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Fault Diagnosis of AC Servo Motor with Current Signals Based on Wavelet Decomposition and Template Matching Methods

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Abstract: This paper presents a diagnosis technique to detect and identify faults in AC servo motors. The first phase of stator currents among three phases is digitized and stored in the time domain. Wavelet transform is employed to convert the signals onto time-frequency domain because the time domain based approach is not suitable for detecting state features of the current signals. Pre-processing algorithms that includes a kind of mean-filtering, synchronization with Hilbert transform and difference are consecutively performed to the raw signal to determinate features. Wavelet decomposition is applied to the difference values by the optimally selected mother wavelet and the features are calculated from the transformed signals. The extracted features are compared with the motor fault templates for the template matching method. The results based on real data show that the proposed approach is very useful to extract features of the signals for fault diagnosis.

1. INTRODUCTION

The most popular way of converting electrical energy to mechanical energy is an induction motor that plays an important role in modern industrial plants. The risk of motor failure can be remarkably reduced if normal service conditions can be arranged in advance. In other words, one may avoid costly expensive downtime of plant by proper time scheduling of motor replacement or repair if warning of impeding failure can be obtained in advance. In recent years, fault diagnosis has become a challenging topic for many electric machine researchers. The major faults of electrical machines can be broadly classified as follows [1]:

- Broken rotor bar or cracked rotor end-rings
- Static and/or dynamic air-gap irregularities
- Bent shaft (akin to dynamic eccentricity)
- Shorted rotor field winding
- Bearing and gearbox failure

Faults in electric machines produce one of more of the following symptoms:

- Unbalanced air-gap voltages and line currents
- Increase losses and reduction in efficiency
- Excessive heating

We will treat four major faults those are cracked bearing, broken rotor, bent rotor shaft, bearing wear or misalignment. These four faults are mechanically related faults. These faults are more frequently happened than others.

The diagnostic methods to identify the above faults may involve several different types of fields of science and technology [1-3]. Several methods are applied to detect the faults in induction motors as the following:

- Electromagnetic field monitoring
- Temperature measurements
- Radio frequency (RF) emissions monitoring
- Noise and vibration monitoring
- Acoustic noise measurements
- Motor current signature analysis (MCSA)

In this research, we use several data mining techniques based on time-series for fault diagnosis. First, we introduce synchronizing method that is very important issue in digitalized time-series measurement equipments. Wavelet transform is a method for time varying or non-stationary signal analysis, and uses a new description of spectral decomposition via the scaling concept. Wavelet theory provides a unified framework for a number of techniques, which have been developed for various signals processing applications. One of its feature is multi-resolution signal analysis with a vigorous function of both time and frequency localization. This method is effective for stationary signal processing as well as non-stationary signal processing. Mallat's pyramidal algorithm based on convolutions with quadratic mirror filters is a fast method similar to FFT for signal decomposition of the original signal in an orthonormal wavelet basis or as a decomposition of the signal in a set of independent frequency bands. The independence is due to the orthogonality of the wavelet function [4]. But, the performance is changed according to selection of mother wavelet. Unfortunately, selection of suitable mother wavelet is very difficult. To overcome this problem, we construct a non-supervising method. It supports the selection of the most suitable mother wavelet for fault diagnosis.

2. FAULTS AND APPROACH METHODS FOR DIAGNOSIS

2.1 Bearing faults

Though almost 4~50% of all motor failures are bearing related, very little has been reported in the literature regarding bearing related fault detection techniques. Bearing faults might manifest themselves as rotor asymmetry faults from the category of eccentricity related faults [5]. The vibration frequency of the fault is as follows,

$$f_1[Hz] = (f_r / N) f_r [1 - b_d \cos(\beta) / d_p] \tag{1}$$

where f_r is the rotational frequency, N is the number of balls, b_d and d_p are the ball diameter and ball pitch diameter respectively, and β is the contact angle of the ball. The following equation includes the vibration frequency and current spectrum [6].

$$f_{bng} = | f_e \pm m.f_v | \tag{2}$$

where m=1, 2, 3, … for the vibration harmonic contributions, f_e is electrical power supply frequency and f_v is one of the bearing characteristic vibration frequency.

Artificial intelligence or neural networks have been researched to detect bearing related faults on line. And also adaptive, statistical time-frequency methods are studying to find bearing faults.

