Intelligent Eddy Current Crack Detection System Design Based on Neuro-Fuzzy Logic

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ABSTRACT

In aircraft engine manufacturing and aircraft maintenance industries, eddy current testing (ECT) is widely used to detect surface or subsurface crack. However, most of the eddy current tests are currently conducted by human inspector, especially for maintenance purpose. The accuracy of the test results largely depends on individual experience and the probe scanning process is time consuming. In this paper, an intelligent eddy current crack detection system is developed based on neuro-fuzzy logic. The system can extract various features such as the amplitude, phase angle and width of the loop from the measured differential eddy current signals. The extracted features represent the change of the electrical impedance of the ECT probe due to a crack in the conductor. A data base has been built for the extracted features from the known notch cracks provided by Pratt and Whitney Canada and Olympus. An adaptive neuro-fuzzy inference engine is trained to map the complex and nonlinear relationship between the extracted features and the crack information. The experimental tests show that the developed intelligent system can provide the user with a decision on whether a defect is present or not and certain properties of unknown crack, such as depth, width and orientation can be also predicted.

Keywords: Fuzzy logic, Eddy current, Feature extraction, Crack detection.
INTRODUCTION

Eddy current testing (ECT) is one of the Non-Destructive Testing (NDT) methods that are widely used for conductive material detection. It can be used for crack detection, thickness and conductive measurement in many industries [1]. Compared to other NDT methods such as Fluorescent Penetrant Inspection (FPI) and ultrasonic, the advantages of ECT are listed as follows. 1. The equipment is portable and easy to use. 2. It provides quick access to inspection result (almost simultaneously). In ECT, two main kinds of probes, absolute and differential probes, are used for different purposes. The advantage of using differential configuration for crack detection is that it is able to eliminate gradual variation on or underneath surface. Whereas, the signal generated from the absolute probe is normally contaminated by the other information such as surface coating, conductivity and thickness shifting. Hence, the signals generated via differential probe are mainly based on crack indication. Another advantage of using differential probe is that the signal of crack indication appears in ‘8’ shape, which is unique and distinctive compared to the “curve line” shape by using the absolute probe. In this project, the differential probe is used specifically for crack detection.

ECT is extensively used in the aerospace industry. For example, in Pratt & Whitney Canada, ECT is performed using a 6 Degree-Of-Freedom (DOF) robotic system for the components with known geometry and size. In some specific rotor manufacturing, the aim of ECT is to ensure that every component is crack free. In their quality control process, ECT is used in conjunction with FPI inspection to detect the cracks under surface. In this case, the eddy current inspection is used to detect the presence of crack, i.e., if there were one crack detected, the component would be discarded. In L-3 Communications, the portable ECT is used for aircraft maintenance. The maintenance work mainly focuses on finding and fixing the cracks with certain depth or shape, which may have the potential of propagation. As a result, it is important and necessary to know the size of the crack and it is preferred that the shape of the crack can also be revealed. However, the robotic ECT system in P&W cannot be used for aircraft maintenance purpose due to the complex surface geometry and the size of robot (some maintenance work require to go inside airplane for ECT scan which is nearly impossible for the bulky 6DOF robot to manoeuvre). The current maintenance work is mainly carried out by the human inspectors and the inspection accuracy largely depends on the human inspectors’ experience. Hence, to accelerate the inspection process and improve the inspection accuracy, a robotic ECT inspection system with intelligent ECT crack detection is sought by the aerospace industry. In this project, we focus on developing an intelligent ECT crack detection algorithm, which is the central part of the robotic ECT inspection system. The developed algorithm can be used in both engine manufacturing and aircraft maintenance industries.

To develop an intelligent ECT crack detection algorithm, the first step is to build a theoretical model to describe the probe impedance using Maxwell equation [2] [3]. Then based on the model, the relationship between the detected inductance and the crack could be established. In [2] [3], both analytical and numerical modeling for ECT phenomena has been developed. Based on numerical model, finite element solution is used to predict eddy current probe trajectory. However, although many theoretical models have been developed [4] [5] [6], it is difficult to use these models to predict the size and shape of crack due to the complexity of crack and unknown coil geometry. In most cases, the detailed coil specification is usually unavailable to the users. In
In order to establish such relationship, we resort to the advanced software computing techniques such as fuzzy logic, neural network [7], which can be trained to map the relationship.

