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Fault Diagnosis Research on Aviation Aircraft

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Abstract: With the development of modern aviation technology, how to ensure the stability of the air cargo process and how to ensure the safety of the aircraft has always been one of the important issues of concern to the air transport industry. During actual transportation, aircraft often lose control due to their own mechanical failures or system failures. In order to solve this problem, based on a comprehensive survey of relevant literature on aircraft fault diagnosis, a classification and introduction of related research was conducted based on different data-driven methods. This review is expected to provide a useful reference for research on aircraft fault diagnosis.

Keywords: Aviation aircraft; Fault diagnosis; Data driven.

1. Introduction

With the development of modern aviation technology, how to ensure the stability of the air cargo process and how to ensure the safety of the aircraft has always been one of the important issues of concern to the air transport industry. During actual transportation, aircraft often lose control due to their own mechanical failures or system failures. In order to reduce the occurrence of accidents, aviation engineers and related researchers have been working hard to study and improve aviation aircraft technology and equipment. Among them, aviation aircraft fault diagnosis technology is one of the important research fields in aviation aircraft quality management, and its importance to the transportation industry is self-evident.

2. Research Purpose and Significance

For quality management of the production process of aviation aircraft, such research can lay the foundation for the research and development of related disciplines. It is also expected to promote the promotion and application of new technologies, promote the sustainable development of the aviation industry, and at the same time improve the reliability and safety of aircraft. It ensures the safety of logistics and transportation, ensures the reliability of logistics and transportation links, and also has certain promotion significance for the establishment of quality management system for aviation logistics equipment.

3. Literature Review

Fast Fourier Transform (FFT) is a method that uses computers to calculate discrete Fourier transforms. Using this algorithm can greatly reduce the number of multiplications required for computers to calculate discrete Fourier transforms and improve calculation efficiency. Some scholars use this algorithm to preprocess parameters of the model. Yu et al. took the six-rotor UAV model as the research object. In order to deal with the fault problem of the aircraft sensor, a probabilistic neural network fault diagnosis model based on fast Fourier transform was established, and FFT was used for fault classification [1]. Li et al. used fast Fourier transform to distinguish the arc fault current from the normal operating current in order to exempt the solid-state power controller (SSPC) from the impact of arc faults, and verified the test results [2]. Naderi et al. proposed and developed a data-driven fault detection, isolation and estimation (FDI&E) method, in which FFT is used to preprocess the parameters of the input and output signals to obtain Markov parameters [3].

Empirical mode decomposition (EMD) decomposes signals based on the time scale characteristics of the data itself. It does not need to set any basis functions in advance. It has obvious advantages in processing non-stationary and nonlinear data and has a high signal-to-noise ratio. Therefore, EMD is widely used by scholars. Shen et al. used empirical mode decomposition to obtain different inherent mode functions (IMFs) from the signals of the aircraft hydraulic system. After extracting features through PCA, they used LSTM to analyze and diagnose the feature data [4]. Cui et al. proposed a method that combines EMD wavelet threshold noise reduction and principal component analysis to conduct in-depth fault diagnosis technology research on aircraft engine airway system fault diagnosis [5]. In order to detect and diagnose aircraft liquid solenoid valves, Tan et al. proposed a new method based on the combination of empirical mode decomposition (EMD) and neighborhood rough sets [6]. Jiao et al. established a fault diagnosis model based on empirical mode decomposition and probabilistic neural network (PNN), and performed fault diagnosis analysis on the airborne fuel pump [7]. In order to solve the problem of fault diagnosis of aeroengine rolling bearings, Han et al. combined EMD to decompose the vibration signal, and applied the singular value difference spectrum method to study the data, and verified the feasibility of their proposed model [8]. Bagherzadeh et al. searched for nonlinear and non-stationary flight data analysis methods under aircraft icing conditions, improved the empirical mode decomposition algorithm, and verified their proposed improved algorithm through some benchmark signals [9]. Hilbert-Huang transform (HHT) first uses EMD to find the intrinsic mode functions IMFs, and then performs Hilbert transform on each IMF component. Li et al. introduced EMD and HHT methods into the vibration signal analysis of cracks in aeroengine hydraulic pipelines, and proved through experiments that this method can overcome the shortcoming of Fourier spectrum that cannot obtain time domain and frequency domain information at the same time [10]. In order to quickly and correctly diagnose aircraft engine rotor faults, Zuo et al. applied wavelet transform and HHT methods to extract the effective values of vibration, and used an improved model to diagnose multi-type hybrid faults [11].

