An Intelligent Monitor for Electric Motor Fault Diagnosis

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Abstract—Many fault detection techniques have been proposed in literature to extract representative features from measurements for motor fault detection, however each has its own merits and limitations. A new intelligent monitoring system is developed in this paper to integrate features from several fault detection techniques to map data features to motor health condition categories and to improve fault diagnosis accuracy. The fault diagnosis will be based on representative features extracted from the time domain, the frequency domain and the time-frequency domain, respectively. The developed intelligent monitoring system will also employ prediction information to enhance fault diagnostic accuracy, and reduce the effect of outliers in fault classification. The effectiveness of the developed intelligent monitoring system is verified by the experiments of induction motors with broken rotor bars and bearing defects.

Index Term—broken rotor bar fault, Bearing fault, fault diagnosis, induction motors, intelligent system.

I. INTRODUCTION

INDUCTION motors (IMs) are the driving force of many industrial applications. Non-destructive IM fault detection and diagnosis has become important aspects to improve productivity and reduce maintenance cost. The IM faults consist of mechanical faults and electrical defects. Mechanical faults include: bearing defects, air gap eccentricity, shaft misalignment; electrical faults encompass stator winding defect, broken rotor bars, etc. [1]. Investigations have revealed that broken rotor bar faults account for 10% of the motor imperfections in industrial and domestic applications [2], Accordingly, this work will focus on IM defect detection associated with broken rotor bars.

IM fault detection can be conducted using vibration signals and/or stator current signals. Although the vibration signals have higher signal to noise ratio (SNR), the vibration sensors require installation expertise [3-5]. Current signal based IM fault detection is noninvasive to the IM structure and will be used in this work.

A rotor bar could be damaged partially or completely due to excessive thermal stress, or manufacturing defects, or of both. Many research work have been focused on IM broken rotor bar fault detection [6-9]. For example, Kim et al. presented a technique to detect broken rotor bar fault in inverter-fed IMs under standstill condition [10]. Ordaz-Moreno et al. suggested a simplified algorithm to detect broken rotor bar fault online [11]. Ayhan et al. employed the Fourier transform and autoregressive-based spectrum method for IM broken rotor bar detection with low sampling frequency [12]. Haji et al. utilized a Bayes minimum error classifier to detect IM broken rotor bar defect under steady state [13]. Zhang et al. employed the wavelet ridge to detect broken rotor bars from IM starting current [14]. Kim et al. suggested a high resolution parameter estimation method to diagnose motor rotor bar breakage [15]. Soualhi et al. employed artificial ant clustering method to facilitate motor fault detection [16]. Rangel-Magdaleno et al. used mathematical morphology and motor current signature analysis for broken bars detection [17]. Xu et al. utilized estimation of signal parameters via rotational invariance technique and Hilbert method to detect rotor fault at low slip [18]. Nevertheless, the aforementioned techniques only focus on limited fault information, thus their diagnostic performance may not be consistent or robust.

To tackle the aforementioned problems, an intelligent monitoring system (IMS) is developed in this work to integrate the steady state spectral information from the time domain, the transient spectral information from frequency domain and signal statistics information from the time-frequency domain to improve fault diagnostic accuracy. The proposed IMS has the following novel aspects: (1) the prediction information is properly incorporated into fault analysis to improve diagnostic accuracy by reducing the effect of outliers and sudden disturbance; (2) a new diagnostic system is proposed to adaptively integrate the forecasting information and the classification information to further enhance the robustness of IM fault diagnosis.

The remainder of this paper is organized as follows. The proposed IMS is discussed in Section II. The effectiveness of the IMS is demonstrated in Section III via experimental tests of IM fault diagnosis. Some concluding remarks are summarized in Section IV.

II. THE INTELLIGENT MONITORING SYSTEM

The proposed IMS will integrate the classification information from a classifier and the forecasting information from a predictor to provide more positive assessment of IM health conditions. In this section, a brief introduction is given...
firstly to the related technologies.

