The technique of entropy optimization in motor current signature analysis and its application in the fault diagnosis of gear transmission

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Abstract. Nowadays, Motor Current Signature Analysis (MCSA) is widely used in the fault diagnosis and condition monitoring of machine tools. However, although the current signal has lower SNR (Signal Noise Ratio), it is difficult to identify the feature frequencies of machine tools from complex current spectrum that the feature frequencies are often dense and overlapping by traditional signal processing method such as FFT transformation. With the study in the Motor Current Signature Analysis (MCSA), it is found that the entropy is of importance for frequency identification, which is associated with the probability distribution of any random variable. Therefore, it plays an important role in the signal processing. In order to solve the problem that the feature frequencies are difficult to be identified, an entropy optimization technique based on motor current signal is presented in this paper for extracting the typical feature frequencies of machine tools which can effectively suppress the disturbances. Some simulated current signals were made by MATLAB, and a current signal was obtained from a complex gearbox of an iron works made in Luxembourg. In diagnosis the MCSA is combined with entropy optimization. Both simulated and experimental results show that this technique is efficient, accurate and reliable enough to extract the feature frequencies of current signal, which provides a new strategy for the fault diagnosis and the condition monitoring of machine tools.
1. Introduction
In recent years, Motor current signature analysis (MCSA) is widely used in the diagnosis of IM (Induction Motor). The current drawn by an ideal IM has a single component at the supply. In the case of any mechanical or magnetic asymmetry, however, other frequency components according to the specific faults will appear in the stator current spectrum of the machine. MCSA is the sensing of the stator current, and utilizing the results of its spectral analysis to pinpoint an existing or incipient failure in the IM [1].

Therefore, many researches have been carried out [2-3]. By reviewing the past work, it is noted that although advanced signal processing methods have been extensively employed, conventional statistical calculations and Fourier series based on spectral analysis still provide vital preliminary information. For instance, both the ANN (artificial neural network) and model-based methods rely heavily on the calculations of motor signature and fault frequencies (via FFT) [4]. However, it is found that in some cases such as high-speed cutting, there are a lot of feature frequencies dense and overlapping in the motor current and it is difficult to identify the feature frequencies accurately. The effective frequency identification method based on MCSA has not yet been established, which directly restricts the application of current detection technology on the online monitoring of machine tools. This paper mainly discusses how to extract the accurate feature frequencies in the MCSA.

For example, when the servo motor is working in the high-speed cutting state, a lot of harmonic components in the motor current signal make the feature frequencies densely overlapping, that brings a lot of difficulties in motor condition monitoring. When the machine tool breaks down, the energy of the current signal will change timely and perform in the frequency distribution. For complex signal, time scale and the energy distribution are the two most important parameters. Because of the strong interference by higher harmonics and the large amount of the current data, there are many advantages using entropy in the signal processing, such as less calculating data, stronger antialiasing, higher noise immunity and so on. Entropy represents the general statistical property and the average uncertainty of the information source.

According to the feature of the motor current, this paper uses entropy optimization in the motor current signature analysis based on minimum entropy principle. This technique first demodulates the current signal, calculates the spectral entropy, and then optimizes to obtain the slice spectrum of higher accuracy.

2. Entropy optimization

2.1 Entropy
Shannon proposed the concept of entropy in 1948, which resolved the quantization of information [5]. The exact amount of information is:

\[ H(P) = H(p_1, p_2, ..., p_q) = - \sum_{i=1}^{q} p_i \log p_i \]  

(1)

Where \( P \) is a \( q \)-dimensional vector,

\[ P = (p_1, p_2, ..., p_q) \]
\[ \sum_{i=1}^{q} p_i = 1 \]
\[ p_i \geq 0 \]

P is called probability vector, and H(P) is called entropy function. Entropy is a concept in information theory for measuring the amount of information. The entropy represents the system’s order. The more orderly the system is, the less its entropy is.