Fuzzy logic is known as an artificial intelligence tool to describe complicated physical phenomena and to anticipate the linear or nonlinear results based on collected input and output data [8]. A lot of research works have been carried out on processing eddy current signal by using artificial intelligence methods such as fuzzy logic or neural network or both to sort or predict flaw size. In [9], the crack sizing algorithm using fuzzy logic based on the signal features of “amplitude” and “phase angle” has been developed and some promising results on crack detection have been achieved. In [10] an EDDYAI diagnostics expert system is developed by utilizing fuzzy logic as crack decision maker and neural network to predict the size of crack. In [9] and [10], the researchers only use “amplitude” and “phase angle” of the loop and ignore the “width” of the signal, which contains some important information of the crack. In this project, fuzzy logic is applied as a decision making tool for developing the intelligent ECT crack detection system. The data can be obtained from mathematical equations, experiment results, and even human experience. Also, the “width” of loop has been used as fuzzy inputs together with “amplitude” and “phase angle”. By using so-called IF THEN rules and choosing the right membership functions (MFs) and numbers of MFs, the accurate results on crack information (depth, width etc.) can be obtained.

The developed intelligent ECT crack detection system consists of four main parts: signal feature extraction, signal de-noise, and fuzzy rules training. The data is collected from ECT by scanning the part with known notch crack. After applying the noise removal algorithm, the signal features representing the crack information can be extracted from the collected data. A fuzzy rule base is built based on the trained IF THEN rules and is used to predict the crack features such as depth, width or shape. In addition, different from pervious researches, a neuro-based fuzzy logic training method is used in this research in order to adapt different data set and have a tuned fuzzy logic interface. Neuro-based fuzzy logic is inspired by neural network, similar to that of neural network which constitutes input and output mapping via their membership functions and related parameters [11]. In the end, a user friendly interface have been developed for the extracting the signal features, training the fuzzy logic system, and making the final decision on the detected crack. The software can be used as a tool to aid or replace human inspector in preforming the daily eddy current test and analysis in aircraft maintenance and other industries.

**DESIGN DIAGRAM**

As shown in Figure 1, the designed intelligent ECT crack detection system mainly contains: signal feature extraction, de-noise, fuzzy logic training section and fuzzy decision making.

![Fig. 1: Overall system diagram](image-url)
Signal noise removal

The design of intelligent detection system starts with the signal noise removal from the collected data of ECT. The collected signal data sometimes contains noises especially for manual operation, which influences the feature extraction measurement and reduces the accuracy of fuzzy logic judgment. It is very important to remove these unwanted noises before we apply signal processing.

In signal processing, the most common tool for signal analysis and noise removal is Fourier analysis which decomposes signal into the segments of sinusoids. In other words, Fourier analysis transforms the signal from time domain into frequency domain [12]. Fourier analysis is very useful when dealing with stationary signal which does not change too much over time. However, in eddy current test, it is very important to know when the signal commences to change. In order to cope with this, Wavelet analysis is used for noise removal. In wavelet transform, the wavelets of different scales and positions are used to approximate the signal. For continuous wavelet transform, it is defined as the time of signal multiplied by scaled, changed versions of wavelet function $\psi$ [12]:

$$C(\text{scale}, \text{position}) = \int_{-\infty}^{\infty} f(t)\psi(\text{scale}, \text{position}, t)dt \quad (1)$$

where $C$ is wavelet coefficient, $f(t)$ is the signal.

The solution of the equation is the wavelet coefficient $C$ which is function of scale and position. The noise is separated via the wavelet transform and by modifying the right coefficient $C$ so that the noise can be reduced to minimum. The wavelet signal de-noise involves three steps: 1. Decompose signal into wavelet components (in which case noises are been separated). 2. Define the right wavelet $C$ coefficient in order to miniature or remove noises. 3. Reconstruct processed signal by defining $C$ coefficient [13].

The mathematical wavelet transform is very complicated and generates a lot of data [12]. An efficient way of to simplify the calculation work is to use Mallat algorithm which applies filters to decompose the signal. Figure 2 shows Mallat wavelet transform and Multi-layer Mallat wavelet transform [12].