A. Selective Boosting Classifier

The selective boosting (sBoost) classification [19] is an ensemble of weak classifiers; it incorporates a weak classifier into the ensemble at each step, and each weak classifier addresses the data with the updated distribution. The sBoost will be adopted in the developed IMS for pattern classification. The classification accuracy of the derived ensemble classifier will be improved by properly adjusting the weight of the weak classifier at each step. Furthermore, noisy samples will be adaptively processed using the proposed sample weight regulator to reduce the overfitting problem.

Consider a binary classification problem with training data samples \((s_1, y_1), (s_2, y_2), \ldots, (s_M, y_M)\), where the class label is \(y_i \in \{ -1, 1 \}\) and \(M\) is the number of samples in the training data set. To conduct classification, the first step is to initialize the distribution of training data set \(L_t(i) = 1/M, i = 1, 2, \ldots, M\). At each update step from \(t = 1\) to \(T\) (where \(T\) is the maximum number of weak classifiers), train the weak classifier \(h_t \in \{-1, 1\}\) using training data set with distribution \(L_t\). The weight of the weak classifier \(h_t\) will be defined as

\[
\beta_t = \frac{1}{2} \ln \left( \frac{e_t}{\tau_t} \right)
\]

where

\[
e_t = \sum_{y_i h_t(s_i) = 1} L_t(i) \exp(-\sigma_t(i))
\]

\[
\tau_t = \sum_{y_i h_t(s_i) = -1} L_t(i) \exp(-\sigma_t(i))
\]

Given \(K\) nearest samples of a target sample in the training data set, if \(p\) samples of these \(K\) samples have the same class label as this target sample \((0 \leq p \leq K)\), the noise degree of this sample will be estimated by

\[
\theta_t = 1 - \frac{p}{K}
\]

The proposed sample weight regulator is given by

\[
\sigma_t(i) = \frac{\xi_t(i)}{\max\{\xi_t(i)\}} \beta_t \theta_t
\]

where

\[
\rho_t(x_i) = \frac{y_i \sum_{t=1}^{T} \beta_t h_t(x_i)}{\sum_{t=1}^{T} \beta_t}
\]

\[
\kappa_t(i) = \frac{\exp(\rho_t(x_i))}{\sum_{i=1}^{N} \exp(\rho_t(x_i))}
\]

If the condition \(0 < \tau_t < \epsilon_x < 1\) is not satisfied, \(L_{t+1}(i) = 1/M, i = 1, 2, \ldots, M\); otherwise, update the weights of the training samples

\[
L_{t+1}(i) = \frac{L_t(i) \exp(-\beta_t h_t(s_i) y_i - \sigma_t(i))}{\sum_{i=1}^{M} L_t(i) \exp(-\beta_t h_t(s_i) y_i - \sigma_t(i))}
\]

Given a weak classifier \(h_t\), after \(T\) update epochs, the ensemble classifier will become

\[
H(s_i) = \text{sign} \left[ \sum_{t=1}^{T} \frac{\beta_t}{\sum_{i=1}^{T} \beta_t} h_t(s_i) \right]
\]

with a confidence rate

\[
C(s_i) = \left| \sum_{t=1}^{T} \frac{\beta_t}{\sum_{i=1}^{T} \beta_t} h_t(s_i) \right|
\]

B. The Fault Diagnostic System

The flowchart of the developed fault diagnostic system is illustrated in Figure 1. In feature extraction, appropriate signal processing techniques are used to extract representative features from collected current signals and generate monitoring indices for fault diagnosis. In IM condition monitoring, signal features from different information domains could provide different perspective of the IM health condition. In this work, three features from three information domains: the time domain, the frequency domain, and the time-frequency domain, will be employed for advanced processing.

![Flowchart of the proposed intelligent monitoring system.](image)
Energy: \[ \sum_{i=1}^{N} x_i^2 \] \hspace{1cm} (12)

Skewness: \[ \frac{\sum_{i=1}^{N} (x_i - \bar{x})^3}{(N-1)\sigma_x^3} \] \hspace{1cm} (13)

Kurtosis: \[ \frac{\sum_{i=1}^{N} (x_i - \bar{x})^4}{(N-1)\sigma_x^4} \] \hspace{1cm} (14)

where \( x_i \) are data samples in a data set, \( i = 1, 2, 3, \ldots, N \); and \( N \) is the size of the data set; \( \bar{x} \) and \( \sigma_x \) are the mean and the standard deviation of the data set respectively. The time-domain monitoring index \( z_t \) will be selected from these three indicators based on experimental tests and comparison as illustrated in Section III.

