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Machine learning-based real-time detection of residual wall thickness in industrial pipelines

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Abstract: Far-field eddy current detection technology is a special eddy current technology that utilizes electromagnetic effect to detect the pipe through the wall. This paper introduces the principle of the far-field eddy current detection technology, including the two propagation modes of direct coupling and indirect coupling, and explains the division of different regions and their effects. The design and composition of the far-field eddy current detection device are then presented. In addition, this paper discusses the application of machine learning in analyzing far-field eddy current detection data, including the basic principles of machine learning, data preprocessing, data segmentation and model building steps. Finally, the evaluation indexes of machine learning models are introduced, as well as specific algorithms and evaluation indexes that may be used in far-field eddy current detection.

1. Introduction

In recent years, with the continuous development and progress of industrial technology, there is an increasing demand for the inspection of pipelines and their materials. Pipelines play a vital role in industrial production and life, such as transporting liquids, gases and other substances, but due to environmental factors, long-term use and the material's own characteristics, pipelines may suffer from a variety of defects, such as corrosion, cracks and so on. Therefore, timely and effective detection of pipeline condition and defects is essential to ensure industrial safety and production operation[1-2].

Traditional pipeline inspection methods include visual inspection, ultrasonic inspection, etc. However, these methods have certain limitations, such as only being able to detect surface defects and requiring downtime for maintenance. In contrast, eddy current inspection technology, as a non-destructive testing method, is able to detect pipelines without destroying their surfaces, and therefore has received widespread attention and application[3].

As a special form of eddy current detection technology, the principle of far-field eddy current detection technology is to utilize the electromagnetic effect to detect the pipe through the wall. Compared with the traditional near-field eddy current detection, the far-field eddy current detection technology has the advantages of long detection distance and high detection efficiency, so it has been more and more widely used in the industrial field.

However, there are some challenges and problems in the far-field eddy current detection technology, such as the frequency and amplitude of the excitation signal need to be adjusted under different pipe materials and thicknesses to ensure the accuracy and reliability of the detection. In order to solve these problems, in recent years, people have begun to introduce machine learning techniques into the field of far-field eddy current detection, and machine learning algorithms are used to analyze and process the detection signals in order to improve the accuracy and efficiency of detection.

Therefore, this paper will focus on the principle of far-field eddy current detection technology, device design, and discuss the application of machine learning in this field, as well as the corresponding data processing, model building and evaluation methods[4-5]. The research in this paper will provide important reference and support for the further development and application of far-field eddy current detection technology.

2. Far-field eddy current detection technology

2.1 Principle of far-field eddy current detection technology

Far-field eddy current detection technology is a low-frequency sinusoidal wave as an excitation source, the use of electromagnetic effects on the implementation of pipe through the wall of the special eddy current detection technology, the original far-field eddy current detection by the detection coil and the receiving coil consists of two parts of the principle of detection as shown in Figure 1:

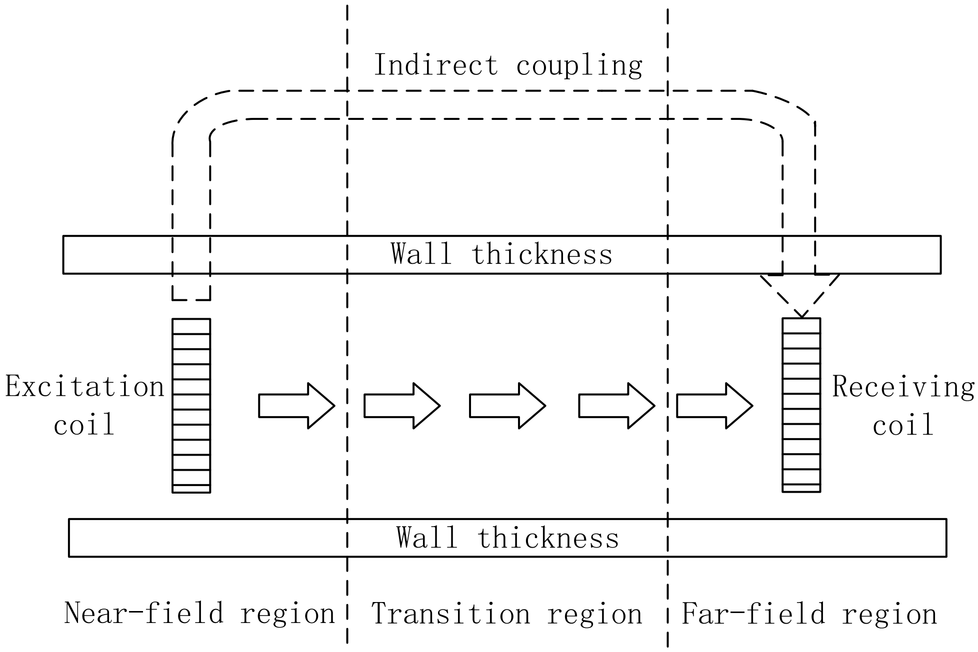

Figure 1: Schematic diagram of far-field eddy current detection

As can be seen from Figure 1, when the excitation coil passes through the AC signal, it generates a magnetic field, and the magnetic field energy is transmitted to the receiving coil by both direct coupling and indirect coupling. Direct coupling refers to the low-frequency signal excitation coil generates alternating magnetic field, electromagnetic signal propagation along the inner wall of the pipeline, the magnitude of the signal amplitude size and the distance between the two coils is inversely proportional to the distance between the two coils, when the distance between the two coils increases, the signal attenuation is sharp. The indirect coupling method originates from the low-frequency signal excitation coil that generates an electromagnetic field in the nearby area of the pipe wall, which will propagate to the outside of the pipe, affecting the amplitude and phase of the detected signal[6]. Due to the decay of the field strength outside the pipe is slower than the field strength generated by the direct coupling method inside the pipe, a new magnetic field is generated outside the pipe and propagated to the inside of the pipe, which again affects the amplitude and phase of the detection signal, and the detection signal is finally received through the receiving coil as the basis for pipeline defect analysis. Various regions are divided according to the basis shown in Table 1:

Table 1: Table of the basis for the division of testing areas

Area Classification	discriminant	Coupling method
Near Field Zone	L<R	Direct coupling is dominant
Transition Zone	R<L<2R	Direct and indirect coupling
Far Field Zone	L>2R	Indirect coupling mainly

As can be seen from the table, the division rules of the detection area are as follows:

When L<R, i.e., when the inner diameter of the pipe is larger than the distance between the two coils, the detection signal propagates by direct coupling propagation. When R<L<2R, i.e., when the spacing between the excitation coil and the receiving coil is in the region of 1-2 times the wall thickness of the pipe, the propagation of the detection signal consists of direct coupling and indirect coupling together. Since this special law cannot be described by the conventional eddy current concept, this region is called the far-field region or the spaced coupling region[7-8].

In the near-field region, the direct coupling signal dominates; while in the far-field region, the detection signal is mainly affected by the far-field coupling. The energy received by the detection coil in the far-field region is mainly generated by indirect coupling, and the received magnetic field energy carries the structural information of the pipe wall, which becomes the basis for RFEC technology detection. According to the relevant theory, the phase lag of the far-field eddy current detection signal can be approximated by the one-dimensional skin effect formula to calculate:

$$\theta = L\sqrt{\pi f \mu\sigma} = 2d\sqrt{\pi f \mu\sigma} \tag{1}$$

where θ denotes the phase difference between the received signal and the excitation signal (expressed in radians), L denotes the thickness of the penetrated pipe wall, d denotes the wall thickness of the detected pipe, and since the signal penetrates the pipe wall twice therefore L = 2d. f is the frequency of the excitation signal, μ represents the magnetic permeability, and σ represents the electrical conductivity.

Therefore, using the internal pass-through detection method, the signal received by the detection coil in the far-field area is analyzed, and from the correlation between the signal amplitude and phase and the wall thickness of the steel pipe, the wall thickness of the industrial pipeline can be calculated.

2.2 Far-field eddy current detection device

Far-field eddy current detection requires two parts: the excitation coil and the receiving coil located in the far-field area, at this time, the phase of the obtained detection signal is compared with the excitation signal, which can reflect the wall thickness of the detected pipeline and defects. According to this theory, a multi-frequency far-field eddy current detection model is designed as shown in Figure 2.