Fig. 2: (a) Mallat wavelet transform. (b) Multi-layer Mallat wavelet transform.

In this study, biorthogonal wavelet with FIR filter is used to preform wavelet analysis and de-noise the $x$-axis data and $y$-axis data collect from eddy current test equipment [12]. Figure 3 shows the ECT signal before and after noise removal.
Signal feature extraction

When eddy current coil interacts with testing samples, the changing of material property causes the changing of coil impedance. The coil impedance can be expressed as a two dimensional variable [1]

\[ Z = R + jX \]  \hspace{1cm} (2)

where \( R \) is the resistance of the coil (y axis), \( jX \) is the reactance of coil which can be influenced by testing frequency (x axis).

As shown in Figure 4 (a), in eddy current equipment display, the signal is redefined as normalized \( Rcn \) and \( Xcn \) using voltage as output data. In impedance panel the “amplitude” and “phase angle” are representing the degree of impedance shifting which corresponded to variation of examining sample.

For differential probe applied in crack detection, the signal is in “8” shape as shown in Figure 4 (b). From the perspective of eddy current test inspectors, the high amplitude and large phase angle indicates the crack with large size. In this work “phase angle” and “amplitude” are calculated and utilized to determine the depth of crack. Another feature “width” will also be taken into account for crack sizing. It is observed that all these features from the “8” shape signal are directly related to the crack information. Hence, to detect the crack and further find out the
size and shape of the crack, we have to extract some signal features which represent the important information of the crack.

Figure 5 demonstrates the differential signal generated with respect to coil position over crack location. The data collected from eddy current equipment is plotted in x-y coordinate (volt). Each individual (x, y) combination represents the impedance at certain time. Under ideal circumstance, the “8” shape signal is symmetric starting from the origin point (0, 0). But in reality, especially in manual operation the center point is not always on the origin (0, 0). In addition, the “8” shape may be asymmetric due to the asymmetric shape of probe coil.

The feature extraction algorithm is designed as shown in Figure 6. The following steps are developed to extract the desired signal features.

1) Find the actual signal center point \((x_0, y_0)\) and then compute the distance between each \(x, y\) coordinates based on equation (2).

\[
\text{normal impedance} = \sqrt{(x_0 - x)^2 + (y_0 - y)^2}
\]  

(2)

2) Locate the maxim “normal impedance” as peak point \((x_{\text{max}}, y_{\text{max}})\), calculate the slope ratio \(k\) and the phase angle.

\[
k = \frac{y_{\text{max}} - y_0}{x_{\text{max}} - x_0}
\]

\[
\text{phas}_{\text{angle}} = \arctan(k)
\]

(3)

3) Based on the peak point and center point, a reference line is formed. For any point \((x_i, y_i)\), the calculation of width of the upper and down loop for the “8” shape signal is to locate the maximum vertical distance \((d)\) between each individual point and the reference line.

\[
d = \left| \frac{(x_{\text{max}} - x_0)(y_i - y_0) - (x_i - x_0)(y_{\text{max}} - y_0)}{\sqrt{(x_{\text{max}} - x_0)^2 + (y_{\text{max}} - y_0)^2}} \right|
\]

(4)

The feature extraction results are shown in Figure 7, where the black dot indicates the center point, blue dots indicate the peak points in each loop, and red points indicate the max width of upper and downside loop.
Fuzzy logic

Fuzzy logic in this study is used as a decision maker, which based on extracted features: amplitude, phase angle, and width. This fuzzy based decision making system contains system input, system output, membership functions (MF) and “IF THEN” fuzzy rules. The inputs are the features of crack such as amplitude, phase angle and loop width. The output of the system is the actual crack information such as depth, width and shape.

As shown in Figure 8, each input is related to one fuzzy set and each fuzzy set has its corresponding membership function (MF). The MF responds to the degree of each fuzzy set as a member in the membership in scale of 0 to 1[8]. Fuzzification is performed in order to associate fuzzy set with MFs. Fuzzy rules are stated in IF-THEN linguistic sentences, which describe the relation between input and output for instance: IF the amplitude (input) is high THEN the crack depth is deep (output). Finally, because more than one fuzzy rule has been applied, and also the execution result is linguistic (deep), a defuzzification process is needed to transfer the linguistic variables into numerical crisp values [8][10]. The flow chart of fuzzy logic is shown in Fig. 8.