Among the techniques in the frequency domain, the spectrum synch technique [20] proposed by the authors has been demonstrated to outperform other related techniques, and thus will be used as the monitoring index in the frequency domain, and denoted by \( z_f \)

\[ z_f = \chi_x \] \hspace{1cm} (15)

where

\[ \chi_x = \begin{cases} \nu_x^4 / \sigma_x^4 & \text{if } \nu_x > 0 \\ 0 & \text{if } \nu_x \leq 0 \end{cases} \] \hspace{1cm} (16)

The local bands containing the fault frequencies are synchronized to enhance the fault features. \( \nu_x \) is the center frequency and \( \sigma_x \) is the variation of the synchronized band.

Based on the analysis in Introduction, although the resolution of the WT is lower than the WPD analysis in terms of the decomposition at the detail end, it applies compact filter bank implementation and the resulting features are relatively easy to explain. Therefore, the discrete WT will be used to derive the monitoring index in the time-frequency domain. The fundamental frequency component in the stator current signal is firstly suppressed by using an elliptic notch filter to reduce its interference in analysis. Then the discrete WT is employed to extract fault related sub-bands. Consider \( n \) sub-bands, the root-mean-square value of the corresponding decomposed signals will be used as a monitoring index:

\[ z_d = \sqrt{\frac{S_1^2 + S_2^2 + \ldots + S_n^2}{L_1 + L_2 + \ldots + L_n}} \] \hspace{1cm} (16)

where \( S_i \) represent the decomposed signals corresponding to \( n \) sub-bands and \( L_i \) denote the length of \( S_i \), \( i = 1, 2, \ldots, n \).

C. Monitoring Index Prediction

The monitoring index prediction could explore the properties of each monitoring index, and synthesize the corresponding prognostic information into fault diagnosis, in order to reduce the effect of outliers and further improve the diagnostic accuracy. The implementation of the predictor [21] for monitoring index prediction takes the following steps:

1) Generate a series of a monitoring index, for example \( \{ z_o, z_f, z_d \} \), to construct the training data set with size \( N_t \), \( i = 1, 2, \ldots, N_t \).
2) Initialize the distribution of the training data set \( O_t(i) = \frac{1}{N_t} \).
3) Train a predictor (e.g., an AR model) \( r_t \), with the training data set and the distribution \( O_t \) at step \( t \) using least square estimate.
4) Compute the error \( \eta_t = \sum_{i=1}^{N_t} O_t(i) |y_r(i) - q_t(i)| \), where \( y_r \) are the desired values, and \( q_t \) are the predicted values at step \( t \) using the predictor \( r_t \).
5) Calculate the weight of the predictor \( r_t \)

\[ \alpha_t = \frac{1}{2M_t} \ln \left( \frac{M_t + \eta_t}{M_t - \eta_t} \right) \] \hspace{1cm} \text{where } M_t \text{ is the maximum value of } |y_r(i) - q_t(i)|.

6) Update the distribution of the training samples:

\[ O_{t+1}(i) = \frac{Q_t(i) \exp(-\alpha_t |y_r(i) - q_t(i)|)}{\sum_{i=1}^{N_t} Q_t(i) \exp(-\alpha_t |y_r(i) - q_t(i)|)} \]

7) Repeat steps 3) to 6) as \( t = 1, 2, \ldots, T \).
8) The predicted monitoring index, \( \{ z'_o, z'_f, z'_d \} \) in this case, is calculated by

\[ P = \sum_{t=1}^{T} \frac{\alpha_t}{\sum_{i=1}^{T} \alpha_t} q_t \]

