.

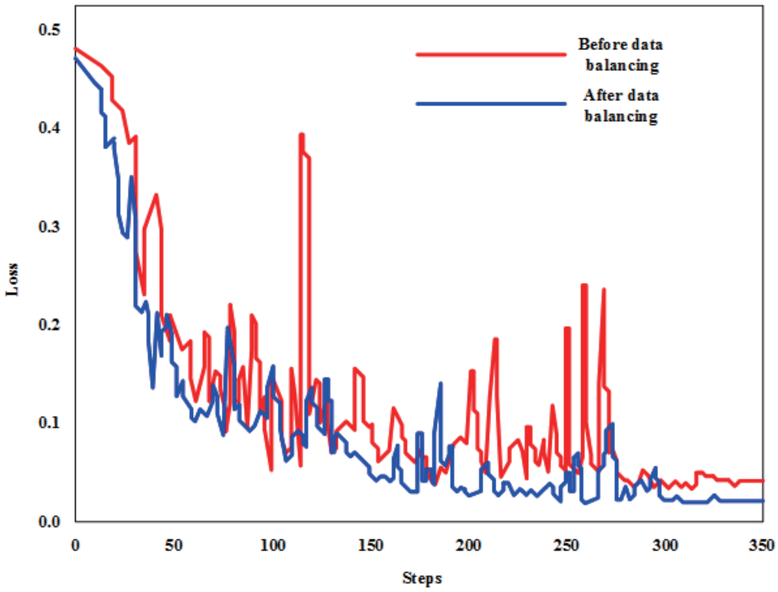

Figure 3. Performance comparison before and after data balancing

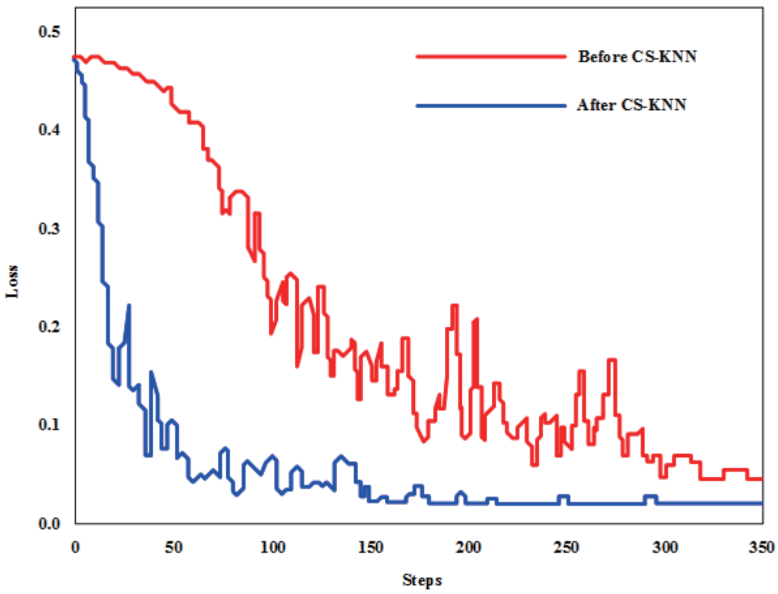

Figure 4. Performance comparison before and after CS-KNN combination

From Figure 4, it can be seen that the iterative training process of the entire algorithm before CS-KNN fusion has a slow convergence speed and low convergence accuracy. The iterative training process of the entire algorithm after CS-KNN fusion has fast convergence speed and high convergence accuracy.

In the previous work, a CS compression method and a CS-KNN fault diagnosis method were constructed for the electrical system of tree obstacle cleaning equipment. The effectiveness of the proposed method was verified through fault diagnosis experiments. According to the three common types of faults and nine minor types of faults in the electrical system of the tree obstacle cleaning equipment shown in Figure 1, a fault variable mapping table is set up, as shown in Table 1.

Table 1. Variable Mapping of Various Faults

Fault type	Primary variable	Fault type	Secondary variable
Circuit fault	A	Open circuit fault	A1
Circuit fault	A	Short circuit fault	A2
Circuit fault	A	Misconnection fault	A3
Control fault	B	Controller fault	B1
Control fault	B	Component failure	B2
Control fault	B	Sensor fault	B3
Aging fault	C	Circuit paint age	C1
Aging fault	C	Circuit cores age	C2
Aging fault	C	Component aging	C3

Next, based on the fault variable mapping relationship in Table 1, 30000 data were continuously collected from the electrical system of the tree obstacle cleaning equipment, and fault diagnosis was carried out using the CS-KNN method proposed in this paper. In order to compare the diagnostic performance with the method proposed in this article, KNN and RNN methods were selected as reference methods. The accuracy of three methods for diagnosing various types of faults is shown in Table 2.

Table 2. Comparison of Closed Solutions and Proposed Method Numerical Solutions

Variable	Fault type	Accuracy		
		RNN	KNN	Ours
A1	Open circuit fault	90.3%	83.2%	95.9%
A2	Short circuit fault	89.2%	85.4%	97.1%
A3	Misconnection fault	88.1%	84.3%	98.4%
B1	Controller fault	89.8%	86.7%	97.7%
B2	Component failure	90.7%	82.9%	96.5%
B3	Sensor fault	87.5%	85.4%	98.2%
C1	Circuit paint age	89.3%	88.6%	97.4%
C2	Circuit cores age	88.9%	86.6%	95.6%
C3	Component aging	87.4%	85.5%	97.9%

From the comparison of the fault diagnosis accuracy of the three methods in Table 2, it can be intuitively seen that the CS-KNN method proposed in this paper achieves the highest fault diagnosis accuracy, all reaching over 95%; Next is the RNN method, with an average fault diagnosis accuracy of over 88.5%; The KNN method is relatively poor. This comparative result fully confirms the advantage of our method in terms of fault diagnosis accuracy.

Further comparing the speed of three methods for fault diagnosis, this method took 51.2 seconds, KNN method took 135.8 seconds, and RNN method took 146.7 seconds for fault diagnosis of 30000 test data. It can be seen that the fault diagnosis speed of the method in this article is the fastest, and the time consumption is much lower than the other two methods. To investigate the reason, this article compressed the electrical system data of the tree obstacle cleaning equipment before fault diagnosis, creating conditions for reducing the time required for subsequent fault diagnosis.

4. Conclusions

Tree obstacle cleaning equipment is a complex electromechanical equipment, and the safety of its electrical system directly affects the overall work efficiency of the equipment. Based on this, a compressed sensing model based electrical fault detection method is proposed. Divide the electrical system faults of the tree obstacle cleaning equipment into three categories and nine subcategories: line faults, control faults, and aging faults, and then balance the processing of different fault data. Based on the compressed sensing model, sparse representation and reconstruction of fault data are performed, followed by clustering analysis of fault types using the KNN algorithm. The experimental results show that data balancing and CS-KNN processing improve the performance of iterative training. Meanwhile, our proposed method has higher detection accuracy for 9 types of faults in the electrical system of tree obstacle cleaning equipment.

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