Scholar Publishing Group
Kinetic Mechanical Engineering
https://doi.org/10.38007/KME.2020.010205
ISSN 2790-2676 Vol. 1, Issue 2: 36-44

Condition Monitoring and Fault Diagnosis of Engineering Ship Power Machinery Based on Edge Detection Algorithm

Rasa Jaber*

Adamson University, Philippines

**corresponding author*

Keywords: Edge Detection, Ship Power, Condition Monitoring, Fault Diagnosis

Abstract: The research of marine engine condition monitoring and fault diagnosis technology has developed for many years. For this reason, the engine fault diagnosis technology has been paid more and more attention by engine manufacturers, and has been taken as an important means to improve the engine operation reliability and reduce the use cost. This paper first introduces the traditional edge detection algorithm, which mainly uses different local operators to detect the acquired data images, and mainly compares and analyzes the detection results of Sobel operator and Canny operator of the first order local derivative. The architecture of the ship structure health monitoring system is designed, and the functional module of the edge computing node is divided into three layers and four functional modules, which respectively realize the collection, processing, storage and release of monitoring data. The module design adopts the software mode of weak coupling and strong cohesion, and establishes the standardization of data transmission format.

1. Introduction

As a kind of equipment for converting electric energy and mechanical energy, motor is widely used in various fields. Low voltage motor is a kind of equipment that converts electrical energy into mechanical energy. It has the characteristics of good performance, simple structure, low price, and wide application. It is widely used in the field of ships. It directly uses or transmits mechanical energy to other equipment for use. It can be said that the low-voltage motor is the most important component in the electric drive system, and it is also one of the most frequently used equipment in the shipbuilding field [1-2]. However, the motor is composed of several mechanical elements, and the working environment may be very harsh. After a long period of power on operation, due to the existence of adverse hidden trouble interference such as failure to conduct regular inspection and maintenance, the probability of motor failure also increases slowly with the passage of time. In particular, the marine fan, due to the impact of factors such as turbulence, shaking, humid air, salt fog and mildew during the actual ship voyage, causes the marine fan to have a worse working environment than ordinary motors, and is more prone to failure [3]. The motor fault, especially the large fault, will cause serious economic losses, and personal safety. From the perspective of motor design, the overall or local quality of the motor can be improved by designing a motor with higher strength and durability, and improving the motor processing technology and process quality [4]. However, the progress in design and technology can only delay the occurrence of motor faults, which is not a fundamental problem. How to find the faults of motors that have been put into operation for a long time has therefore become an urgent pain point when using motors [5]. The motor condition monitoring and diagnosis system also came into being.

With the continuous promotion of the use of motors, the treatment and judgment of motor faults have gradually appeared in people's sight. The research on motor condition monitoring and fault diagnosis has been gradually valued by experts and scholars since the second half of the 20th century, and has made many achievements so far [6]. The major electronic and electric power enterprises are conducting research and manufacturing of motor condition monitoring and fault diagnosis one after another. The American WHEC Company, the Swedish SKF Group and the German Prouf Company have all carried out research on the motor online diagnosis system [7]. Some scholars applied Wigner Ville distribution method to condition monitoring and fault diagnosis of induction motors. The stator current and rotor current are introduced into the WVD method, and the short circuit fault diagnosis between the rotor and winding of the induction motor is realized by using the time-frequency analysis of the current signal [8]. Some scholars collected vibration signals during motor operation, used EMD data analysis method for signal analysis, used Wigner Ville distribution method to adaptively select the IMF component and band-pass filter bandwidth that best represent fault characteristics in EMD decomposition results, used band-pass filter to further screen signals in IMF components, and then analyzed the upper and lower envelope spectra of optimized IMF components, Motor fault diagnosis and condition monitoring are realized by comparing with normal model parameters of bearing [9]. The research on motor condition monitoring and fault diagnosis system in our country dates back to the live line test method in the 1960s. Due to the complexity of the method and the inaccuracy of the results, the test has not been popularized. The online diagnosis of motor faults in the 1980s provided great technical support for the research of motor condition monitoring and fault diagnosis in China. Since then, the research in the field of motor condition monitoring and fault diagnosis in China has entered the fast lane [10].