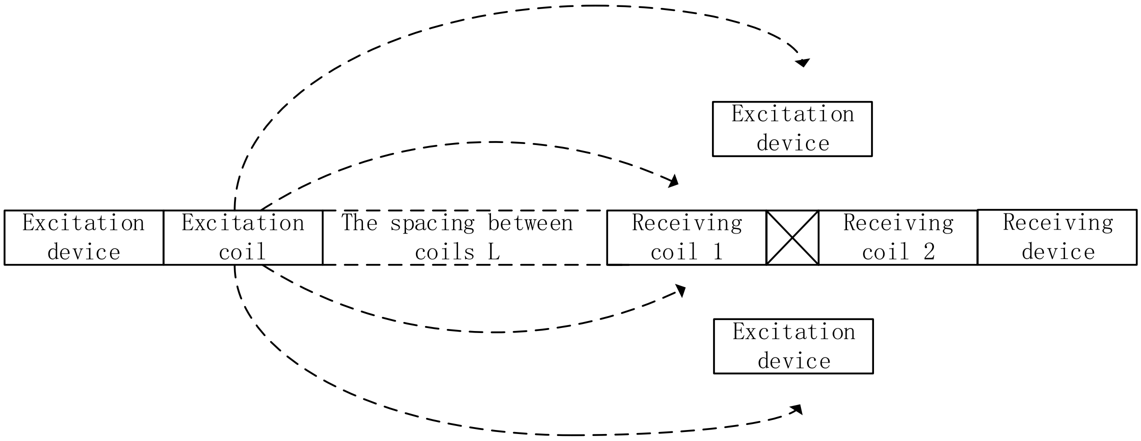

Figure 2: Far-field eddy current detection model

As can be seen from the above figure, the multi-frequency far-field eddy current detection model consists of three parts, namely, the excitation coil part, the dual-coil receiving part, and the array circumferential receiving part. At the same time, it is necessary to design the excitation device to stimulate the low-frequency sinusoidal signal of the excitation coil, and to design the receiving device to collect the detection signal obtained by the receiving coil with pipeline information and calculate the phase difference value generated by penetrating the pipe wall, so it is necessary to design the excitation experimental circuit and the receiving experimental circuit. At the same time, according to the function, the multi-frequency far-field eddy current detection model can be divided into two parts: the excitation module and the receiving module[9-10].

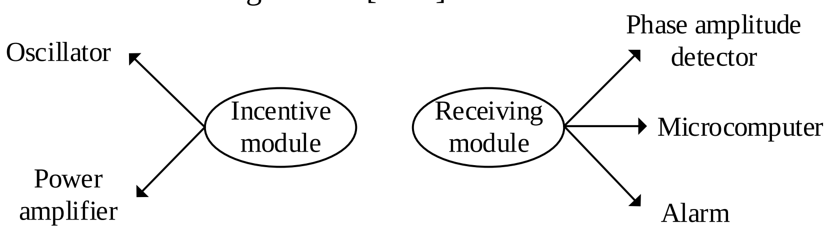

Figure 3: RFEC detection model

In Figure 3 above, the oscillator is used to drive the coil, the power amplifier is used to increase the power of the excitation source, the phase amplitude detects the phase signal of the coil, the alarm is used to provide feedback on the corrosion of the pipe wall thickness, the microcomputer is used to store the data, and finally, the data is transmitted to the computer through the signal transmission module.

3. Machine learning to analyze far-field eddy current detection data

3.1 Application of machine learning in analyzing far-field eddy current detection data

The far-field eddy current detection technique uses amplitude and phase differences to analyze the excitation signal and the received signal to obtain pipe wall thickness data. However, when the phase difference is greater than 360° it causes an error and needs to be corrected. For different pipeline environments, selecting the appropriate frequency and amplitude of the excitation signal is a challenge. To solve this problem, the introduction of machine learning algorithms can automatically optimize the excitation signal parameters and improve the detection accuracy. The machine learning algorithm successfully solves the problem of excitation signal frequency for different pipelines, thus increasing the application value of far-field eddy current detection technology. Machine learning algorithm application logic is shown in figure 4.