The PCA method has been used in process control since the 1990s [12]. Since the traditional PCA method is based on many assumptions such as linearity, its applicable scope is also subject to certain limitations. Therefore, relevant scholars will combine other algorithms to improve PCA when using the PCA method. Yu et al. used the bonding graph (BG) to preprocess the system parameters for the aircraft operating system to obtain the adaptive threshold and fault characteristic matrix (FSM), and based on this, developed a new integration method [13]. Zhang et al. proposed a model based on principal component analysis (PCA) and improved rotationally symmetric block support vector machine (RSPSVM) to study composite damage detection of aircraft [14]. In order to detect fault information of engine bearings, Zhang et al. used k-nearest neighbor algorithm (kNN) and principal component analysis (PCA) to preprocess the feature information, and used the new model proposed to detect aircraft engine faults [15]. Sun et al. proposed an improved method using k-means clustering and sliding time window kernel principal component analysis (MWKPCA) method for the problem of turbofan engine detection [16]. Chen et al. developed a method based on k-nearest neighbor algorithm (kNN), k-means clustering algorithm and kernel principal component analysis (KPCA) to achieve real-time fault detection of turbine engine components [17]. Rabcan et al. used principal component analysis to perform the required data dimensionality reduction on the feature matrix, and combined it with fuzzy decision tree (oFDT) to diagnose the presence or absence of faults in aeroengine gas turbine blades [18]. In order to deal with the problem of hinge deformation of the aircraft braking system, Wang et al. further explored spatial transient patterns on the thermal pattern comparison results based on eddy current pulse thermal imaging by constructing principal component analysis to obtain better fault diagnosis results [19]. Ji et al. proposed a remaining service life prediction model based on principal component analysis and bidirectional long short-term memory neural network, which shows better prediction accuracy in engine failure prediction compared to other types of methods [20].

Support vector machine (SVM) is a binary classification model. SVM considers mapping the feature vectors of instances into some points in space. The purpose of SVM is to draw a line to best classify these points. It is more suitable for small and medium-sized data samples, nonlinear, and high-dimensional classification problems. Due to the superior performance of SVM, many scholars use it as one of the research methods for fault diagnosis. Zhang et al. used a support vector machine (SVM) optimized by an immune algorithm to mine engine oil monitoring ferrogram analysis data to achieve fault diagnosis of aircraft engine wear, and proved through examples that their model has good robustness [21]. Wang et al. also proposed a fault diagnosis and optimization method for engine control systems based on probabilistic neural networks and support vector machines in order to improve the safety and reliability of aeroengines [22]. Grehan et al. designed a data-driven algorithm using support vector machines (SVM) to investigate efficiency loss faults of aircraft actuator failures, and their results showed that the SVM algorithm can detect efficiency loss faults almost immediately [23]. The aileron actuator is a key component of the aircraft flight control system. For related fault diagnosis research, Qin et al. proposed a new method that combines principal component analysis, grid search, support vector machine and other methods [24]. Wang et al. proposed an intelligent diagnosis method based on support vector machines. In order to obtain better performance than traditional kernel functions, particle swarm optimization was used to optimize relevant parameters and achieve quantitative intelligent diagnosis of aviation high-speed bearing faults [25]. Zhu et al. also studied the problem of engine fault detection and proposed an engine fault detection algorithm based on single-class support vector machine (OC-SVM) and transfer learning (TL) to help achieve high-precision fault detection [26]. Du et al. introduced twin support vector machine (TWSVM) into aircraft engine air circuit fault diagnosis, and combined hybrid kernel function and grid search to improve the generalization ability and learning ability of the algorithm [27].Neural network is an algorithm that has become increasingly popular in recent years. Due to its excellent performance such as strong parallel distributed processing capabilities, strong robustness to data noise, and fault tolerance, it has been used by many scholars in fault diagnosis research. . Chen et al. developed a stochastic discrete time series deep convolutional neural network (SDCNN) method for avionics fault diagnosis [28]. Gao et al. used a deep quantum-inspired neural network, which was constructed by combining the characteristics of a deep belief network (DBN) and a quantum-inspired neural network (QINN), and applied it to model fault diagnosis of aircraft fuel systems [29] . Ma et al. proposed a deep autoencoder multi-model fault diagnosis algorithm for aircraft, and proposed a recursive formula for selecting the number of hidden layer nodes of the neural network to adapt to the multi-model fault diagnosis algorithm [30]. Chen et al. conducted research on fault diagnosis of aircraft landing gear systems, aiming to solve this problem through one-dimensional dilated convolutional neural network (1-DDCNN) [31]. Zhang et al. proposed an aerospace engine fault diagnosis method based on deep learning technology [32]. Kordestani et al. developed a hybrid fault prediction model based on published neural network and recursive Bayesian algorithm to address the problems that are prone to occur in MFS systems on aircraft [33]. Ouadine et al. developed a neural network model based on genetic algorithm optimization for diagnosing aircraft air compressors, and verified the diagnostic performance of this model through comparative analysis [34]. Ezzat et al. proposed a new fault diagnosis method (BGOA-EANNs) using deep learning technology [35]. Taimoor et al. proposed a higher-precision aircraft sensor fault model based on radial basis function neural network (RBFNN) and extended Kalman filter (EKF) algorithm [36]. Coincidentally, Abbaspour et al. also used the extended Kalman filter (EKF) algorithm, which they used for weighted parameter update of neural networks [37].

4. Summary

This article conducts a literature survey based on the classification of aviation logistics equipment quality monitoring methods. With the development of the concept of quality management, aviation logistics equipment fault diagnosis methods based on signal processing, feature extraction, and machine learning have gradually emerged, and the accuracy and applicability of aviation aircraft fault diagnosis have also increased. At the same time, with the deepening of research on related technologies, relevant scholars are gradually transitioning to machine learning methods for aircraft fault diagnosis methods at this stage. Fault diagnosis problems will be studied through improved machine learning algorithms or a combination of multiple machine learning methods.

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