2.2 Rotor bar faults

Rotor failures now account for 5-10% of total induction motor failures. Broken rotor bars give rise to a sequence of side bands given by:

$$f_b = (1 \pm 2ks) f, \qquad k = 1, 2, 3, \ldots \tag{3}$$

where f is the supply frequency and s is the slip. Frequency domain analysis and parameter estimation techniques have been widely used to detect this type of faults.

In practice, the current side bands around fundamental may exist even when the machine is healthy [7]. Also rotor asymmetry, resulting from rotor ellipticity, misalignment of the shaft with the cage, magnetic anisotropy, etc. shows up at the same frequency components as the broken bars [8]. Therefore other features of this fault need to be investigated.

2.3 Eccentricity faults

Eccentricity faults are the condition of unequal air-gap between the stator and rotor. It is called static air-gap eccentricity when the position of the minimal radial air-gap length is fixed in the space. This caused by the ovality of the stator core or by the incorrect positioning of the rotor or stator at the commissioning stage. In case of dynamic eccentricity, the center of rotor is not at the center of rotation, so the position o minimum air-gap rotates with the rotor. This maybe caused In case of dynamic eccentricity, the center of rotor is not at the center of rotation, so the position o minimum air-gap rotates with the rotor. This caused by a bent rotor shaft by a bent rotor shaft, bearing wear or misalignment, mechanical resonance at critical speed, etc. In practice an air-gap eccentricity of up to 10% is permissible. Both static and dynamic eccentricities tend to exist in practice. Using MCSA the equation describing the frequency components of interest is:

$$f\left[(kR \pm n_d) \frac{(1-s)}{p} \pm v \right] \tag{4}$$

where n_d=0 in case of static eccentricity, and n_d=1, 2, 3, … in case if dynamic eccentricity f is fundamental supply frequency, R is the number of rotor slots, s is slip, p is the number of pole pairs, k is any integer and υ is the order of the stator time harmonics.

Other equations are also presented in the literature as low frequency components for mixed eccentricity [7]. As it is obvious, sometimes, different faults produce nearly the same frequency components or behave like healthy machine, which make the diagnosis impossible. This is the reason why new techniques must also be considered to reach a unique policy for distinguishing among faults. Park's vector based upon voltage and current has been proposed to detect the motor fault.

3. SYNCHRONIZATION WITH HILBERT TRANSFORM

3.1 Hilbert transform

The Hilbert transform of the signal $x(t)$ is defined to be the signal whose frequency components are all phase shifted by -π/2 radians. The resulting signal is denoted

$$\hat{x}(t) = H\{x(t)\} \tag{5}$$

$\hat{x}(t)$ is produced by passing $x(t)$ through a filter with transfer function[9].

$$H(f) = -j\,\mathrm{sgn}(f) \tag{6}$$

The magnitude and phase of $H(f)$ are

$$|H(f)| = 1 \tag{7}$$

$$\angle H(f) = -\frac{\pi}{2}\,\mathrm{sgn}(f) \tag{8}$$

This phase shift is very useful to synchronize each measured signals.

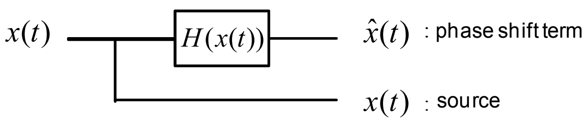

Fig. 1 Hilbert transform.

3.2 Synchronization

We use Hilbert transform to align phase of each measured signal. We can get the phase of the original signal by using arctangent from a created phase shift term in result of Hilbert transform and the original signal. We align each signal to zero degree, as shown in Fig. 2.