D. IMS Diagnostic System

Let \( z_o', z_f', \) and \( z_d' \) be the predicted values of the monitoring indices of \( z_o, z_f, \) and \( z_d \) respectively. \( M_1 \) and \( M_2 \) represent healthy state and damaged state of the IM component (e.g., rotor bar or bearing), respectively. Given the monitoring index vector \( z = \{ z_o, z_f, z_d \} \), and the predicted monitoring index vector \( z' = \{ z_o', z_f', z_d' \} \), the IMS diagnostic system is given as follows:

\[ \text{R}_1: \text{IF } (z \subset M_1) \text{ AND } (z' \subset M_1) \text{ THEN (IM component is healthy)} \] \hspace{1cm} (17)

\[ \text{R}_2: \text{IF } (z \subset M_2) \text{ AND } (z' \subset M_2) \text{ THEN (IM component is damaged)} \] \hspace{1cm} (18)

\[ \text{R}_3: \text{OTHERWISE (IM component is possibly damaged)} \] \hspace{1cm} (19)

If the IM is damaged (\( \text{R}_2 \)), an alarm signal is triggered for repair operations. If the IM is possibly damaged (\( \text{R}_3 \)), the following two rules (operations) will be performed:

\[ \text{R}_4: \text{IF } \text{R}_3 \text{ AND } \frac{H(z)C(z) + H(z')C(z')}{2} < 0 \text{ THEN (IM component is healthy)} \] \hspace{1cm} (20)
where \( H(\cdot) \in [-1, 1] \) indicates a monitoring index vector that belongs to one of the health condition categories (damaged or healthy) of the IM component, which is calculated using Equation (10). \( H(\cdot) = 1 \) indicates the damaged IM state; \( H(\cdot) = -1 \) represents the healthy IM state. \( C(\cdot) \in [0, 1] \) is the confidence rate, which is calculated using Equation (11) to indicate the extent a monitoring index vector belongs to a health condition category. The larger the \( C(\cdot) \) is, the higher the probability that a monitoring index vector belongs to a specific health condition category. For example, \( H(z)C(z) \geq 0 \) indicates the IM component is damaged based on the index vector \( z \) with confidence rate \( C(z) \).

### III. PERFORMANCE EVALUATION AND IM FAULT DIAGNOSIS

#### A. Overview

The effectiveness of the proposed IMS will be evaluated in this section by experimental tests of IM with three broken rotor bars fault diagnosis and IM outer race bearing fault diagnosis. Figure 2 shows the experiment setup employed in the current work. The speed of the tested IM is controlled by a VFD-B AC speed controller (from Delta Electronics) with output frequency 0.1-400Hz. A magnetic particle clutch (PHC-50 from Placid Industries) is used as a dynamometer for external loading. Its torque range is from 1 to 30 lb-ft (1.356-40.675 N·m). The motor used for this research is made by Marathon Electric. The gearbox (Boston Gear 800) is used to adjust the speed ratio of the dynamometer. The current sensors (102-1052-ND) are used to measure different phase currents. A rotary encoder (NSN-1024) is used to measure the shaft speed with the resolution of 1024 pulses per revolution. Stator current signals are collected using a Quanser Q4 data acquisition board, which are then fed to a computer for further processing. The supply frequency was set at 50 Hz and the sampling frequency \( f_s = 10 \, \text{kHz} \).

In the spectrum synch technique, the local bands containing first-order left-side fault harmonic \( f_{br1} \) and first-order right-side fault harmonic \( f_{br1} \) of IM broken rotor bar fault are synchronized to generate the monitoring index \( z_f \) in the frequency domain. In discrete WT, the sub-bands containing \( f_{br1} \) and \( f_{br1} \) are used to generate the monitoring index \( z_f \) in the time-frequency domain.

![Fig. 2. The motor experiment setup: (1) the tested IM, (2) the speed controller, (3) the gearbox, (4) the load system, (5) current sensors, (6) the data acquisition system, (7) the computer.](image-url)
B. IM Bearing Fault Diagnosis

Similar to the analysis of IM rotor bar condition monitoring in the previous subsection, three fault detection techniques (i.e., indices) from different information domains (i.e., the time, frequency, and the time-frequency) are selected for bearing fault diagnostic processing.