The research in this paper can ensure the normal operation of the system: the motor can be monitored in real time without shutdown, and the location and type of faults can be found and accurately located in time, so as to reduce the number of shutdown inspections caused by long-time operation.

2. Marine Motor Monitoring and Fault Diagnosis Based on Edge Detection

2.1. Edge Detection Algorithm

The principle of edge detection is to use some algorithm to detect the boundary between foreground and background, which is the theoretical basis for image segmentation, target detection and recognition of relevant shapes [11]. Edges often exist in different regions, different objects, and between the object subject and the background. The edge of an image is an important boundary line to distinguish an image. There is a lot of effective information, and it is the most basic feature of an image. It is specifically manifested in sudden changes in texture structure, color, and gray level, that is, where the signal mutation occurs [12]. At present, there are two kinds of edge detection, namely color detection and gray detection, and the latter is used in most cases [13].

Gray edge detection detects edges by gray value. The edge of an image has two common features, namely, amplitude and direction. Moving along the edge, the gray value changes little. Moving perpendicular to the edge, the gray value fluctuates violently. The gray value is divided into different gradients, and the image changes can be observed through the gray gradient distribution. This variability can be detected by deriving continuous image pixels, generally using the first derivative and the second derivative [14]. Based on the above detection principle, the edge points of the image can be obtained by using the local derivative operator and connected into the edge contour curve.

The image pixels are discrete, and f (x, y) can be used to approximate the pixel value at (x, y), so its gradient at (x, y) is a vector, and the first derivatives of x and y directions are Gx and Gy respectively, and the gradient size can be calculated:

$$\nabla f(x,y) = [G_x \; G_y]^T = [\frac{\partial f}{\partial x} \; \frac{\partial f}{\partial y}]^T \tag{1}$$

In order to simplify the calculation, the operator template is usually used for convolution approximate derivation in practice. The gradient value of the central pixel of the region is calculated by sliding the template. After sliding, the gradient map of the image is obtained. A gradient operator consists of two templates, one for Gx and one for Gy [15]. The common ladder operators are Roberts operator, Prewitt operator and Sobel operator.

Among first-order operators, Sobel operator has the best detection effect. Sobel detection principle is to calculate the gray scale weight of the upper, lower, left and right adjacent points of each pixel. It is not only accurate in extracting edge direction information, but also can smooth various noises. However, the edge positioning effect is not good, which will produce false edges. In the case of low edge detection accuracy, Sobel edge detection is a simple and effective method [16].

In addition to the first derivative edge detection, the second derivative can also be used. Common operators, including Laplace operator and Canny operator, can also use operator templates to convolve images. Laplace operator is a second order difference operator, which belongs to isotropic operator. Because Laplace operator is very sensitive to noise in the graph, it will produce a large number of double edges, so it is rarely used for edge detection alone. Laplace operator and Gaussian smoothing are usually used to detect edges, or determine the distribution of light and dark areas after determining the edges.

Canny operator is an improvement on Laplacian operator. It skillfully contrasts the problem of solving maximum in function with the problem of edge detection. Based on the concept of image filtering and the concept of Gaussian model, it defines three indicators of edge detection [17-18].

Test standards: important edges shall not be lost during detection, and false edges shall be reduced as much as possible.

Positioning standard: the edge detection point must be on the boundary line of the real image.

For a single response standard, the multiple response probability of a single edge parameter is low, the edge can only be identified once, and the pseudo edge response is suppressed to the maximum.

Considering the directivity of the detected edge and the sensitivity to interference, most of the traditional edge detection uses Canny operator edge detection.

First, Gaussian filtering is used to preliminarily process the image to eliminate the interference of useless noise.

