NEURAL NETWORK BASED PATTERN RECOGNITION FOR DEFECT
DETECTION OF LOAD/LOCK SLOTS

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PROBLEM DESCRIPTION

The Load (Lock) Slot viewed from the top is shaped like a running track around a soccer field (see Figure 1.1). The minimum size of the crack required to be detected is 0.005"x0.010". For modeling cracks, there are altogether 9 notches in the Slots as marked in the Figure 1.1. The minimum notch at the 9th stage is 0.005"x0.010". For inspection of this complex geometry, an eddy current probe with a double reflection coil was developed. Scanning occurs in the minor elliptical axis direction while indexing takes place along the major axis. The split of the coil is perpendicular to the scan direction (or in another word, parallel to the Slot edge). The challenge here is the changing scan surface length due to the elliptic shape and the small size (the minor axis is about 1/8" long) of the inspection area.

DEFECT DETECTION THROUGH PATTERN RECOGNITION

In Figure 2.1, some of the scan waveforms are depicted. It can be seen that these scan waveforms are of different shape. This is because that the scan surface length is different from one to another and that the eddy current signal is influenced by both edges at the narrow scan surface.

We tried first to process the signal in time domain. The basic idea is to compare scan waveforms after aligning them. This involves the waveform shape alignment through stretching the waveform in both direction (vertical and horizontal) and the waveform supporting points alignment through interpolation. It didn’t work out in this way. The reason we think is that it is hard to find a scan waveform which can serve as a good templet for comparison. Then, we turned to work in frequency domain.
Figure 1.1 Load/Lock slots at the 9th stage of 4-9 spool.

Figure 2.1 Signal at left arc of bottom load slot.
In Figure 2.2, some scan waveforms are analyzed using Fourier transform. Comparing Figure 2.2A and Figure 2.2B, we can see significant difference between Fourier coefficients of notched signal and the non-notched, either in complex plane or in spectrum plot. This motivates us to use pattern recognition for defect detection.

![Figure 2.2A Fourier analysis of notch signal.](image)

For pattern recognition, there are two basic requirements on patterns [1]. First, the pattern should be able to represent the waveform in the sense of containing enough flaw information for detection. Second, the pattern should not have too many parameters, for this will complicate the calculation. Through the observation, we decided to use Fourier coefficients #3-#7 to form the pattern. This is in consistence with the fact that low frequency coefficients represent DC and inspection surface length and that high frequency coefficients are of small magnitude and hence less important. As a result, each pattern contains 5 Fourier coefficients, or 10 real numbers.
Taking x for real part of a Fourier coefficient and y for imaginary part, subscript b for notched signal and subscript g for non-notched signal, a pattern i representing notched signal can be expressed as

\[ P_{bi} = [x_{bi1}, x_{bi2}, \ldots, x_{bi3}, y_{bi1}, y_{bi2}, \ldots, y_{bi3}] \]

while a pattern j representing non-notched signal as

\[ P_{bj} = [x_{bj1}, x_{bj2}, \ldots, x_{bj3}, y_{bj1}, y_{bj2}, \ldots, y_{bj3}] \]

In the case of two-classes pattern recognition, a decision function \( f(P) \) is to be found which should function as follows:

\[ f(P_{bi}) = +1, \quad f(P_{bj}) = -1. \]

For linear pattern recognition, \( f(P) \) is linear. We are to define and tune a vector

\[ W = [w_1, w_2, \ldots, w_{11}]', \]
such that

\[ f_0(P_a) = [x_{a1} \ldots x_{a5} \ y_{a1} \ldots y_{a5}]^T W = +1, \]

\[ f_0(P_b) = [x_{b1} \ldots x_{b5} \ y_{b1} \ldots y_{b5}]^T W = -1. \]

This algorithm is simple, for it involves less computation. However, it does not always work, because the real problem is not that simple.

For nonlinear pattern recognition, \( f(P) \) is nonlinear. This means that we are to find a nonlinear function \( f_n(P) \) so that

\[ f_n(P_a) = +1, \ f_n(P_b) = -1 \]

for any \( P_a \) and \( P_b \). This is a nonlinear mapping problem. It has been shown by Hecht-Nielsen [2] that any nonlinear map can be approximated with a neural network to any predefined degree. This result can be utilized to define a nonlinear decision function for solving our pattern recognition problem.

We chose a neural network which has 10 inputs, 1 output, and 1 hidden layer. With the fixed structure, the neural network is simply a nonlinear function with some free parameters (weights) to be fixed. Using the existing flaw information on Load/Lock Slots, these free parameters are fixed through training (parameter optimization) such that

\[ f_n(P_a) = +1, \ f_n(P_b) = -1. \]

The pattern recognition result using our neural network decision function is shown in Figure 2.3. The first 230 points are results of inspection of the notched 4-9 Spool depicted in Figure 1.1, and second 230 points are results of inspection of a non-notched 4-9 Spool. Obviously, all the 9 notches are detected.

Figure 2.3 Neural network pattern recognition.
CONCLUSIONS

For nondestructive inspection of a complex geometry in the engine parts, we presented a neural network based pattern recognition algorithm which can detect the parts flaw through processing scan signal in frequency domain.

For features extraction, we applied a FFT (Fast Fourier Transform) to the data collected at each scan and then selected a set of five Fourier coefficients which alone contain enough critical information for defect detection. These Fourier coefficients form a set of key coefficients, and each set of key coefficients forms a pattern representing a scan waveform. For pattern recognition, we use neural network as a decision function. This neural network based pattern recognition algorithm has been tested with success.

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REFERENCES