The time domain test results are summarized in Table III. It is seen that the skewness of the notch-filtered stator current signal is the most accurate one, which will be utilized as the monitoring index in the time domain, $z_t$. The spectrum synch technique will also be used as the monitoring index in the frequency domain. Based on test analysis, the local bands containing $7^{th}$ to $14^{th}$ IM bearing fault harmonics are synchronized using spectrum synch technique to generate the monitoring index in the frequency domain $z_f$. These fault harmonics are selected because they are less affected by the supply frequency component (50Hz) and have relatively higher peak magnitudes.

Similarly, the discrete WT is employed to extract fault features in the time-frequency domain. By testing analysis, the sub-bands containing $f_{ch}$ and $f_{cr1}$ are selected to generate the monitoring index $z_{tf}$ in the time-frequency domain. $f_{ch} = |p - f_t|$ and $f_{cr1} = |f_p + f_t|$ are two of the first-order fault harmonics; $f_p$ is the supply frequency and $f_t$ is the outer race bearing vibration characteristic frequency.

Figure 4 illustrates the training convergence and test convergence of Methods #4 and #5. It is seen that the training error effectively converge to zero; the test error converges as the number of base learners increases.

![Figure 3. Convergence comparison using Method #4 (blue solid line) and Method #5 (red dotted line) in IM broken rotor bar fault diagnosis: (a) training error and (b) test error.](image)

![Figure 4. Convergence comparison of Method #4 (blue solid line) and Method #5 (red dotted line) in IM outer race bearing fault diagnosis: (a) training error and (b) test error.](image)

<table>
<thead>
<tr>
<th>Diagnostic Scheme</th>
<th>False Alarms</th>
<th>Missed Alarms</th>
<th>Overall Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method #1</td>
<td>28</td>
<td>34</td>
<td>79.3%</td>
</tr>
<tr>
<td>Method #2</td>
<td>12</td>
<td>35</td>
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<tr>
<td>Method #3</td>
<td>21</td>
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<tr>
<td>Method #4</td>
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<tr>
<td>Method #5</td>
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<tr>
<td>Method #6</td>
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<td>99.0%</td>
</tr>
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<table>
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<tr>
<th>Diagnostic Indices</th>
<th>False Alarms</th>
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<td>Skewness</td>
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<td>Kurtosis</td>
<td>49</td>
<td>50</td>
<td>67.0%</td>
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</table>
The test results using these six methods are summarized in Table IV. It is seen that Methods #4 and #5 diagnose IM bearing defect more accurately than Methods #1 to #3, because the intelligence information is more sensitive to the IM health states. The proposed sample weight regulator in the sBoost classifier can adaptively resolve reasoning conflicts (i.e., noise samples) and improve diagnostic accuracy. The developed IMS (i.e., Method #6) outperforms Methods #4 and #5 due to its effective integration of the information from both the classifier and the predictor.

<table>
<thead>
<tr>
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<th>Missed Alarms</th>
<th>Overall Accuracy</th>
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<tbody>
<tr>
<td>Method #1</td>
<td>51</td>
<td>19</td>
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<tr>
<td>Method #2</td>
<td>25</td>
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<tr>
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</tr>
<tr>
<td>Method #5</td>
<td>7</td>
<td>3</td>
<td>96.7%</td>
</tr>
<tr>
<td>Method #6</td>
<td>0</td>
<td>0</td>
<td>100%</td>
</tr>
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</table>

IV. CONCLUSION

An intelligent monitoring system, IMS, has been developed in this work to synthesize the information from both classifier and predictor for IM health condition monitoring. The sBoost technique adaptively classifies IM health states and assigns each sample diagnosis a confidence rate for further analysis. In the proposed IMS, a confidence-rate-based diagnostic system has been proposed to address uncertain IM fault diagnostic decisions, in order to improve the accuracy of fault diagnosis. The effectiveness of the developed IMS has been verified by experiment tests corresponding to the common IM faults (e.g., broken rotor bars and bearing outer race defects) under different load conditions (i.e., light-load, medium-load and heavy-load). The test results have demonstrated that the proposed IMS is a reliable IM fault diagnosis tool, and it could provide a more accurate assessment of IM health conditions.

ACKNOWLEDGEMENT

This work is supported in part by the Natural Sciences and Engineering Research Council of Canada (NSERC) and eMech Systems Inc.

REFERENCES


