Electric Motor Fault Detection Using Fusion of Acoustic Signal Features

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ABSTRACT

Non-destructive fault detection of industrial induction motors and their gearboxes is widely required. Faults may be shorted coils of the auxiliary or primary winding, broken rotor bar, and looseness between two gears of the gearbox. In this respect, statistical, spectrum, Shannon Entropy, and wavelet decomposition features of the signals are computed. The fusion of features is applied to enhance the classification performance, and the Principle component analysis (PCA) technique is employed to remove the redundancy among features and compact them. The test results indicate that the wavelet features are work relatively well. However, the best and reliable outcomes are obtained where the fusion of spectrum and wavelet features is utilized, leading to 100% accuracy.

Keywords: Fault Diagnosis, Acoustic Signal, Single phase motor, Fast Fourier Transform, Wavelet, ANN.

1 INTRODUCTION

An electric rotating motor's performance degrades due to heat, moisture, and operation time. Early fault detection prevents accidents, financial loss, and unscheduled downtimes. In this respect, automatic fault diagnosis has gained much attention to guarantee the safe operations of machines. It can be carried out by analyzing its vibration [1], acoustic [2], thermal image, electric current [3], and magnetic field [4].

Fault detection based on the acoustic signal has its own advantages and disadvantages. In practice, acoustic signals of motors are mixed up by the other sounds such as the environmental noise and voices, reflected signals, signals of different devices, and making the fault detection process challenging. The capacitor microphone is less efficient than the vibration sensors and thermal cameras. So, the acoustic signal is more inferior than the vibration signal and thermal image, and it isn't straightforward to extract its characteristic features. But, it is easy to implement, low cost, capable of revealing both electrical and mechanical faults and is a non-invasive approach [5].

A hybrid ensemble empirical mode decomposition and the sample entropy of acoustic signal for fault diagnosis have been analyzed in [6]. Diagnosis of stator faults of a single-phase induction motor using acoustic signals has been presented in [5]. Acoustic emission-based condition monitoring was described in [7]. In [8], automatic bearing fault localization using vibration and acoustic signals was analyzed. An approach for surface roughness diagnosis in hard turning using acoustic signals has been discussed in [9]. Identification and monitoring of noise sources of CNC machine tools by acoustic holography methods have also been presented in [4]. In [10], extraction of faulty components from abnormal sound in diesel engines using acoustic signals is described. Analysis of acoustic emission signal for bearing fault detection was also presented in [11].

In this paper, signals from a set of electrical and mechanical faults are collected; and the classification potential of algorithms is assessed. Statistical features, the signal spectrum, their wavelet decomposition, and nonlinear Shannon entropy features are among them. The method features alone and fusion of them are incorporated. The results indicate that the fusion of the spectrum and wavelet decomposition is well suited for accurate detection and classification of the understudy faults.

The paper is organized as follows. In section 2, the feature extraction and classier methods used in this work have been briefly introduced. Analysis of acoustic signals and proposed approach for fault diagnosis is presented in Section 3. Finally, the conclusion comes in section 4.

2 Fault detection

Generally, there are two categories of fault detection methods: model-based and signal-based. In cases that an approximate mathematical model of the system is provided, the model-based method works well [12, 13]. In others, the

remaining choice is the signal-based approach [14-16]. Original time-domain signals in simple cases may be adequate for fault detection and classification, but in complicated situations often leads to poor decision making. Therefore, it is necessary that the appropriate feature of the time domain signal, which is, of course, problem-dependent to be extracted and the features then used for decision making. Hence, signal-based fault detection is composed of feature extraction and classification algorithms briefly described in the sequel.

2.1 Signal Features

There are various algorithms for feature extraction. The choice of algorithm is always problem-dependent. Several of them used in this work are briefly described here.

Statistical features

The most used statical features in various fields, including engineering, are mean, standard deviation, root mean square, skewness, and kurtosis, which have been defined in (1) [17].

$$mean = \mu = \frac{1}{N}\sum_{n=1}^{N} x_n \qquad Standard\ dev. = \sigma = \sqrt{\frac{\sum_{n=1}^{N}(x_n-\mu)^2}{N-1}},$$
$$Skewness = \frac{1}{N}\frac{\sum_{n=1}^{N}(x_n-\mu)^3}{\sigma^3} \qquad Kurtosis\frac{1}{N}\frac{\sum_{n=1}^{N}(x_n-\mu)^4}{\sigma^4} \tag{1}$$

where x_n (n=1, 2,… ,N) is the observed samples of the signal and N is the number of the samples.

