Electromagnetic Signal Preprocessing and Feature Extraction

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Abstract. The electromagnetic wave can lead to electrical equipment failure, which is really a serious problem to electrical power unit, which not only destroy the circuits but also may lead to fire. Therefore, This research focused on electromagnetic signal preprocessing and feature extraction based on wavelet transform. After building the model of electromagnetic waveform, the collecting signals of electrical spark affected by noise signals were processed, wavelet transform was used to filter the noise interference so that the features of electromagnetic waveform can be extracted. The result shows that the preprocessing of electromagnetic signal can achieve accurate feature parameter information and after extracting the features, which provide convenience to the further processing of electromagnetic signals.

1. Introduction

People initially knew that electrical sparks came from the acousto-optic effect of electrical sparks. Light, also known as visible light, is a specific band of electromagnetic wave. Recent studies have shown that electrical sparks exhibit a wider frequency band distribution in the whole frequency band of electromagnetic waves. Because there are various kinds of noise interference in the three types of discharge spark electromagnetic waveforms, the directly converted parameter information is not accurate enough\textsuperscript{[1]}. In this case, the three types of discharge sparks are forcibly recognized and the effect is not necessarily good, and the waveform data Defects in itself will lead to the results of our research is not of practical value. In order to effectively solve this problem, we need to denoise and filter the acquired spark waveform to obtain the parameter characteristics after waveform denoising, which is used to identify the type of spark discharge\textsuperscript{[2]}.

2. Features Extraction and Model Establishment of Electromagnetic Signal

Compared with electrostatic discharge and lightning discharge, the electromagnetic pulse is the same generated by discharge\textsuperscript{[3]}. But the electromagnetic pulse generated by electric spark has certain advantages, such as transient, high frequency, short rise time and short duration, this is because the spark does not have the electrostatic field generated by the initial accumulation of electrostatic charges.

2.1. Extraction Features of Electromagnetic Signal

A strong electric field or a gradual increase in the current density of the contact electrode will cause the gas to be punctured\textsuperscript{[5]}. This is because the current will ionize the air when the switch closes or the distance between the electrodes decreases sharply. The discharge current reaches its peak value at the
The moment of contact or at the maximum electric field, and then decreases exponentially to zero\cite{6} like the battery discharges. At this point, the voltage can be described as:

\[ u_{c} = U_{c}e^{-\theta}\left(\cos\omega t + \delta \frac{\theta}{\omega}\sin\omega t\right) + \frac{U_{c}}{T_{LR} - T_{RC}} e^{-\frac{\theta}{T_{RC}}} \sum_{n=1}^{\infty} \frac{\sin\left(2n-1\right)\omega t}{2n-1} \]

The discharge current is as follows:

\[ I_{c} = C_{i}u_{c} = \frac{U_{c}}{L\omega} \sin\omega t - \frac{C_{i}U_{c}}{T_{LR} - T_{RC}} e^{-\frac{\theta}{T_{RC}}} \sum_{n=1}^{\infty} \frac{\sin\left(2n-1\right)\omega t}{2n-1} \]

Where

\[ T_{LR} = \frac{2L}{R}, \quad \omega = \sqrt{T_{LR}^2 - T_{RC}^2}, \quad \delta = \frac{R}{2L} = \frac{1}{T_{LR}} \]

The parameters of electromagnetic signals obtained from the above formulas have great impact on results. The great differences of different types of electromagnetic wave signals because of the first four parameters\cite{7,8}. Therefore, the four parameters are chosen to be the object of following analysis of electromagnetic wave signals.

2.2. Electromagnetic Waveform Model Establishment

The mathematical characteristics of EDM\cite{9} should be a set of Gaussian distributions of random functions, which have a certain degree of homogeneity on the spatial scale. In particular, from the viewpoint of electromagnetic wave energy data, the signal-to-noise ratio of the electromagnetic wave energy data is relatively small. If a more comprehensive wavelet transformation is not performed, the analysis of the electromagnetic wave energy data will be more difficult.