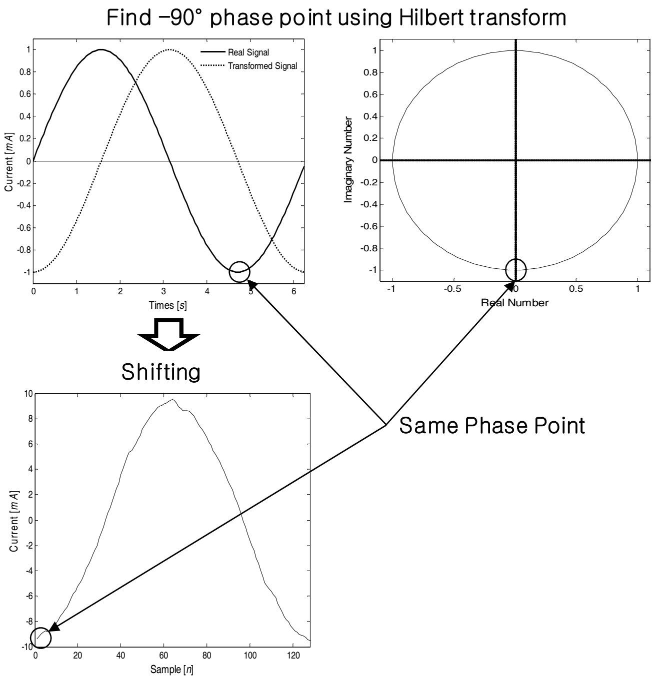

Fig. 2 Synchronization procedure of the raw data.

4. WAVELET DECOMPOSITION

Wavelet transform was applied to extract fault features from the difference signals. A wavelet is a function ψ belonging to $L^2(R)$ with a zero average. It is normalized and centered in the in the neighborhood of t=0. A family of time-frequency atoms is obtained by scaling ψ by a^j and translating is by b [10-13]:

$$\psi_{a,b} = |a|^{\frac{-j}{2}} \psi\left(\frac{t-b}{a^j}\right) \tag{9}$$

These atoms also remain normalized. The wavelet transform of f belonging to $L^2(R)$ at the time b and scale a^j is:

$$Wf(b,a^j) = \left\langle f, \varphi_{b,a^j} \right\rangle = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{a^j}} \varphi^*\left(\frac{t-b}{a^j}\right) dt \tag{10}$$

A real wavelet transform is complete and maintains energy conservation as long as the wavelet satisfies a weak admissibility condition which is:

$$\int_0^{+\infty} \frac{|\Psi(w)|^2}{|w|} dw = \int_{-\infty}^{0} \frac{|\Psi(w)|^2}{|w|} dw = C_\psi < +\infty \tag{11}$$

When $Wf(b,a^j)$ is known only for $a < a_0$ to recover f, we need a complement of information corresponding to $Wf(b,a^j)$ for $a < a_0$. This is obtained by introducing a *scaling function* ϕ that is an aggregation of wavelet at scales larger than 1. $\hat{\psi}(w)$ and $\hat{\varphi}(w)$ are Fourier transforms of $\psi(t)$ and $\varphi(t)$ respectively. $\psi(t)$ is a band pass filter, and $\varphi(t)$ is a low-pass filter. Taking positive frequency into account $\hat{\varphi}(w)$ has information in [0, π] and $\hat{\psi}(w)$ in [π, 2π]. Therefore they both have complete signal information without any redundancy. Decomposition of the signal in [0, π] using Mallat's wavelet algorithm gives:

$$\begin{aligned} h(n) &= \left\langle 2^{-j}\varphi(2^{-1}t)\varphi(t-n) \right\rangle \\ g(n) &= \left\langle 2^{-j}\psi(2^{-1}t)\varphi(t-n) \right\rangle \end{aligned}, \quad j = 0,1,2,\ldots \tag{12}$$

Wavelet decomposition does not involve the signal in [π, 2π]. In order to decompose the signal in whole frequency band, wavelet packet can be used for this purpose. After decomposition for l times, we will get 2^l frequency bands each with the same bandwidth. That is:

$$\left[\frac{(i-1)f_n}{2}, \frac{(i)f_n}{2}\right], \quad i = 1,2,\ldots,2^j \tag{13}$$

where f_n is the Nyquist Frequency, in the i^{th} frequency band. Wavelet packet de-composes the signal into one low-pass filter $h(n)$ and 2^l-1 band-pass filters $g(n)$, provides diagnosis information in 2^l frequency bands.

Functions $h(n)$ and $g(n)$ can be obtained by inner product of $\psi(t)$ and $\varphi(t)$.

$$\begin{aligned} h(n) &= \left\langle 2^{-j}\varphi(2^{-1}t)\varphi(t-n) \right\rangle \\ g(n) &= \left\langle 2^{-j}\psi(2^{-1}t)\varphi(t-n) \right\rangle \end{aligned}, \quad t \in R, n \in Z \tag{14}$$

$$\begin{aligned} A_j(n) &= \sum\nolimits_k h(k-2n)A_{j-1} \\ D_j(n) &= \sum\nolimits_g g(k-2n)A_{j-1} \end{aligned}, \quad n = 1,2,3,\ldots \tag{15}$$

where $A_0(k)$ is the original signal and A_j is the low frequency approximation at the resolution j. D_j is called high frequency detail signal. After de-composition of j time, we can obtain one approximation signal A_j and D_1, D_2, …, D_j detail signals.