The first derivative operator is used to derive the image pixels in the x and y directions respectively, find the derivatives Gx and Gy in the x and y directions, and determine the gradient value:

$$|G| = \sqrt{G_x^2 + G_y^2} \tag{2}$$

Calculate the direction of the gradient:

$$\theta = \arctan\left(\frac{G_y}{G_x}\right) \tag{3}$$

Find the direction of the edge (0 °, 90 °, 45 ° and 135 °) and find the adjacent pixels in the gradient direction.

Traverse the image for non maximum suppression. If the gray value of the front and back pixels in the gradient direction is not the maximum, it will be removed and only the candidate edges will be retained.

Small threshold T1 and large threshold T2 are adopted. If the edge intensity is greater than T2, it must be an edge point. If the edge strength is less than T1, it must not be the edge point. If it is exactly between T1 and T2, it is necessary to find whether there is a point larger than T2 in the adjacent image pixels. If it exists, it is an edge point; If not, it will be discarded.

2.2. Detection and Fault Diagnosis System

The process of ship structure monitoring is as follows: First, select a certain number of measuring points on the ship, and the selection of measuring points shall be based on the structural response that can reflect the key position of the ship; Then, FBG strain sensors and FBG temperature sensors are installed at the selected measuring points to sense the real-time state of the ship structure and transmit it to the FBG demodulation unit in the form of optical signals through optical fibers; Next, the FBG demodulation unit demodulates the incoming optical signal, and sends it to the local area network formed by the route after the completion of processing; At the same time, Raspberry Pie captures UDP data packets in the network through the data collection module and completes data processing and storage inside Raspberry Pie; Finally, the monitoring data will be sent to the browser user interface or the central server in the form of Web services as required.

Compared with the traditional monitoring system architecture, adding edge computing nodes as the computing center during data transmission has the following three advantages:

(1) It can effectively reduce the dependence of massive data processing on the computing performance of the central computer by means of data pre-processing within the node.

(2) The node design enables each node to form data interaction with users or central servers through the network in the wireless monitoring of ship structures, thus breaking through the limitations of space scenes and making the monitoring system more intelligent.

(3) The data release through edge computing nodes is more conducive to the needs of ship science workers for the local response of the hull structure.

As the basic unit of the system architecture, the design and implementation of the functional modules of the edge computing node are the basis for the implementation of the entire system architecture. In combination with the requirements of wireless monitoring of ship structures, this paper divides the functional modules of the edge computing node into four modules according to the data flow path, and each module includes three levels: the system layer, the application layer, and the support layer.

The first layer is the system layer, which is mainly composed of four functional modules: data acquisition, data processing, data storage and data release. The data acquisition module is responsible for capturing the original data packets; The data processing module is responsible for doing some basic processing on the captured data packets, and then using SQL statements to store the completed monitoring data to the database inside the node; The data storage module is based on the MariaDB database, and the data storage table is established and optimized; The data publishing module uses Django to develop network applications and provide Web services for users.

The second layer is the application layer, which is composed of data processing module, real-time monitoring module, history query module, user information module, monitoring data table, channel configuration information table, user information table and network card. This layer is below the system layer, and subdivides the internal functions of each module to provide services for the realization of the system layer.

The third layer is the support layer, which is mainly used to provide theoretical methods and data support for the implementation of application layer functions, and ensure the long-term stability of edge computing nodes.

3. Fault Diagnosis Function Test

To test the fault diagnosis function of the system, the following preparations are required. Firstly, the characteristic parameters of normal, overload and reverse power states are collected by the target power station; Then, save the collected state characteristic parameters to the fault database; Finally, keep the communication between the local server and the Internet of Things cloud platform, and between the remote client and the Internet of Things cloud platform to ensure normal data transmission. So far, the preparatory work has been completed.