2.2 Entropy-optimization

Based on Minimum Cross-entropy Principle in information theory, [6] built the entropy optimization model that can be used to revise the direct consumption coefficients to process complex data. [7] proposed introducing the approximate entropy algorithm to the feature extraction from the power system fault signal. [8] proposed using minimum entropy deconvolution to improve the existing AR model filtering technology to detect gear’s local fault. All above show that using entropy to process complex data is an effective method.

Entropy-optimization is a signal processing method expanded from the Minimum Entropy Principle. First, find the signal spectrum features by minimum entropy; then take this feature frequency called fb as basic point and recalculate them in the range of \( fb \pm 3 \sigma \) to relocate the frequency still by minimum entropy; repeat this process and get the final feature frequency. This method can extract the feature frequency of complex signal effectively and find it precisely.

2.3 Cyclostationary demodulation based on entropy-optimization

In the analysis of current signal, when feature frequency is the slice frequency, the spectral energy is concentrated on feature components; while the non-feature frequency is the slice frequency, the spectral energy is similar to uniform distribution. Based on the minimum entropy principle, the entropy of every cycle frequency can be easily calculated. To feature frequency and its crossover frequency, the entropy is small; otherwise the entropy is comparatively large. In the entropy curve of the cyclostationary spectrogram, every minimum point is associated with the feature frequency or an aliasing point between feature frequencies. Therefore, we can determine the feature slice frequencies based on minimum points of their entropy to improve the searching efficiency.

The feature information usually appears as the form of feature frequency modulated by driving frequency. Therefore, these components appear around the driving frequency, especially the same to the motor current signal of complex systems. In addition, the driving frequency component contains the main energy. This paper presents techniques for the extraction of the feature frequency in the motor current signal.

3. Simulations

A modulated current signal was simulated by MATLAB.

\[ x(t) = (1 + \sin(2\pi \cdot 7.2t) + \sin(2\pi \cdot 9t)) \cdot (100\sin(2\pi \cdot 50t)) \]  \hspace{1cm} (2)

Where the frequency of carried wave is 50Hz, the modulated frequencies are 7.2Hz and 9Hz. The 3-dimensional cyclostationary spectrogram of this simulated signal is as Figure 1.
In Figure 1, there are obvious peaks in some slice frequencies, but the cycle frequencies are too dense for the feature frequencies to be identified. Of course, we can take every slice frequency to be analyzed, but it will cost a long time to identify the feature frequencies. In this paper, based on frequency analysis, we first find the signal spectrum features, and get the accurate feature frequencies by using entropy optimization.

Figure 2 shows the frequency spectrogram. In this figure, there are 4 feature frequencies, 41Hz, 43Hz, 57Hz and 59Hz, so the modulated frequencies are 7Hz and 9Hz.

Using entropy optimization, we take 0.1 Hz as steps and get the entropy curve around 9Hz and 7Hz. Figure 3 shows the entropy curve around 9Hz and 7Hz.
In Figure 3(a), we can clearly identify the modulated frequency 9Hz. At the meantime, we can also clearly identify the modulated frequency 7.2Hz in Figure 3(b).

Compared Figure 3 with Figure 2, we find only feature frequencies 9Hz and 7Hz via FFT, but we get the accurate frequencies 9Hz and 7.2Hz via entropy optimization, because the feature frequencies 9Hz and 7.2Hz are simulated pre-preparedly. Moreover, entropy optimization makes a simple and rapid method to identify the feature frequencies. Therefore, this technique paves the way for accurate, simple and rapid analysis in the future.

4. Experimental method
A complex gearbox was obtained from machine tools of an iron works made in Luxembourg, which consists of drive gearbox, top gearbox, middle tilting gearbox and middle rolling gearbox. Figure 4 shows the structure of the gearbox. Table 1 shows the parameters of the gear.

Because of the complex and bad working condition, it is difficult to install the vibration sensor on the gearbox. The traditional vibration analysis is not suitable. However, MCSA (Motor Current Signature Analysis) has some advantages because of its non-invasiveness [8].