Wavelet packet decomposition is:

$$\begin{aligned} x_{2n}(t) - \sqrt{2}\sum_k h(k)x_n(2t-k) \\ x_{2n+1}(t) - \sqrt{2}\sum_k g(k)x_n(2t-k) \end{aligned} \tag{16}$$

where $x_1(t)$ is the original signal. Comparing (16) with (14), we can find that A_j in (14) is decomposed but also D_j in (14) is decomposed in (16).

Wavelet and wavelet packet decompose the original signal that is non-stationary or stationary into independent frequency bands with multi-resolution. We assume that most of fault characteristic is embedded in high frequency band and apply wavelet decomposition to find a characteristic of each fault in stator current. It can produce approximation coefficient (cA) and detail coefficient (cD) in first step decomposition. Fig. 3 shows characteristics of discrete wavelet transform. The detail coefficient means high frequency of source signal. We use this detail coefficient as a feature of each fault. The produced coefficients depend on a kind of mother wavelet. Because of that, selection of a suitable mother wavelet is also important.

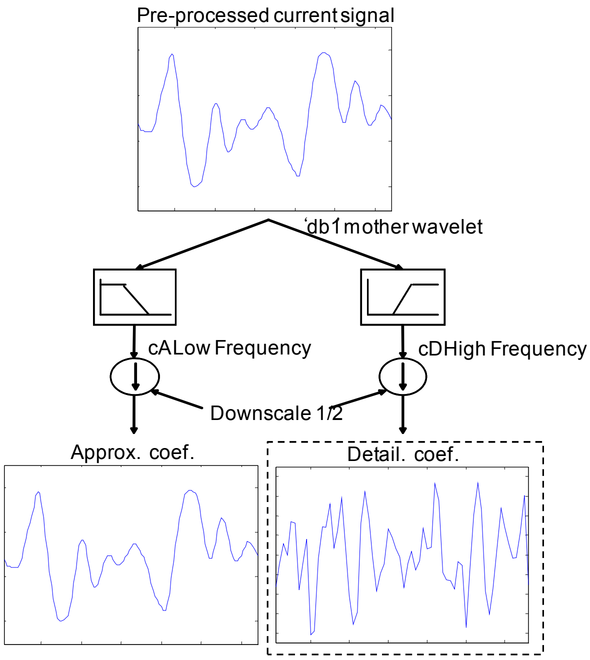

Fig. 3 Characteristics of DWT (ex: bearing fault current).

5. FAULTS DIAGNOSIS AND EXPERIMENTAL RESULTS

In this chapter, we propose an algorithm to diagnose and exactly explain each state. The proposed method was tested and verified by Matlab software. In Fig 4, this flow chart shows whole processes of our proposed diagnosis. First, a measured unknown coming signal has pre-processing stage same as making templates. And this is mathematically compared with 4 templates by correlation.

5.1 Current signals and data pre-processing

Motor rating applied in this paper is dependent on the electricity conditions. The rated voltage, speed, and horsepower are 220*V*, 3450*rpm*, and 5*kW*, respectively. And the implemented motor specification includes the number of slot, the number of pole, slip, etc. The specification of used motor is 34 numbers of slots, 4 numbers of poles, and 24 numbers of rotor bars. The slip is determined by calculating an actual motor speed and a rated speed. The specification of measured input current signals under this condition consists of 16,384 sampling numbers, 3*kHz* maximum frequency, and 2.1333 measuring time.