When diagnosing test data, first set the background diagnostic model to the program. This test is about the diagnostic model proposed in this paper and the other two diagnostic models. After the model is set, you can click "Fault Data Training" (the model for this test has completed the training, and no longer click training). After selecting the fault data in the fault data list, click the "Fault Diagnosis" button to conduct fault diagnosis. The diagnosis results and troubleshooting suggestions are displayed in the pop-up window.

4. Analysis of Fault Diagnosis Test Results

4.1. Machine Learning Model

Table 1. Fault recognition rate based on machine learning model

Test specification	Normal	Valve leakage	Valve clearance	Average recognition rate
Recognition rate	80%	85.7%	87.5%	84.4%

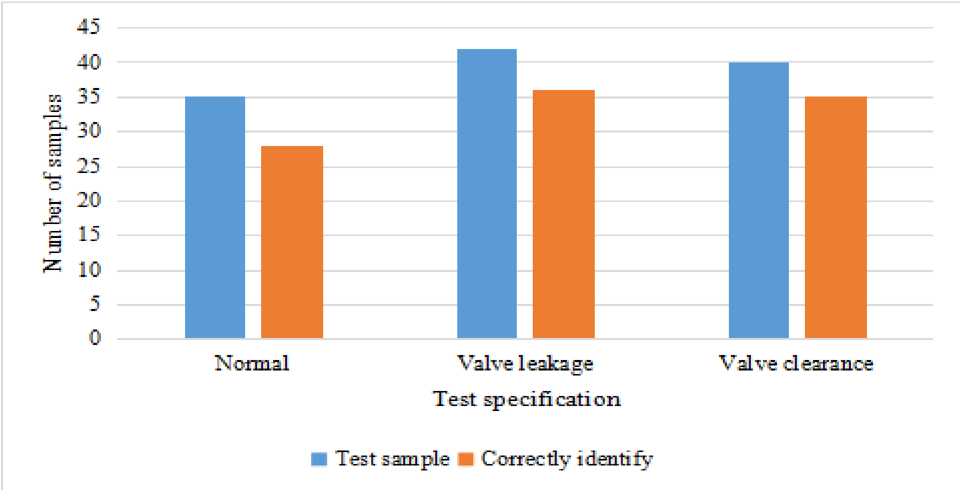

Figure 1. Machine learning fault diagnosis results

It can be seen from Table 1 and Figure 1 that the average recognition rate is 80% for normal conditions, 85.7% for valve leakage and 87.5% for valve clearance. The results show that the machine learning model can diagnose various abnormal conditions of the engine, but the overall recognition rate is relatively low.

4.2. BP Neural Network Model

Table 2. Fault recognition rate based on BP network

Test shows that	Normal	Valve leakage	Valve clearance	Average recognition rate
Recognition rate	94.2%	97.6%	92.5%	94.8%