In this research, different frequencies are applied to exam crack with different depths and shapes. For each MF, the numbers of MFs as well as the fuzzy rules should be developed independently according to different feature groups. In this work, ANFIS (Adaptive-Network-Based Fuzzy Inference System) in Matlab is utilized as system learning process to obtain fuzzy logic interface. Then this trained fuzzy logic interface is applied to predict the crack information based on the extracted features or features’ combination such as phase, amplitude and width.

Figure 9 (a) shows the ANFIS mapping. The input features are: amplitude, phase angle and max width. The known output is the depth of the crack. By using hybrid learning rule with linear
output, Sugeno fuzzy logic system (MISO) with multiple inputs single output is generated [14]. Figure 9 (b) shows the trained fuzzy IF THEN rules.

\[ \text{accurate rate} = \frac{\text{test data}}{\text{actual data}} \times 100\% \]  

**Table 1:** Fuzzy logic decision making result

<table>
<thead>
<tr>
<th>test frequency</th>
<th>type of membership</th>
<th>input</th>
<th>numbers of MFs</th>
<th>depth of crack (mm)</th>
<th>test results</th>
<th>accurate rate</th>
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<tbody>
<tr>
<td>300(KHz)</td>
<td>trapmf</td>
<td>4</td>
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<td>0.5</td>
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<td>96.52%</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>0.8</td>
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<tr>
<td></td>
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<td></td>
<td></td>
<td>1.0</td>
<td>1.00</td>
<td>100%</td>
</tr>
<tr>
<td>400(KHz)</td>
<td>trapmf</td>
<td>5</td>
<td>3</td>
<td>0.5</td>
<td>0.50</td>
<td>99.9%</td>
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<tr>
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<td>1.60</td>
<td>97.36%</td>
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EXPERIMENTAL RESULTS

Various experiments of the developed intelligent ECT system are carried out on the known notch cracks with different depths. The eddy current equipment is Nortec® 500S testing unit from Olympus® and the probe is differential reflection probe (PRL/500 kHz - 3 MHz/D). Eddy current scan is processed manually in order to simulate the industrial scan process. The test is performed using different frequencies. Six different depths of cracks are distributed in two aluminum samples as sample1: 0.2mm, 0.51mm, 1.02mm and sample2: 0.8mm, 1.5mm, 2mm.

After the feature extraction process, 5 sets of the features are used to train fuzzy logic and one set is used to validate the training result. The training results are shown in Table 1. We developed a semi-auto MF and numbers of MF tuning program to find the proper MF and the number of MF, which can be used for ANFIS training parameters. In Table 1, the verifying result is close to the actual depth of crack and the accuracy is shown by accurate rate. With adequate sets of data it is possible to find a universal MF as well as the numbers of MFs for data from fixed frequency. Whereas as shown in Table 1, due to lack of data (only 6), different MF as well as numbers of MFs are obtained via training program at same frequency.

Furthermore, a user friendly interface is developed which embeds the functions of data filtering, data plotting, feature extraction and crack depth prediction. The interface will be used as computer aid software to help inspectors.
When we train the fuzzy logic with the width of loop, it is noticeable that the width of the signal is not only related with the depth of crack but also corresponding to the opening width of notch crack. When the width increases, the width of the “8” loops increases as well.

Another experience is carried out by using the angled crack Figure 10 (b). According to signal plot Figure 11, the crack angle could have relation with the ratio of upper loop width and down side loop width which will be investigated in the future.

It is known that the accuracy of the intelligent detection system largely depends on the fuzzy logic rules. A complete set of fuzzy rules are expected to include all possible cracks that could exist in the inspection parts. Hence, large amount of data on smaller cracks are needed in this study.

CONCLUSIONS AND FUTURE WORK

In this paper, an intelligent detection system based on Neuro-fuzzy has developed including signal feature extraction, signal de-noise and crack decision making. A user friendly interface is developed for the convenience of data input, fuzzy logic membership choosing and final detection display etc. The experimental results demonstrate that the developed intelligent detection system can detect the crack and predict the crack depth with reasonable accuracy. The future works include detecting the smaller cracks and the cracks with more complicated shapes and improving the user interface for real industrial application.

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