A New Method of Defects Identification for Wire Rope Based on Three-Dimensional Magnetic Flux Leakage

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Abstract. Most traditional wire rope sensors produce the integrated volume of magnetic leakage around the whole circumference of wire rope, which is insensitive to the circumferential distribution of wire rope defects. In this paper the three-dimensional magnetic flux leakage of rope surface is obtained by the aid of Hall sensors array distributed around the wire rope. Then a spatial notch filter is designed to eliminate the strand-waveform signal, and the real defect signal is emphasized. The signal of any defect is transformed to the corresponding gray-scale map. Then an algorithm of two-dimensional image recognition is introduced to extract features from these gray-scale maps and identify defects. The experiment results show the degree and the width of defects, the circumferential distribution of localized flaw such as concentrated or dispersive broken wire can be well distinguished. The discrimination of this method for several typical defects under the condition of laboratory can reach 90%.

1. Introduction

The non-destructive detection of defects in wire ropes is a challenging task in the application and manufacturing industry of wire ropes for many decades. Most wire rope testing instruments available on the market identify localized flaws according to the summation of circumferential magnetic leakage of magnetized wire ropes with coils, Hall effective sensors or flux-gates. Therefore the circumferential distribution of defects, which is an effective factor of wire rope’s residual load-carrying capacity for the defects of the same degree, is ignored.

Then the testing instrument based on Hall sensors array that provides a map of stray field over the unwrapped surface of the rope is proposed [1-2]. In this paper the three-dimensional magnetic flux leakage of rope surface is obtained by the aid of 30 Hall sensors array uniformly distributed around the wire rope. A spatial notch filter is designed to eliminate the strand-waveform from the original signal, and then a feature extraction and defects identification system based on the method of image recognition is derived in this paper, which is sensitive to the circumferential distribution of defects and can detect the quantity and width of broken wires correctly.

2. Elimination of the strand-waveform

Usually the original magnetic flux leakage signal of wire rope surface contains considerable strand-waveform signal due to the structure of the rope, which is true of the three-dimensional magnetic leakage signal acquired by Hall sensors array. The original signals of 3 broken wires of a rope with the
diameter of 38mm are shown in figure 1(a) (concentrated breaks) and (b) (dispersive breaks) and the corresponding counter lines of them are respectively shown in figure 1(c) and (d), in which the fluctuation induced by the strands of wire rope is dominating at the expense of the required broken wire signal. So the elimination of the strand-waveform is critical for an accurate inspection of wire rope defects.

![Figure 1](image)

**Figure 1.** Original signals and the corresponding counter lines of 3 concentrated and dispersive broken wires: (a) original signal of 3 concentrated broken wires, (b) original signal of 3 dispersive broken wires, (c) counter line of 3 concentrated broken wires, (d) counter line 3 dispersive broken wires.

For a wire rope with certain structure, the axial strand-waveform comes on as a sine wave with a stable frequency approximately. So a spatial notch filter with the notch frequency equals to this frequency can eliminate the strand-waveform easily. The transfer function of the filter is shown in Equation (1) [3-4].

\[
H(z) = \frac{(z - e^{-j\omega_0})(z - e^{-j\omega_0})}{(z - \alpha e^{-j\omega_0})(z - \alpha e^{-j\omega_0})} = \frac{1 - 2\cos \omega_0 z^{-1} + z^{-2}}{1 - 2\alpha \cos \omega_0 z^{-1} + \alpha^2 z^{-2}}
\]  

(1)

where \( \alpha \) is related to the width of the notch of the filter, \( 0 < \alpha < 1 \); for a small \( \alpha \), the notch will be wide. \( \omega_0 \) is the spatial frequency of strand-waveform, that is, \( \omega_0 = 2\pi / N_p \), where \( N_p \) is the number of samples in one strand-waveform period.

Assign \( \alpha = 0.8 \), the data of each column of the signals in figure 1(a) and (b) is filtered one by one through Equation (1), and the final filter results are shown in figure 2(a) and (b) respectively. The corresponding counter lines of these filtered signals are shown in figure 2(c) and (d). Form the filtered signal, the distinct magnetic distortion of defects can be achieved, and the concentrated breaks and dispersive breaks can be distinguished visually.
Figure 2. Filtered signals and the corresponding counter lines of 3 concentrated and dispersive broken wires: (a) filter result of 3 concentrated broken wires, (b) filter result of 3 dispersive broken wires, (c) counter line of filtered signal of 3 concentrated broken wires, (d) counter line of filtered signal of 3 dispersive broken wires.

3. Algorithms of defect identification

The filtered signals of all defects can be transformed to corresponding gray-scale maps. Then a method of image recognition can be introduced to identify defects, which includes size and amplitude normalization of images, feature extraction with Karhunen-Loève transformation, and defect classification with BP neural network (NN).