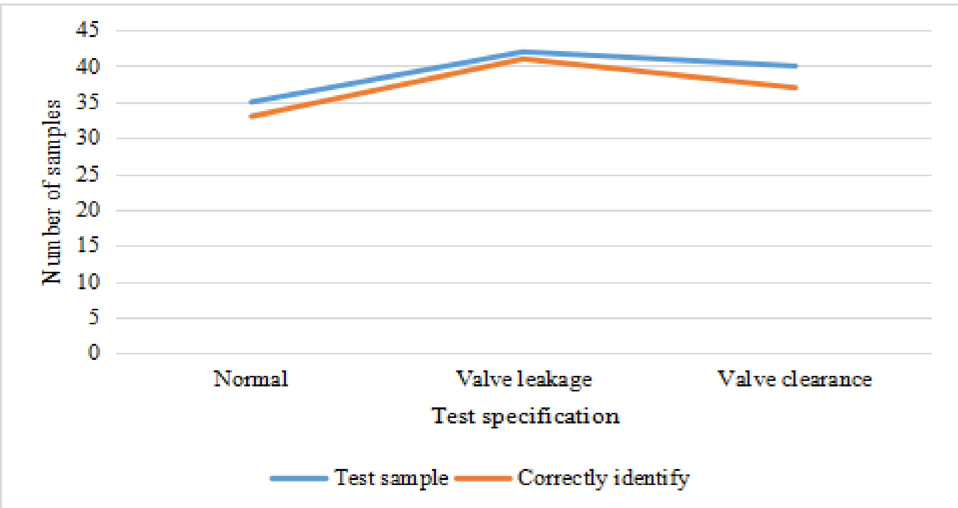

Figure 2. BP network fault diagnosis results

It can be seen from Table 2 and Figure 2 that the average recognition rate is 94.27% for normal conditions, 97.6% for valve leakage and 982.5% for valve clearance. The results show that the combination of marginal spectrum and BP network can diagnose various abnormal conditions of the engine, and the overall recognition accuracy and average recognition rate have been greatly improved.

4.3. Edge Detection Algorithm

Table 3. Fault recognition rate based on Edge detection algorithm

Test shows that	Normal	Valve leakage	Valve clearance	Average recognition rate
Recognition rate	100%	95.2%	97.5%	97.6%

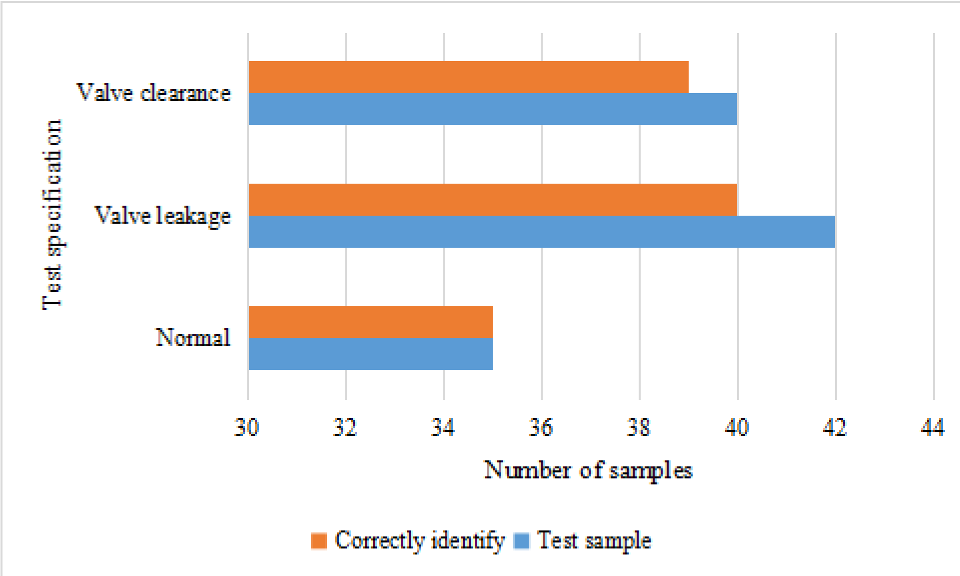

Figure 3. Diagnosis results based on edge detection algorithm

It can be seen from Table 3 and Figure 3 that the average recognition rate is 100% for normal conditions, 95.2% for valve leakage and 97.5% for valve clearance. The results show that using the edge detection algorithm, various abnormal conditions of the engine can be diagnosed. Relatively speaking, the overall recognition accuracy and average recognition rate have been greatly improved.

5. Conclusion

Based on the current research status, this paper analyzes the importance of marine engine, according to the complexity and diversity of engine faults, puts forward the idea of this paper, and designs the research of marine engine fault diagnosis system. Due to the limitations of technical conditions and other factors, it is hoped that improvements can be made in the following aspects: the ship will encounter a variety of climate, temperature, humidity and other conditions during operation, and more conditions need to be considered in the next step of research. The system also lacks a fault location technology. Using the fault location technology, you can accurately judge the fault location, making the fault diagnosis of the engine more accurate and timely.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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