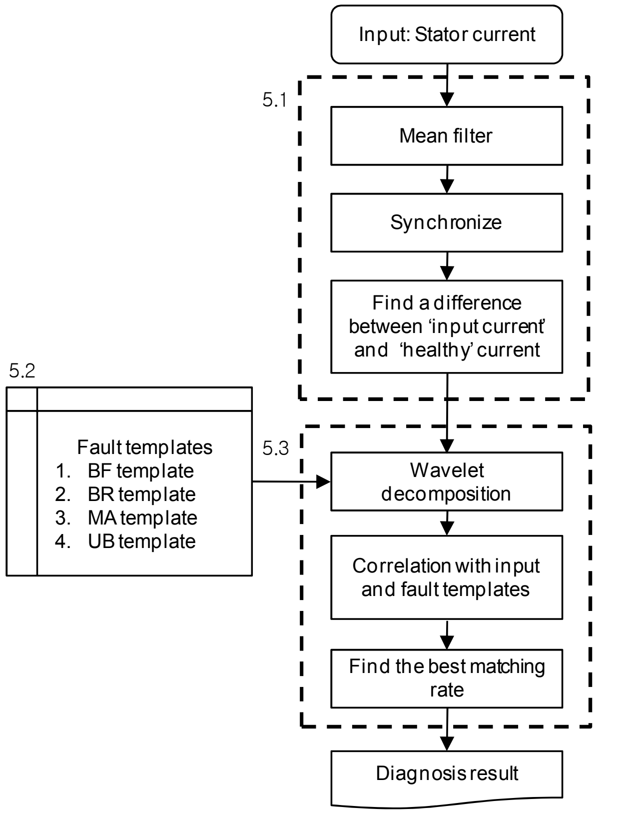

Fig. 4 Flow chart of diagnosis processes. (*BF*: *bearing fault*, *BR*: *broken rotor bar*, *MA*: *misalignment*, *UB*: *unbalance*)

Applied fault types in this study are broken rotor, faulted bearing, bowed rotor, unbalance, and static and dynamic eccentricity case. If the wavelet decomposition is implemented in the fault detection of induction motors, the unsynchronized current phase problem should influent the detection results much. The result of wavelet decomposition has time element. If target signals are not synchronized as shown in Fig. 5, the unexpected results will appear in the wavelet decomposition.

Therefore the signals are re-sampled by synchronizing signals with phase 0 by using Hilbert transform. And the average value divided by one cycle signal is calculated to reduce the noise of original signals which is named by mean filtering as shown in Fig. 6. A fault current has two elements those are a healthy current element and fault current element. The fault current element was caused from illegal condition of fault motor which is kind of electromagnetic pulse. We can get these faults element from difference between averaged fault signal and healthy signal. In Fig. 7, the template is produced by difference between averaged fault signal and healthy signal. Theses produced templates have high frequency terms that relate with characteristics of each fault. In this reason, we apply wavelet decomposition and extract the detail term. It is considered to improve the performance and introduced in next section.

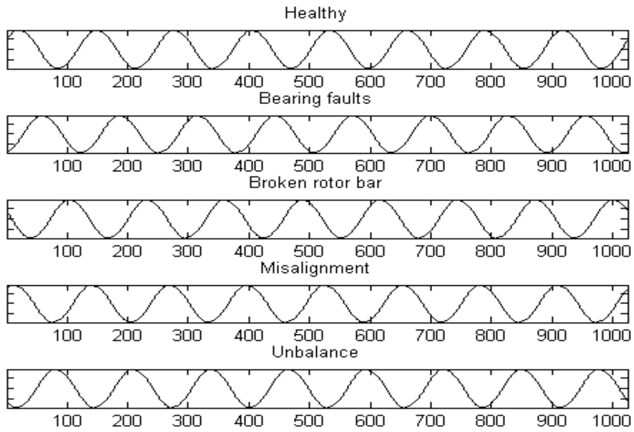

Fig. 5 Original current signals.

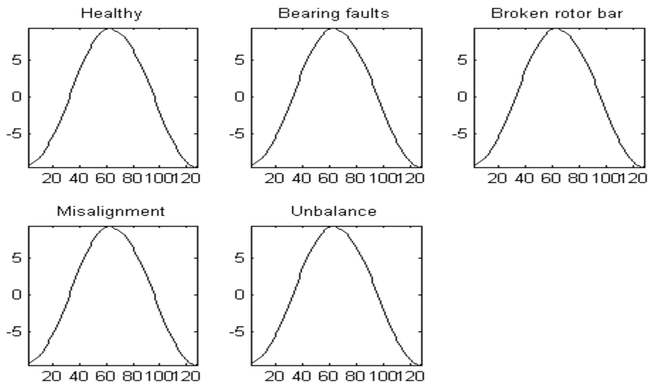

Fig. 6 Data synchronizing and mean filtering results.