In this model, we divide its energy signal into two parts:

The first part of the coefficient sub-value is smaller and more in number\cite{10}, which is obtained by noise transformation.

The second part of the coefficients is derived from the signal transformation, which includes the noise data. This part of the noise data can be masked by the difference in amplitude. That is, setting a threshold, below the threshold threshold, we consider it to be noise data\cite{11}. The following formula can define continuous wavelet transform:

\[ W_{j}(a,b) = f \left( \Psi_{ab} \right) = \left| a \right|^{-\frac{1}{2}} \int f(t) \left( \frac{t-b}{a} \right) dt \]

Under the control of the normalization factor \(|a|^{\frac{1}{2}}\), different scale wavelets can maintain equal energy in the wavelet transform. For different basic wavelets, the continuous wavelet changes of the same signal are different. Therefore, the electromagnetic wavelet reconstruction formula should be written as:

\[ f(t) = \frac{1}{C_{n}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_{j}(a,b) \Psi \left( \frac{t-b}{a} \right) da db \]

3. Preprocessing of Electromagnetic Waveforms Based on Wavelet Variations

3.1. Extraction Features of Electromagnetic Waveform

Due to the complex mechanism of various fault electrical sparks, the electromagnetic wave signal is weak, and the range of signal frequency is large, the signal is unstable, and transient changes are easily occurred\cite{12}. Under such circumstances, a single time-domain analysis method has been difficult to identify the information features. Therefore, wavelet transform is one of the effective tools for signal reconstruction, perform denoising, which can extract the information features that need to be processed and identified.
The choice of wavelet basis needs to consider several aspects such as its orthogonality\textsuperscript{[12]}, compactness and support length. Usually, DBN wavelet is often chosen as the wavelet basis. This’s because DBN wavelet basis is more than the above Harr wavelet, Morlet wavelet. The effect is good. The number of decomposition layers depends on the reconstructed part of the wavelet decomposition and the error of the original signal. The smaller the error value, the more coincident the signal obtained after wavelet decomposition and reconstruction with the original signal is, and the high-frequency detail component of the EDM feature information is included\textsuperscript{[13]}. The more thorough the decomposition, that is to say, the similarity of the signals before and after the decomposition can be evaluated by counting the magnitude of the two variances. Select the DB1, DB2, DB3, DB4, DB5 and DB6 wavelet bases for wavelet decomposition and reconstruction of electrical spark electromagnetic signals. The mean square error of the signal before and after statistical decomposition reconstruction is shown in Table 1.

| Wavelet function | DB1 | DB2 | DB3 | DB4 | DB5 |
|------------------|-----|-----|-----|-----|-----|
| Variance         |     |     |     |     |     |
| Number of layers | N=2 | 0.00865 | 0.00873 | 0.00872 | 0.00870 | 0.00867 |
|                  | N=3 | 0.00752 | 0.00757 | 0.00753 | 0.00741 | 0.00769 |
|                  | N=4 | 0.00847 | 0.00844 | 0.00825 | 0.00814 | 0.00832 |
|                  | N=5 | 0.00795 | 0.00791 | 0.00787 | 0.00783 | 0.00798 |

From the table above, it can be seen that the spark signal has the smallest error and the highest degree of similarity before and after the DB3 wavelet base decomposition and reconstruction with three layers of decomposition layers. That is to say, the wavelet decomposition and reconstruction of the signal and the original signal using the wavelet basis of the DB3 wavelet base Approximation, the resulting high-frequency detail component is closest to the part of the spark signal that we want to represent.