Frequency domain features

The frequency-domain features are calculated by taking the fast Fourier transform of the signal samples [11].

$$X(k) = \sum_{n=0}^{N} x(n)e^{-j\frac{2\pi kn}{N}}, \qquad k = 0,\ldots,N-1 \tag{2}$$

where n and k are the time and frequency indices, respectively. Often the power of specific frequency bands is calculated and regarded as the signal feature.

(Discrete) wavelet transform

The wavelet transforms is a methodology to obtain both time and frequency resolutions simultaneously. The complementary filter concept applies the DWT method, wherein each step there is a highpass and its complementary low-pass filters. The output of the highpass filter is saved as (d_1) and the low pass filter signal (a_1). a_1 signal is again partitioned by another high pass filter for d_2 to be reserved and low pass output a_2. a_2 again may experience another level of decomposition to the extend of the required level. Thus, by the wavelet, x(t) is decomposed to several signals belonging to some specific frequency band expressed by,

$$x(t) = A_J + \sum_{k=1}^{J} D_k \tag{3}$$

where a_J and d_k represent the approximation and the detail coefficients of the Jth level [2].

Nonlinear features

One of the time-domain features of signals which may be helpful is the Shannon Entropy given by [18]:

$$H(X) = \sum_{i=1}^{N} x_i \log_2 \frac{1}{x_i}$$

Where X is random variables; X=[x_1, x_2,…, x_N] is the probabilistic set of X;

2.2 Fusion and compression of features

Fusion of features

Typically, one data source (e.g., an acoustic or vibration sensor) is used for condition monitoring and fault diagnosis. However, it is shown that by fusion of information, more accurate results and better decisions are made. Examples of it are robotic, navigation, and condition monitoring [19].

Data fusion may be conducted at data, feature, and decision levels. In the data level fusion, the data must be from similar sources, and it is its main limitation. In feature level fusion, the previous shortcoming is bypassed, and the signal features are then collectively introduced to the classifier. In the decision level fusion, the features undergo their own classifier, and the results are analyzed for final decision making.

There are various feature fusion methods, including the traditional concatenation, the summation, the product, the maximum, and the weighting fusion methods. In the concatenation method, the augmented vector of features is formed.

PCA: Feature compression

Feeding classifiers with redundant (similar) information disrupts the system performance and adds useless cost to the computation burden. Therefore, it is required that independent features are isolates and the rest put aside. This becomes more prominent where the fusion of information in the form of concatenation is used. By feature compression using the Principle Component Analysis (PCA) technique, the concern is obviated. Singular value decomposition (SVD) and eigenvalue decomposition (EVD) are popular algorithms for performing PCA. The EVD steps for x with M features by N samples is as follows [20],

$$\overline{x}_j = \frac{1}{N}\sum_{n=1}^{N} x_{jn}, \qquad \delta_{jn} = x_{jn} - \overline{x}_j, \quad C = \frac{1}{N-1}\delta\delta^T$$

where M by M dimension C matrix is the covariance of δ, the by row by row mean removed x. Then the eigenvalues (λ) and their corresponding eigenvectors (u) of C are calculated. The eigenvalues are sorted in a reduced order, and the largest K of them and their corresponding eigenvectors ũ are picked. Now the reduced-order feature vector is obtained as below

$$\tilde{\delta} = \tilde{u}'^{*}\delta$$

which is an N by K<M matrix.

2.3 Classifiers

Artificial Neural Network

The architecture of an ANN usually consists of three parts, an input layer, one or more hidden layers, and an output layer. Each layer may have various numbers of neurons. ANN serves as a black box module that can identify unknown systems or classify their inputs.

The output of ANN with one hidden layer is constructed as below,

$$o = f_o\left(\sum_{j=1}^{P} w_j f_j\left(\sum_{n=1}^{N} w_{nj} x_n + b_j\right)\right)$$

where x_n, f_*, w_*, P, b, and N are the input samples, certain activation functions, network weights, the number of hidden layer nodes, bias, and the number of samples. The activation function such as hard limit (hardlim), logarithmic sigmoid (logsig), linear (purelin), symmetric sigmoid (tansig) transfer is often employed.

In the training process, the error is minimized by modifying the network weights and biases. Afterward, the trained ANN can be used for predicting the outputs for the inputs that have not been introduced in the training process.

K Nearest Neighbor

In statistics, the k-nearest neighbor algorithm (k-NN) is a non-parametric classification method that collects together neighboring inputs in a group. Its typical distance metric for continuous variables is Euclidean distance. The best choice of k (number of clusters) is data-dependent; generally, its large values reduce the effect of noise on the classification but make boundaries between classes less distinct. A heuristic technique can assign a good choice of k.

3 RESULTs and discussion

The test rig consists of a single-phase motor (MORISON, 1~, 0.25 HP) coupled to a gearbox with two gears in this study. The whole set is mounted on a steel table supported by two anti-slip clamps, as it is shown in Fig. 1.

