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Research Article

An approach for automated fault diagnosis based on a fuzzy decision tree and boundary analysis of a reconstructed phase space

Ilhan Aydin *, Mehmet Karakose, Erhan Akin

Computer Engineering Department, Firat University, 23119 Elazig, Turkey

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ABSTRACT

Although reconstructed phase space is one of the most powerful methods for analyzing a time series, it can fail in fault diagnosis of an induction motor when the appropriate pre-processing is not performed. Therefore, boundary analysis based a new feature extraction method in phase space is proposed for diagnosis of induction motor faults. The proposed approach requires the measurement of one phase current signal to construct the phase space representation. Each phase space is converted into an image, and the boundary of each image is extracted by a boundary detection algorithm. A fuzzy decision tree has been designed to detect broken rotor bars and broken connector faults. The results indicate that the proposed approach has a higher recognition rate than other methods on the same dataset.

1. Introduction

Condition monitoring of critical components plays an important role in current manufacturing equipment. A fault occurring in a critical component disrupts the process, causes costly machinery repair, and extends the process down time. Induction motors constitute a large part of the industrial workhorse [1]. These motors are reliable but they may be exposed to faults because of dusty and moist environments [2]. Induction motor faults are related to three main components: the stator, the rotor, and the bearings [3]. Broken rotor bars and broken connectors are the most common rotor-related faults. These faults affect the induction motors, and the symptoms cannot be observed in the current signals because the operation of the motor is similar to the normal motor condition.

Fault detection of induction motors can be separated into two approaches. The first one is based on a mathematical model of the motor. However, it is hard to obtain a model of motor with a sufficiently high precision [4]. In addition, some assumptions will be made in the model. A nonlinear Kalman filter-based technique was proposed to detect broken rotor bar faults [5]. A model-based fault detection scheme was established to monitor rotor resistance. The estimated rotor resistance was compared to its nominal value to detect broken rotor bar faults. The second approach uses signal processing-based methods. Signal processing-based condition monitoring techniques utilize specific signals from such easily-measured electrical or mechanical quantities as current, flux, voltage, speed, and torque. Among these signals, the motor phase currents and vibration signals can be obtained most easily and they have been used for the detection of stator, rotor and bearing faults [6,7]. Motor current signature analysis (MCSA) is the most widely used method to detect various motor faults [8–10]. The MCSA-based method was applied to three phase current signals to detect the stator winding condition [10]. The effect of a voltage unbalance was reduced using a three-phase current spectrum. However, this method fails to detect broken rotor bar faults when the motor is operating under a no-load condition. To overcome this problem, discrete wavelet transform and higher order spectra were proposed to detect broken rotor bars where the motor is in an unloaded condition [11,12]. The Hilbert transform was used to process the current signal and extract a signature related to a broken rotor bar fault under a no-load condition [13]. In industrial systems, nonlinear time series analysis and phase space reconstruction are used to detect the faults of different systems. Broken rotor bar faults were detected using a nonlinear time series analysis [14–16]. A phase space is a technique of time series analysis used to represent the dynamics of a signal in at least a two-dimensional space. However, a distribution model should be constituted to separate the healthy and faulty conditions. Intelligent methods were integrated with signal processing methods for automating fault diagnosis. Recently, fuzzy logic [17], neural networks [18], support vector machines [19–21], and artificial immune systems [4,22,23] are popular techniques used

* Corresponding author. Tel.: +90 424 237 00 00-6308; fax: +90 424 241 55 26.
E-mail addresses: iaydin@firat.edu.tr (I. Aydin), mkarakose@firat.edu.tr (M. Karakose), eakin@firat.edu.tr (E. Akin).

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a

Algorithm: Mutual information

Min_MI>>1// Threshold value
for $\tau = 1 : \max_\tau$

$$M(\tau) = \sum_{x_n, x_{n+\tau}} P(x_n, x_{n+\tau}) \log\left(\frac{P(x_n, x_{n+\tau})}{P(x_n)P(x_{n+\tau})}\right)$$

if $M(\tau)$<min_MI **then**
min_MI= $M(\tau)$
else
break
endif
endfor

b

Algorithm: False nearest-neighbor algorithm

$X_t = (x_{t+(d-1)\tau}, x_{t+(d-2)\tau}, \ldots x_t)$
for d=1:M
for i=1: $N-1-m\tau$
Find $X_d^{NN}(j)$

$$a(i,d) = \frac{\| x_{d+1}(i) - x_{d+1}^{NN}(j) \|}{\| x_d(i) - x_d^{NN}(j) \|}$$

endfor

$$E(d) = \frac{1}{N-d\tau} \sum_{i=0}^{N-1-d\tau} a(i,d)$$

if d>=2 **then**
E_1(d-1)=E(d)/E(d-1)
endif
if d>=3 **then**
if $\|E_1(d-1)-E_1(d-2)\| < d_0$ **then**
break //embedding dimension is d-1
endif
endif
endfor