3.2. Data Processing

The wavelet program was used to analyze and process the three types of discharge spark waveforms\textsuperscript{[14]}. The three kinds of discharge spark waveform data were opened by using the Ultrascope for DS1000 Series software and converted into .CSV format to obtain the waveform data information. Then according to the format required by the program, load it into txt and call the program. The collected 45 waveforms are analyzed by wavelet, and the five parameters are extracted, and Table 2 is finally obtained. In the table, A represents amplitude, C represents discharge current, F represents frequency, G represents Glow discharge spark, R represents rising time, V represents discharge voltage, High-voltage discharge spark will be replaced by HV and Low-voltage discharge spark will be token place by LV.

| No. | A (V) | F (MHz) | R (ns) | C (mA) | V (V) | Type |
|-----|-------|---------|--------|--------|-------|------|
| 1   | 3.2   | 2.8     | 400    | 380    | 200   | HV   |
| 2   | 1.8   | 2.5     | 300    | 380    | 200   | HV   |
| 3   | 2.8   | 2.5     | 200    | 350    | 200   | HV   |
| 4   | 3.8   | 3.7     | 550    | 400    | 200   | HV   |
| 5   | 2.2   | 2.7     | 200    | 360    | 200   | HV   |
| 6   | 2.8   | 4.5     | 400    | 370    | 250   | HV   |
| 7   | 4.6   | 2.3     | 200    | 400    | 250   | HV   |
| 8   | 3.4   | 2.4     | 200    | 400    | 250   | HV   |
| 9   | 1.6   | 2.8     | 200    | 390    | 250   | HV   |
| 10  | 2.6   | 2.6     | 180    | 370    | 250   | HV   |
Table 2, cont.