One Hall effect current sensor was used to acquire the stator current as shown in Figure 4. The gearbox was working normally. The data were sampled, using a National Instruments 16-channel 24-bit resolution A/D board PCI-9234, at 2.5 kHz and for 20 s.

5. Experimental results
Figure 5(a) shows the amplitude spectrum of the current signature. Figure 5(b) shows the partial enlarged detail around the driving frequency 50 Hz. Under normal condition, we can see the sidebands of the driving frequency 50 Hz, but not clearly. The amplitudes of the sidebands are aliasing, and some frequency leaks exist. In Figure 5(b), we can clearly identify the feature frequency 18.5Hz. After calculated, we know that 18.5Hz is the mesh frequency between Gear 11 and Gear 12. However, we are puzzled in some slice frequencies. For example, after calculated, we can know the mesh frequency between Gear 13 and Gear 14 is 11.1Hz, but we feel puzzled around 11Hz. We cannot identify the
Figure 4. The kinematic sketch of the gear box.

Table 1. The gear parameters of the gearbox.

| gear number | gear code | toothnumber | gear number | gear code | toothnumber | gear number | gear code | toothnumber |
|-------------|-----------|-------------|-------------|-----------|-------------|-------------|-----------|-------------|
| 1           | Z₁       | 29          | 7           | Z₇       | 41          | 14          | Z₁₄       | 140         |
| 2           | Z₂       | 130         | 8           | Z₈       | 3           | 15          | Z₁₅       | 128         |
| 3           | Z₃       | 34          | 9           | Z₉       | 24          | 16          | Z₁₆       | 23          |
| 4o          | Z₄₀      | 170         | 10          | Z₁₀      | 180         | 17          | Z₁₇       | 1           |
| 4i          | Z₄ᵢ      | 72          | 11          | Z₁₁      | 25          | 18          | Z₁₈       | 31          |
| 5           | Z₅       | 18          | 12          | Z₁₂      | 140         | 19          | Z₁₉       | 13          |
| 6           | Z₆       | 36          | 13          | Z₁₃      | 25          | 20          | Z₂₀       | 57          |

According to the analysis above, we can calculate the entropy curve of the cyclic spectrum from 10.8Hz to 11.3Hz. After calculated, the result is shown in Figure 6. Figure 6 illustrates that the minimum entropy appears in 11.1Hz, so we conclude that 11.1Hz is the modulation frequency. Compared with the calculated results, we get the accurate frequency via entropy optimization which is the mesh frequency between Gear 13 and Gear 14.
Therefore, we calculate the slice cyclic spectrum at 11.1Hz and revise it. The result is shown in Figure 7 and Table 2. After revise, the amplitudes of feature components increase about 6.8%. In the view of practical fault diagnosis, we can distinguish the feature components absolutely after the revise to identify gear faults.

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**Figure 5.** The amplitude spectrum of the current signature.

**Figure 6.** Entropy curve of the cyclic spectrum from 10.8Hz to 11.3Hz.

**Figure 7.** 11.1Hz slice cyclic spectrum diagram before and after revise.
Table 2. Result of the slice cyclic spectrum after revise.

|                        | Before revise | After revise | Amplitude differences |
|------------------------|---------------|--------------|-----------------------|
| Lower modulation       |               |              |                       |
| frequency              | 38.91         | 38.93        | 0.02                  |
| Amplitude              | 0.700         | 0.732        | 0.032                 |
| Higher modulation      |               |              |                       |
| frequency              | 61.07         | 61.04        | -0.03                 |
| Amplitude              | 0.526         | 0.562        | 0.036                 |
| Driving frequency      |               |              |                       |
| Amplitude              | 0.111         | 0.159        | 0.048                 |

6. Conclusions
A new procedure by using entropy optimization in motor current signature analysis has been presented. The proposed method has been proved to be efficient for identifying the modulation frequency. Simulated and experimental results show that this method based on entropy optimization is efficient enough to get more accurate modulation frequency. Especially in the slice cyclic spectrum diagram, the driving frequency is suppressed effectively, and the feature components are obvious. This technique paves the way for accurate, simple and rapid analysis in the future.

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