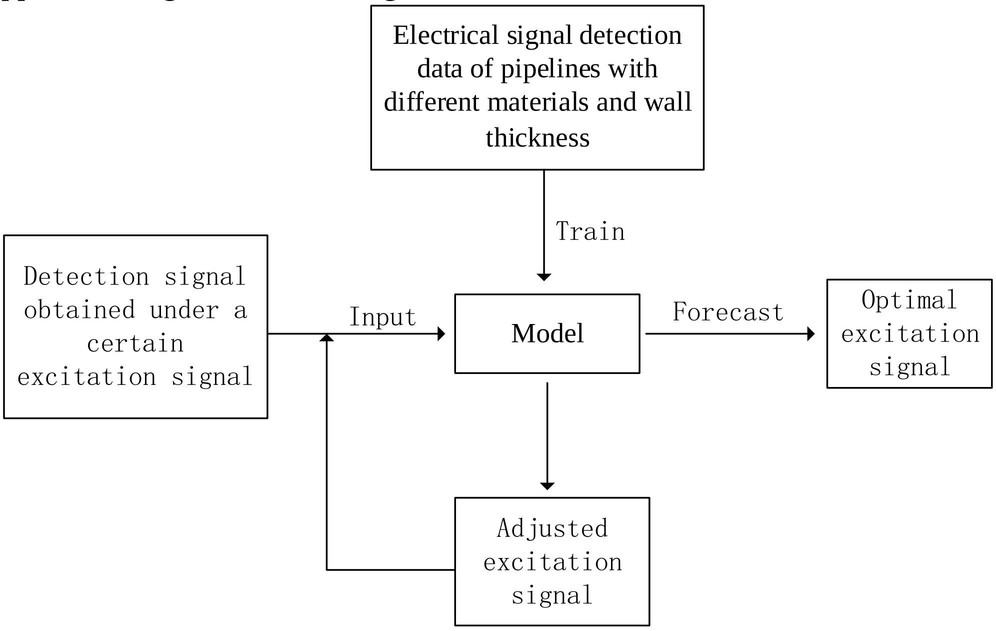

Figure 4: Machine learning algorithm application logic

3.2 Training of machine learning models

3.2.1 Machine Learning Datasets

The detection signals obtained in far-field eddy current testing need to be analyzed to determine what type of data is discriminative, whether the signal can be used to derive information such as the wall thickness or age of the pipe, such as the amplitude or frequency of the detected signal. Exploratory data analysis (EDA) is performed to gain an initial understanding of the data. In a typical data science project, the first thing that needs to be done is to "get eyes on the data" by performing EDA in order to better understand the data. The three main EDA methods commonly used include: descriptive statistics: mean, median, mode, standard deviation; data visualization: heat maps, box plots, scatter plots, principal component analysis, etc.; and data shaping: pivoting, grouping, filtering, etc., the data.

3.2.2 Data segmentation

How to obtain a large number of far-field eddy current detection signals to train the machine model is a problem to think about. In order to obtain enough far-field eddy current detection data, first of all, we need to collect a variety of known materials and wall thickness of the pipe, respectively, for a pipe to send a kind of excitation signal, and then get the detection signal, through the analysis of the detection signal data to inverse the pipe wall thickness and the material used, if the analysis of the wall thickness of the pipe and the material data are consistent with the analysis, then the characteristics of the excitation signal and the detection signal will be recorded as a set of machine Learning training data, and vice versa, the value of the excitation signal is constantly changed until the detection data that meets the requirements is obtained, and then the group of data is recorded. By inspecting pipes of different materials and wall thicknesses, we can get enough data for modeling.

3.3 Machine Learning Modeling

3.3.1 The main machine learning algorithms

In this project, the detection signal needs to be analyzed to derive the best excitation signal to reduce the detection error, so the algorithm is required to have the ability to extract the features of the data and then classify the detection data. Below we list the algorithms that may be used for machine learning in this project.

(1) Linear regression algorithm

According to figure 5, regression analysis is a statistical data analysis method that aims to understand whether two or more variables are correlated, the direction and strength of the correlation, and to develop a mathematical model that allows observation of specific variables to predict changes in other variables. The modeling process of the linear regression algorithm is to use data points to find the line of best fit. The formula, $y = m \cdot x + c$, where y is the dependent variable and x is the independent variable, is used to find the values of m and c using the given data set. Linear regression is subdivided into two types, i.e., simple linear regression, which has only 1 independent variable, and multivariate regression, which has at least two or more sets of independent variables