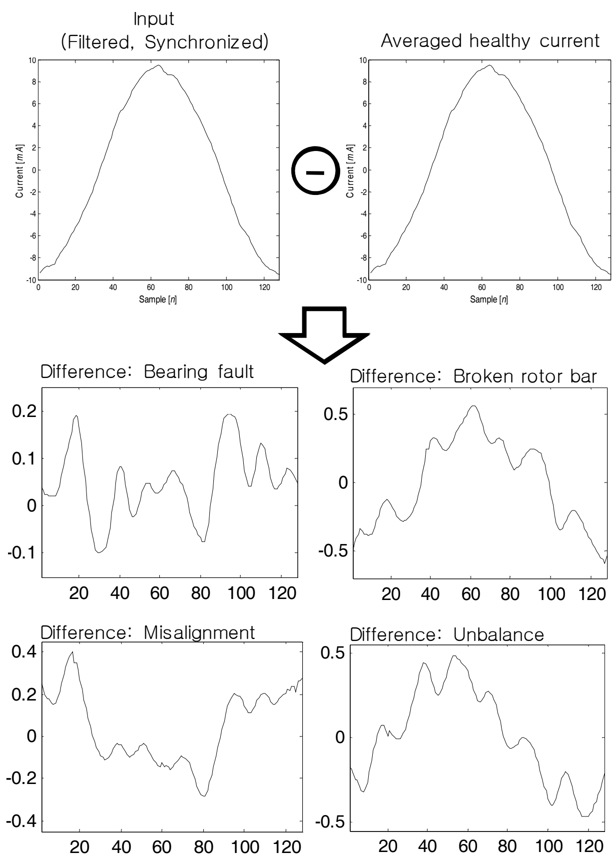

Fig. 7 Difference results of 4 faults.

5.2 *Fault templates*

We make four fault templates consist of broken rotor bar, bearing fault, misalignment, and unbalance cases to apply a template matching method for diagnosis. Each fault case has 40 test sets and averages these sets to make fault templates. These processes are shown in Fig 8.

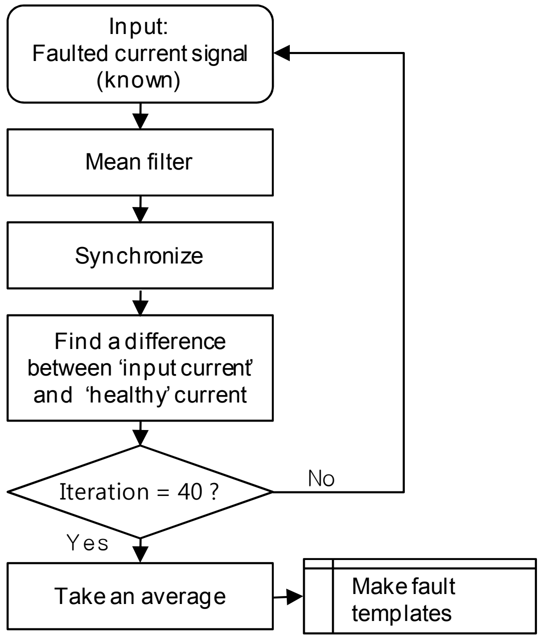

Fig. 8 Difference results of 4 faults.

5.3 Applying Wavelet Decomposition and Finding a Suitable Wavelet for Mother Diagnosis

We apply wavelet decomposition in produced templates. We use equation (16) for decomposition of each template then produce approximation coefficient and detail coefficient in first step decomposition. The detail coefficient means high frequency of source signal. These become new fault templates and these are used for a template matching method. A correlation is used to find out matching rate. But, before this process, we need to find most suitable mother wavelet for the motor diagnosis. We seek out best suitable mother wavelet in various mother wavelet sets investigated in Table 1. We try a template matching and find out diagnosis results in each mother wavelet at 40 times (totally 200 samples data, each fault 40 samples). The criterion for evaluation is used hit rate of diagnosis. And we find that the Daubechies wavelet of window size 1 (same as Harr wavelet) is a best suitable mother wavelet for our diagnosis as shown in Table 2. The diagnosis result of Daubechies wavelet has about 97.5% accuracy rate. Especially, misalignment and unbalance cases have 100% accuracy rate.

6. CONCLUSIONS

The proposed method is bases upon several time-series data mining techniques. The stator currents are measured by the current meters and stored in the time series data. Pre-processing methods are applied to treat the signals, because the intact time series data is not suitable to represent the current signals. After preprocessing of the signals, the features have to be extracted by the time series data mining methods that include synchronization and wavelet analysis. The discovered features are constructed to the motor faults templates for the template matching method. The wavelet analysis is possible method to detect faults of induction motors, but it needs to find most suitable mother wavelet for the motor diagnosis. Then we know that Daubechies wavelet is the most suitable mother wavelet for diagnosis of motor. It can increase the diagnosis accuracy rate of about 97.5%.