The six test states are healthy and five faulty conditions listed below,

1	Motor: Healthy
2	Motor: shorted coils of the auxiliary winding
3	Motor: shorted coils main winding

4	Motor: shorted coils of auxiliary winding and main winding
5	Motor: broken rotor bar
6	Gearbox: looseness of gears

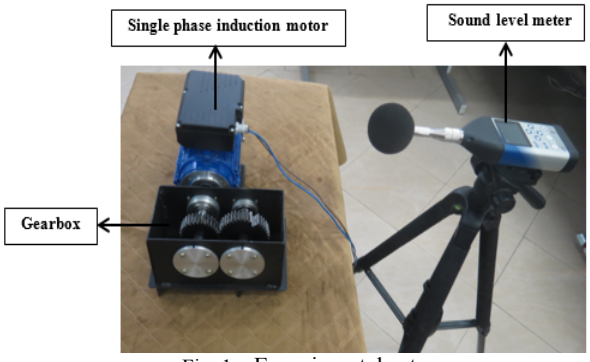

Fig. 1. Experimental setup.

An SVANTEK sound meter is used for acoustic signal recording. The test is carried out in a room of 5×6 meters. For each scenario, a 120s signal was recorded with WAV format and sampling frequency of 48kHz. The signals are then converted to high-quality mp3 format. To increase the number of training samples, the 120second length data are partitioned into 1second intervals. An example of them has been exhibited in Fig. 2.

From the set of signals, 4 statistical features (μ, σ, Skewness, Kurtosis) are computed for each 1s sample of every 6 states.

To extract the frequency domain feature of the signals, the FFT algorithm is applied. The signal spectrum of one of the 1s samples of the 6 states has been shown in Fig. 3. From the spectrum, three of the peak locations are extracted as the signal features.

The third set of features are calculated using wavelet transform. The type Daubechies 10 mother wavelet is used for processing the acoustic signals as it is widely used for fault diagnosis of mechanical systems [21]. The acoustic signals are decomposed into 4rd level wavelet components using wavelet packet decomposition. One of its samples for the healthy condition has been shown in Fig. 4. The normalized energies of d_1 to d_4 and a_4 are used as the fault features from the decomposition.

The final feature is theShannon entropy feature which has been calculated for the set of signals.

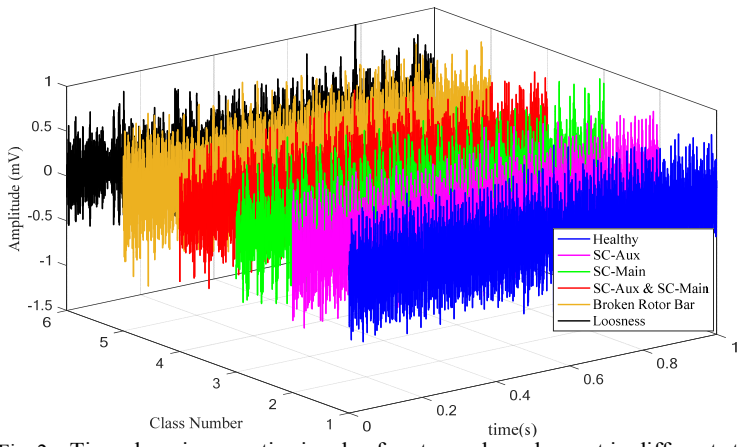

Fig. 2. Time-domain acoustic signals of motor and gearbox set in different states.

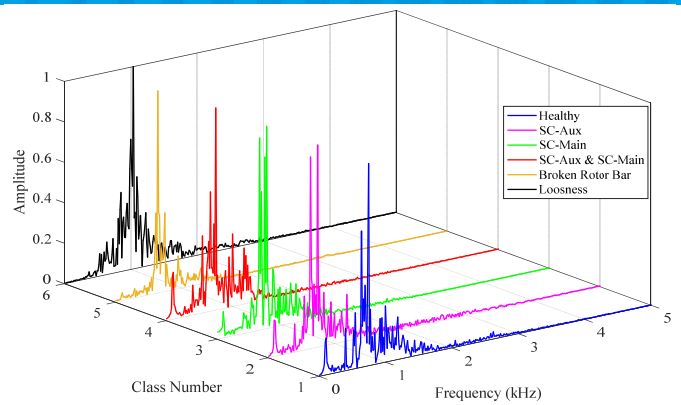

Fig. 3. The spectrum of one 1sec sample of the states.