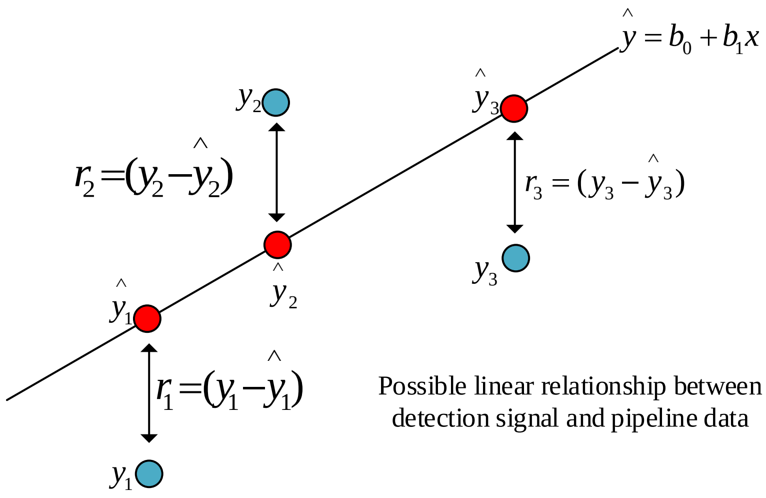

Figure 5: Linear regression analysis

(2) K-nearest neighbor algorithm

K-nearest neighbor is a classification algorithm, the idea is: if a sample in the feature space of the k most similar (i.e., the feature space of the closest neighbor) samples in the majority of samples belong to a certain category, the sample also belongs to this category. k is usually an integer not greater than 20. k-nearest neighbor algorithm, the selected neighbors are already correctly categorized objects. The method bases its decision on the classification decision only on the class of the nearest neighbor or samples to determine the class to which the sample to be classified belongs.

3.3.2 Evaluation of machine learning models

In the process of using machine learning algorithms, we need to establish different evaluation metrics for different algorithms. Evaluation metrics are used to measure the effectiveness of a model, which is a numerical quantification of the effectiveness of a model. The algorithms that may be used for machine learning to analyze the far-field eddy current detection data in this project are classification algorithms and regression algorithms, and the evaluation metrics for each of the two types of algorithms are described below.

3.3.3 Evaluation metrics for regression fitting

(1) Mean Absolute Error (MAE)

$$MAE(y,\hat{y})=\frac{1}{n_{samples}}\sum_{i=1}^{n_{samples}}\left|y_i-\hat{y}\right| \tag{2}$$

The above equation is used to calculate the absolute value of the difference between the predicted and true values for each sample of far-field eddy current data and then summed and then averaged. It is used to assess the closeness of the prediction results to the real data set, and the smaller the value is, the better the fit is.

(2) Mean squared error (mean square error (MSE))

$$MAE(y,\hat{y})=\frac{1}{n_{samples}}\sum_{i=1}^{n_{samples}}(y_i-\hat{y})^2 \tag{3}$$

The above formula is used to calculate the square of the difference between the predicted value and the true value for each sample and then summed and then averaged. This indicator calculates the mean of the sum of the squares of the errors of the fitted data and the original data corresponding to the sample points, and the smaller the value, the better the fit.

(3) Root Mean Square Error (RMSE)

$$RMSE=\sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i-f(x_i))^2} \tag{4}$$

The root-mean-square error is the square on top of the mean-square error, and the smaller its value, the better the fit is.

3.3.4 Evaluation metrics for clustering algorithms

(1) Rand index

$$RI=\frac{a+b}{C_2^{n_{samples}}} \tag{5}$$

Where the total number of pairs of elements in the dataset that can be composed, RI takes a value in the range of [0,1], the larger the value means that the clustering results are more consistent with the real situation.

(2) Contour coefficients

$$s=\frac{b-1}{\max(a,b)} \tag{6}$$

For a collection of far-field eddy current data samples, its profile coefficient is the average of the profile coefficients of all samples. The contour coefficients take values in the range [-1,1], with higher scores the closer the samples of the same category are to each other and the further apart the samples of different categories are from each other.

4. Conclusions

In this paper, we systematically introduce the far-field eddy current detection technology and its application in the industrial field. Firstly, we deeply discuss the principle of far-field eddy current detection technology, including direct and indirect coupling methods, and the rules for the division of the detection area. By analyzing the amplitude and phase changes of the excitation signal and the received signal, the wall thickness and defect information of the pipe can be accurately obtained. Next, we introduce the design and composition of the far-field eddy current detection device, including the excitation coil, the receiving coil, and the corresponding circuit design. Then, we discuss the application of machine learning in the analysis of far-field eddy current detection data and how machine learning algorithms can be utilized to improve the accuracy and efficiency of detection. Finally, we introduce the establishment and evaluation methods of machine learning models, including data preprocessing, model selection and evaluation indexes.

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