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REFERENCES

[1] P. Vas (1993), *Parameter Estimation, Condition Monitoring*, and Diagnosis of Electrical Machines, Clarendron Press, Oxford.

[2] G. B. Kliman and J. Stein (August 1990), Induction motor fault detection via passive current monitoring, *International Conference in Electrical Machines*, Cambridge, MA, pp. 13-17.

[3] G.K. Singh and SAS AlKazzaz (2003), Induction machine drive condition monitoring and diagnostic research—a survey, *Electric Power Systems Research*, vol. 64, pp. 145–158.

[4] K. Abbaszadeh, J. Milimonfared, M. Haji, and H. A. Toliyat (2001), Broken Bar Detection In Induction Motor via Wavelet Transformation, *IECON'01: The 27th Annual Conference of the IEEE Industrial Electronics Society*, pp. 95-99.

[5] Masoud Haji and Hamid A. Toliyat (30 Sept.-4 Oct. 2001), Pattern Recognition-A Technique for Induction Machines Rotor Fault Detection Eccentricity and Broken Bar Fault, *Conference Record of the 2001 IEEE Industry Applications Conference*, vol. 3, pp. 1572-1578.

[6] Jafar Zarei and Javad Poshtan (2007), Bearing fault detection using wavelet packet transform of induction motor stator current, *Tribology International*, vol. 40, Issue 5, pp. 763-769.

[7] S. Nandi, H. A. Toliyat (1999), Condition Monitoring and Fault Diagnosis of Electrical Machines – A Review, *IEEE Industry Applications Conference*, vol. 1, pp. 197-204.

[8] B. Yazici, G. B. Kliman (March/April 1999), An Adaptive Statistical Time-Frequency Method for Detection of Broken Bars and Bearing Faults in Motors Using Stator Current, *IEEE Trans. On Industry Appl.*, vol. 35, no. 2, pp. 442-452.

[9] B. Sklar (2001), *Digital Communications Fundamentals and Applications. 2nd edition*, Prentice-Hall, 2001.

[10] C. Gasquet, P. Witomski (1998), *Fourier Analysis and Applications: Filtering, Numerical Computation, Wavelets*, Springer Verlag, New York.

[11] S. Mallat (1998), *A Wavelet Tour of Signal Processing*, San Diego, CA: Academic.

[12] I. Daubechies (1992), *Ten Lectures on Wavelets*, Philadelphia, PA: SIAM.

[13] Y. Meyer (1993), *Wavelets: Algorithms and Applications*, Philadelphia, PA: SIAM.

Table 1. Mother wavelets for DWT.

Wavelets	Window size
Daubechies	1-15
Symlets	2~15
Coiflets	1~5
Meyer	-

Table 2. A list of results of diagnosis test sets in various mother wavelets (Each 40 times).

Wavelets	BF	BR	MA	UB	Total
Haar	37	39	40	40	156
coif1	31	38	20	33	122
db2	28	38	19	34	119
sym2	28	38	19	34	119
db3	25	40	18	28	111
sym3	25	40	18	28	111
db4	23	37	16	25	101
db5	25	36	12	26	99
sym7	26	32	15	26	99
sym11	25	31	13	24	93
db10	25	31	11	24	91
db11	19	29	16	27	91
db12	22	33	10	26	91
sym4	25	37	6	22	90
sym15	24	31	12	23	90
coif3	25	34	7	24	90
dmey	25	31	9	25	90
db9	25	33	8	23	89
sym5	23	35	7	24	89
coif2	24	36	6	23	89
sym14	25	32	8	22	87
db6	25	34	4	23	86
sym12	25	32	7	22	86
coif4	25	33	6	22	86
sym6	24	32	7	21	85
coif5	25	32	7	21	85
db7	24	34	5	21	84
db13	25	31	4	22	82
sym8	24	33	4	21	82
db14	25	30	5	21	81
db15	25	31	5	20	81
sym10	25	31	5	20	81
db8	23	33	5	19	80
sym9	23	32	6	19	80
sym13	25	31	5	18	79

**BF: bearing fault, BR: broken rotor bar, MA: misalignment, UB: unbalance.*