Fig. 1. Two algorithms for time delay and embedding dimension (a) Mutual information (b) False nearest neighbor algorithm.

in fault detection problems for induction motors. An intelligent system learns features generated in the preprocessing stage via a signal processing method and uses them with an online signature to identify the fault type.

This paper proposes a new fault diagnosis scheme for induction motor faults based on a boundary analysis for feature extraction and a fuzzy decision tree (FDT) for classification. The proposed method reduces the number of points examined in phase space for fault diagnosis. The method constructs a characteristic image of each phase space for detecting faults in induction motors. The fault-related features are used to construct the binary decision tree and fuzzy classification rules are obtained. A FDT-based diagnosis scheme selects the optimal feature set. The selected optimal set improves the learning speed and classifies overlapping faulty and healthy patterns accurately. The approach is compared with Gaussian Mixture Models (GMMs) to evaluate different preprocessing methods [16]. We apply phase space analysis, as presented in [16], to compare to the diagnostic ability reported previously. The GMMs, Artificial Neural Networks (ANNs), Binary Decision Tree (BDT), Genetic Algorithm based Negative Selection Algorithm (GA_NSA) [22], and Artificial Immune Classifier with Swarm Learning (AICSL) [23] were also tested with the same training and test datasets.

a

Algorithm: Pseudo code of left boundary detection

function boundary_detection(I,M,N)
I← Original image
BI← Boundary image
M, N← Number of rows and columns
BI← ones(M,N)*255
For i=1:M
for j=1:N
if I(i,j)==0 then
B(i,j)=0;
break;
endif
endfor
endfor

b

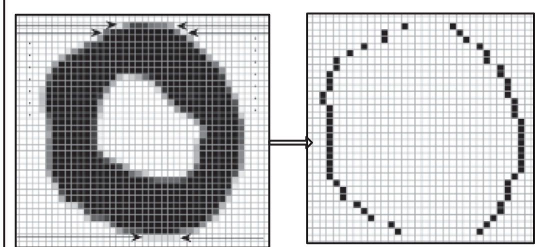

Fig. 2. Boundary detection based feature extraction (a) Boundary detection (b) Illustration of boundary detection.

The organization of the paper is as follows. Section 2 defines the extracted feature and phase space reconstruction. Section 3 describes the image composition of phase space and boundary analysis. Section 4 explains the fuzzy decision tree-based approach for pattern recognition. Section 5 provides experimental results of the proposed system. Section 6 presents the paper's conclusions.

2. Feature extraction and phase space reconstruction

The first step of the proposed approach is to extract the feature signal from one phase current signal. The feature signal is obtained by applying the Hilbert transform to the current signal. The Hilbert transform is used to extract the local features of a signal. It is a convolution between the original signal $i(t)$ and $1/\pi t$, as shown in (1).

$$H(i(t)) = h(t) = 1/\pi t \times I(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{1}$$

When the Cauchy principal value is taken at $t=\tau$, a new signal called the analytic signal is created. The analytic signal is given in (2).

$$AS(i) = i(t) + jh(t) = a(t)e^{j\theta(t)} \tag{2}$$

In (2), the analytic signal returns a complex sequence from a real data sequence [24]. The analytic signal has a real part, $i(t)$, which is the original data and an imaginary part, $h(t)$, which contains the Hilbert transform. The parameters of $a(t)$ and $\theta(t)$are the instantaneous amplitude and the phase of $AS(i)$, respectively. These parameters can be computed as follows.

$$a(t) = \sqrt{i^2(t) + h^2(t)}, \ \theta(t) = \arctan(h(t)/i(t)) \tag{3}$$

We utilize the Hilbert transform and the analytic signal to extract the feature signal from one phase motor current. After the Hilbert transform is applied to the original signal, the envelope of