3.1. Size and amplitude normalization

First a number of signals for the standard samples of several typical defects, such as 1 broken wire of 12 mm width, 1 broken wire of 3 mm width, 1 broken wire of gap width, 2 concentrated broken wires gap width, 3 concentrated wires gap width, and 1 raised wire, are acquired and notch filtered through Equation (1). Assuming the filtered signal is $u_i$ and the size of any actual defect segment is below $(2\Delta x+1) \times (2\Delta y+1)$, then the size normalization can be realized through the following procedure:

- Searching for the coordinates $(x_c, y_c)$ of the local maximum value of $u_i$;
- Assuming the size normalized signal of $u_i$ is $d$ which is given by Equation (2).

$$d(x,y) = \{u(x,y) \mid x \in [x_c - \Delta x, x_c + \Delta x], y \in [y_c - \Delta y, y_c + \Delta y]\}$$  \hspace{1cm} (2)

Assuming the range of the circumferential coordinate of $u_i$ is $[0, Y]$, if $y_c - \Delta y < 0$, $u_i$ should be modified through the following formula before the step (2) above

$$\begin{aligned}
&u(x, y + \Delta y - y_c) \leftrightarrow u(x, y), \quad 0 \leq y \leq Y + y_c - \Delta y \\
u(x, i - 1) \leftrightarrow u(x, Y + y_c - \Delta y + i), i = 1, 2, \ldots, \Delta y - y_c
\end{aligned}$$

Then the size normalized signal is magnitude normalized through Equation (3).

$$g(x, y) = \frac{d(x, y) - \min(d)}{\max(d) - \min(d)} \times 255$$  \hspace{1cm} (3)
where $g$ is the final normalized signal and a gray-scale map as well. The normalization results of the typical defects above are shown in figure 3.

![Figure 3. Normalization results of 6 typical defects: (a) 1 broken wire, 12mm width, (b) 1 broken wire, 3mm width, (c) 1 broken wire, gap width, (d) 1 raised wire, (e) 2 concentrated broken wires, gap width, (f) 3 concentrated broken wires, gap width.](image)

3.2. Feature extraction using K-L transformation

Denoting the gray-scale map $g$ with a vector $x$, Karhunen-Loève transformation is used to extract its feature which is given by

$$x = \Lambda y$$  \hspace{1cm} (4)

where $y$ is the eigenvector of the covariance matrix of $x$ which is given by Equation (5)

$$C = E[(x - \mu)(x - \mu)^T]$$  \hspace{1cm} (5)

then $\Lambda = \text{diag}[\lambda_1, \lambda_2, \lambda_3, \ldots \lambda_m]$, the vector $\lambda$ is composed of the eigenvalues of $C$. In Equation (5), $\mu$ is the mean vector of the set of $x$, if it has no practical significance, the equation can be reduced to $C = E[x x^T]$. Through the transformation above, the correlation among each component of $x$ is eliminated, so the extremely tiny eigenvalues which related to the minor characteristics can be omitted without the significant characteristics affected. Arranging $\lambda$ in descending order, the omitting can be implemented by the following inequation

$$\sum_{j=1}^{k} \lambda_j \left( \frac{\sum_{i=1}^{m} \lambda_i}{\sum_{i=1}^{m} \lambda_i} \right)^{-1} \geq \alpha$$  \hspace{1cm} (6)

where $m$ is the number of all eigenvalues in $\lambda$, $k$ is the number of the eigenvalues to be preserved. The value of $k$ depends on $\alpha$, and generally $\alpha = 99\%$. In the experiments of this paper, $k = 10$, that is, 10 dominant eigenvalues of each defect signal are kept to be inputs of the subsequent neural network.

Each normalized gray-scale map of all standard samples of defects is processed by this transformation. As a result, each two-dimensional image signal is reduced to a one-dimensional vector of characteristic value. Otherwise the NN would contain more input layer neurons and be more time consuming.

3.3. Defect identification based on BP neural network

As a three-layer back propagation (BP) neural network can approximate any continuous mapping$^{[5]}$, the number of the extracted eigenvalues is 10, and the number of the types of the typical defects to be classified is 6, a three-layer BP network with 10 inputs, 4 hidden nodes and 6 outputs can be established to classify the typical defects above. The transfer function between layers is logarithmic sigmoid function which is given by

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$  \hspace{1cm} (7)

where the output $\sigma(x)$ can never reach the value “0” and “1” for any finite network weight$^{[6]}$. So it is not suitable to set “0” and “1” as the target value of the network. In this paper, “0” and “1” are respectively replaced with “0.1” and “0.9”.

As to the training strategy, a method that combines sampling training and complete training is adopted for it shows a better discrimination in face recognition$^{[7]}$. First the features of the normalized signals of all typical defects are divided into two parts, $P$ and $P_n$, $P$ is the study samples for NN
training and $P_t$ is the testing samples to measure the network performance, both of them including the features of all the 6 types of defects. The NN training can be implemented through the following steps:

- For every typical defect, extracting one sample from its study samples and recombining a new set $P_1$, training the NN with $P_1$;
- $P_2 = P - P_1$, then training the NN with $P_2$;
- Evaluating the NN with $P_t$.

In the experiment of this paper, there are totally 90 study samples, 15 for each typical defect, taking part in the training. The number of $P_1$ and $P_2$ is 6 and 84. And 30 samples, 5 for each typical defect, are used to testing the NN performance, the result is 2 errors and 28 successes. So the NN has a discrimination of 93.3% for the testing samples $P_t$. Using NN, the discrimination for the 6 typical defects can reach 90% in the experiments under the condition of laboratory.

4. Conclusion

With the Hall sensors array uniformly distributed around the wire rope, the three-dimensional magnetic flux leakage of rope surface is obtained. Then a method of two-dimensional image recognition is used to identify defects with higher accuracy. The circumferential distribution of defects can be captured with this method, the degree and the width of defects can be distinguished distinctly, so the method can be utilized as quantitative testing to a certain extent. Secondly, only the most dominant characters are extracted through K-L Transformation and act as the inputs of NN, which improves the operational capability of NN, and the minor characters are truncated, which results in a higher generalization capability of the NN. For future work, samples that can distinguish depths of wire rope defects, and more samples related to other types of defects such as corrosion, twist and so on, should be collected to participate in the experiments.

References

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