|   | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 | 43 | 44 | 45 |
|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
|   | 2.8 | 2.8 | 2.8 | 400 | 400 | 300 | 200 | 4.7 | 100 | 100 | 800 | 1.6 | 5 | 600 | 290 | 300 | HV | 0.8 | 65 | 900 | 90 | 220 | LV | 0.8 | 0.8 | 100 | 115 | 220 | LV | 0.8 | 0.75 | 105 | 85 | 220 | LV |
|   | 2.8 | 2.4 | 3 | 200 | 400 | 300 | 200 | 2.5 | 150 | 390 | 300 | 1.4 | 0.55 | 120 | 100 | 220 | LV | 1.2 | 0.9 | 120 | 90 | 220 | LV | 0.8 | 0.8 | 100 | 115 | 220 | LV | 0.8 | 0.75 | 105 | 85 | 220 | LV |
|   | 1.6 | 5 | 600 | 290 | 300 | HV | 2.8 | 2.8 | 2.8 | 400 | 400 | 300 | HV | 2.2 | 2.5 | 150 | 390 | 300 | HV | 1.4 | 0.55 | 120 | 100 | 220 | LV | 1.2 | 0.9 | 120 | 90 | 220 | LV | 0.8 | 0.65 | 900 | 90 | 220 | LV |
|   | 2.8 | 2.8 | 2.8 | 400 | 400 | 300 | 200 | 2.8 | 2.8 | 2.8 | 400 | 400 | 300 | HV | 2.2 | 2.5 | 150 | 390 | 300 | HV | 1.4 | 0.55 | 120 | 100 | 220 | LV | 1.2 | 0.9 | 120 | 90 | 220 | LV | 0.8 | 0.65 | 900 | 90 | 220 | LV |
|   | 0.8 | 0.8 | 100 | 115 | 220 | LV | 0.8 | 0.8 | 100 | 115 | 220 | LV | 0.8 | 0.75 | 105 | 85 | 220 | LV | 0.7 | 0.7 | 100 | 100 | 600 | LV | 0.7 | 0.7 | 100 | 110 | 600 | LV | 0.8 | 0.85 | 170 | 100 | 600 | LV |
|   | 0.8 | 0.7 | 100 | 130 | 800 | LV | 0.9 | 0.7 | 150 | 130 | 800 | LV | 0.9 | 0.95 | 120 | 120 | 800 | LV | 1.0 | 0.9 | 140 | 100 | 800 | LV | 0.9 | 1.25 | 900 | 100 | 800 | LV | 0.9 | 0.9 | 100 | 130 | 800 | LV |
|   | 0.8 | 0.9 | 100 | 130 | 800 | LV | 0.9 | 0.95 | 120 | 120 | 800 | LV | 1.0 | 0.9 | 140 | 100 | 800 | LV | 0.9 | 1.25 | 900 | 100 | 800 | LV | 0.9 | 0.9 | 100 | 130 | 800 | LV | 0.8 | 0.9 | 100 | 110 | 600 | LV |
|   | 0.9 | 0.5 | 500 | 6 | 600 | G | 0.8 | 0.05 | 500 | 5 | 600 | G | 1.4 | 0.08 | 700 | 8 | 600 | G | 1.0 | 0.06 | 500 | 5 | 600 | G | 0.8 | 0.06 | 600 | 10 | 800 | G | 0.9 | 0.05 | 600 | 6 | 600 | G |
|   | 0.8 | 0.05 | 500 | 5 | 600 | G | 1.4 | 0.08 | 700 | 8 | 600 | G | 1.0 | 0.06 | 500 | 5 | 600 | G | 0.8 | 0.06 | 600 | 10 | 800 | G | 0.9 | 0.05 | 600 | 6 | 600 | G |
|   | 0.9 | 0.05 | 600 | 6 | 600 | G | 0.9 | 0.06 | 600 | 8 | 800 | G | 1.3 | 0.07 | 800 | 6 | 100 | G | 1.5 | 0.08 | 800 | 8 | 100 | G | 1.2 | 0.08 | 600 | 8 | 100 | G | 1.6 | 0.08 | 800 | 7 | 100 | G |
|   | 1.0 | 0.06 | 500 | 5 | 600 | G | 1.4 | 0.08 | 700 | 8 | 600 | G | 1.5 | 0.08 | 800 | 8 | 100 | G | 1.2 | 0.08 | 600 | 8 | 100 | G | 1.6 | 0.08 | 800 | 7 | 100 | G | 1.1 | 0.05 | 700 | 7 | 100 | G |
|   | 1.5 | 0.08 | 700 | 9 | 100 | G | 1.2 | 0.07 | 700 | 10 | 100 | G | 1.3 | 0.07 | 700 | 8 | 100 | G | 1.5 | 0.08 | 700 | 9 | 100 | G | 1.2 | 0.07 | 700 | 10 | 100 | G | 1.3 | 0.07 | 700 | 8 | 100 | G |
|   | 1.6 | 0.08 | 800 | 7 | 100 | G | 1.1 | 0.05 | 700 | 7 | 100 | G | 1.5 | 0.08 | 700 | 9 | 100 | G | 1.2 | 0.07 | 700 | 10 | 100 | G | 1.3 | 0.07 | 700 | 8 | 100 | G | 1.5 | 0.08 | 700 | 9 | 100 | G |
|   | 1.2 | 0.07 | 700 | 10 | 100 | G | 1.3 | 0.07 | 700 | 8 | 100 | G | 1.5 | 0.08 | 700 | 9 | 100 | G | 1.2 | 0.07 | 700 | 10 | 100 | G | 1.3 | 0.07 | 700 | 8 | 100 | G | 1.5 | 0.08 | 700 | 9 | 100 | G |

From the table above, the five parameters of the three discharge spark waveforms are obtained. The spark parameters\[^{15,16}\] of the same type are also in the same phase. Although the waveforms of different types of sparks are generally different, there are sometimes crossovers.

4. Conclusion

First, the electromagnetic field model was established and analyzed. Secondly, the principle of wavelet transform and its decomposition and reconstruction algorithm are mainly introduced. Then, according to the particularity of spark discharge, the research objects using DB3 wavelet are determined. Discharge sparks, analysis, denoising. Waveforms were selected for each waveform analysis. The results of the analysis were compared with the original waveforms. It was proved that the DB3 wavelet was effective and effective for de-noising electromagnetic waves in spark discharge. Finally, wavelet analysis was performed on each set of waveforms, and the corresponding five parameters were obtained, which can be used as follow-up research objects.
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