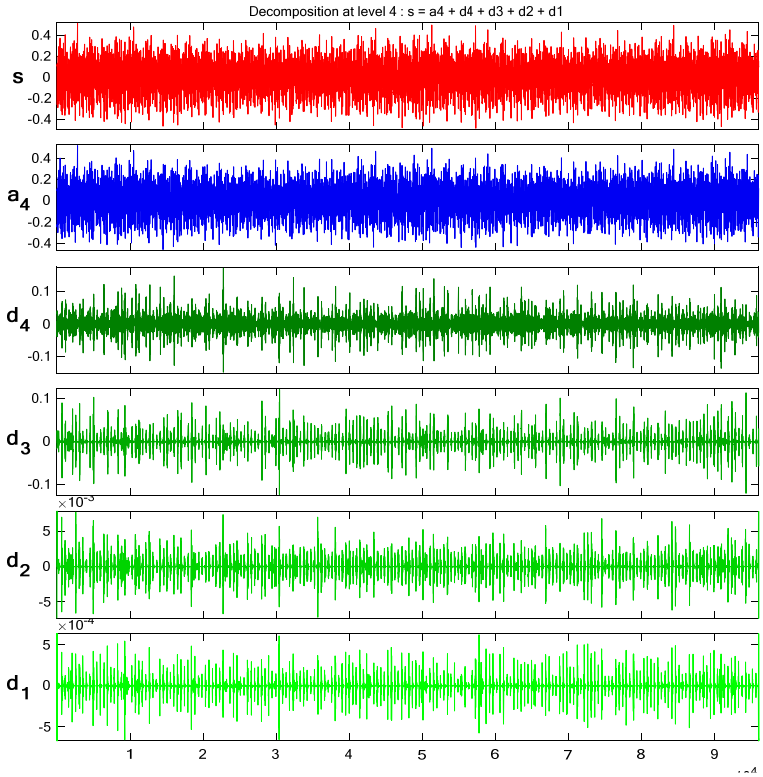

Fig. 4. Wavelet decomposition of acoustic signals in the healthy state.

The extracted features are used as inputs to an artificial neural network for the classification of the 6 states: healthy and five faulty states. In this respect, the following tests are conducted.

Test1: 4 statistical features

- Features: mean, standard deviation, skewness, and kurtosis of the signals.
- Feature compression: PCA
- Classifier: Artificial Neural Network

The results obtained and the accuracy of the classification have been reported in The Test results. The accuracy of the classification is 74% that can be considered inferior.

Test2: 3 spectrum features

- Features: Location of 3 peaks of the spectrum.
- Feature compression: PCA
- Classifier: Artificial Neural Network

The 96.5 % accuracy of this method is notable.

Test 3: 5 wavelet features

- Features: Normalized energy of five bands of wavelet decomposition
- Feature selection: PCA
- Classifier: Artificial Neural Network

The results obtained and the accuracy of the classification have been reported in The Test results. The 99.8% accuracy is excellent.

Test 4: 4 fusion of Shannon entropy and spectrum features

- Features: statistical and spectrum features
- Feature selection: PCA
- Classifier: Artificial Neural Network

The accuracy is 99.2% which is not as good as Test3.

Test 5: 9 fusion statistical and wavelet features

- Features: statistical and wavelet features
- Feature selection: PCA
- Classifier: Artificial Neural Network

The accuracy is 99.8% which is comparable with test 3 using fewer features.

Test 6: 8 fusion of spectrum and wavelet features

- Features: spectrum and wavelet decomposition features
- Feature selection: PCA
- Classifier: Artificial Neural Network

Test 7: 12 fusion of statistical, spectrum, and wavelet features

- Features: statistical, spectrum, and wavelet decomposition features
- Feature selection: PCA
- Classification: Artificial Neural Network

The results obtained and the accuracy of Test 6 and 7 classification approaches are perfect as listed in The Test results.

TABLE I. The Test results

Class of Faulty state							
	1	2	3	4	5	6	Accuracy (%)
Test 1	93.7	95.5	37.8	43.2	100	100	78.4
Test 2	100	97.3	98.2	83.8	100	100	96.5
Test 3	100	100	99.1	100	100	100	99.8
Test 4	100	100	95.5	100	100	100	99.2
Test 5	100	100	99.1	100	100	100	99.8
Test 6	100	100	100	100	100	100	100
Test 7	100	100	100	100	100	100	100

4 Conclusion

This paper investigates the detection and classification of induction motors and their gearbox faults. The acoustic signals of the setup are captured during the operations in six states: healthy, shorted coils of auxiliary winding, shorted coils of primary winding, broken rotor bar, and gearbox looseness. Statistical, spectrum, and wavelet features of the signals are calculated, and feature compressing is pursued using PCA. The classifier is an ANN. Among the features, the wavelet ones render alone the best, 99.8% accuracy; however, by the fusion of wavelet and spectrum features, perfect 100% accuracy is achieved. Results indicate that the proposed methodology performs successfully in detecting and classifying all of the understudy faults.

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