Induction Motor Bearing Fault Detection based on Ica and Ann

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ABSTRACT
Independent component analysis (ICA) is one of the robust methods to extract the features. Many researchers have indicated a great potential for this approach to analyze the signals using ICA to detect the similarity or non-similarity between two signals. We have proposed a novel method which is extension of ICA to detect the faults associated with any machine by collecting vibration signals of machine. This paper presents the details of this method. The classification of the faults, if detected, is carried out using suitable classification technique.

General Terms
Induction motor, ICA Algorithm, Fourier Transform, Blind Source Separation Techniques.

Keywords
Independent Component Analysis (ICA), Fast Fourier Transform (FFT), Classifier.

1. INTRODUCTION
Induction motors play a significant role as essential power in transportation, production and manufacturing industries due to their robust design, simplicity in construction and relatively low cost. The performance of induction motors is closely related to guarantee its health operational condition. Although the robustness and reliability of induction motors is relatively high, some unforeseen faults are unavoidable. If they are badly damaged, problems such as rotor bar failures, stator winding failures and bearing failure will occur. The unexpected failure of induction motors will lead to catastrophic consequences in case of marine vessel, transportation vehicles and other situations.

Previous research developed varieties of methods to detect and diagnose motors fault on vibration signal, including the Fourier spectrum, wavelet package, and the Kullback index of complexity, pseudo-phase diagrams, singular spectrum analysis, and fuzzy logic classification techniques, neural networks, [1]. These methods can be classified into time domain, frequency domain, time-frequency domain, higher-order spectra analysis, neural-network, and model-based techniques [2]. ICA is one of the promising method to extract the features which can be further used to detect the fault.

In the development work of this paper, the time domain vibration signals generated by the laboratory induction motor (both good and faulty) are collected from CWRU database [3]. These are converted into frequency domain using Fast Fourier Transform (FFT) and then to removed low amplitude frequency components. The spectral features of a good as well as faulty induction motor are extracted using ICA. ICA algorithm selects the signatures from high dimensional space into underlying informational components. These are further used to detect and classify the faults using a classifier to determine the health condition of the induction motor. The flow of the method implemented to carry out this task is as shown in the Fig. 1.

PROPOSED SYSTEM

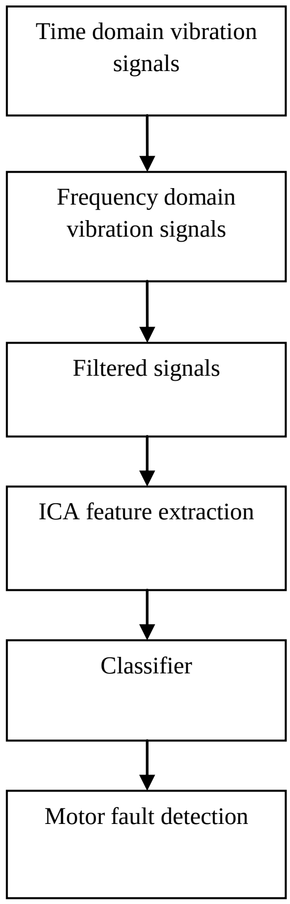

Fig 1: Proposed motor fault detection and diagnosis scheme

2. INDEPENDENT COMPONENT ANALYSIS ALGORITHM
Independent Component Analysis (ICA) [4] belongs to a blind source separation algorithm, which transforms the high dimensional features into underlying components with rich information contents. The basic condition of ICA is that these components are independent in complete statistical sense and have non-Gaussian distributions.

2.1 Data Preprocessing for ICA

Preprocessing steps needed to apply on vibration signals for better performance of ICA algorithm. Time domain induction motor vibration signals collected from laboratory are as shown in Fig. 2 and Fig. 3.

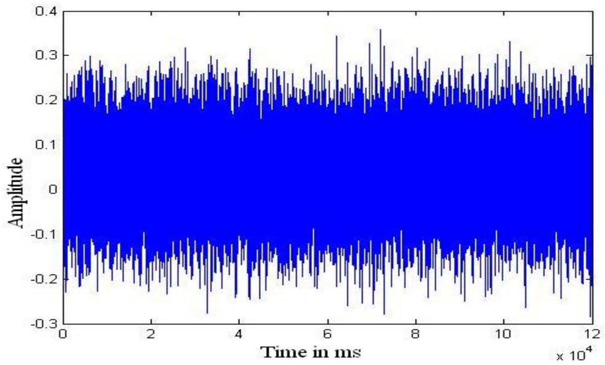

Fig. 2: Normal condition motor vibration signal in time domain

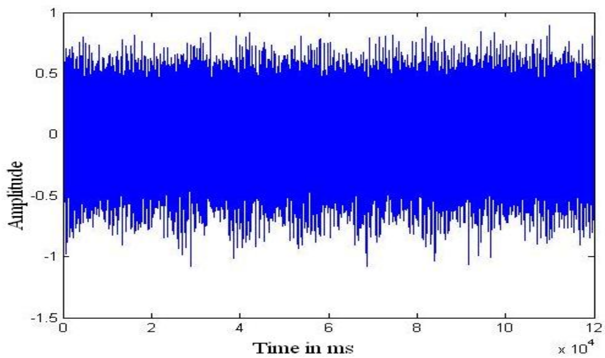

Fig. 3: Faulty condition motor vibration signal in time domain

2.1.1 Conversion of Time Domain Signal into Frequency Domain

First step in preprocessing is to convert time domain signal into frequency domain for further processing as shown in Fig. 4 and Fig. 5.

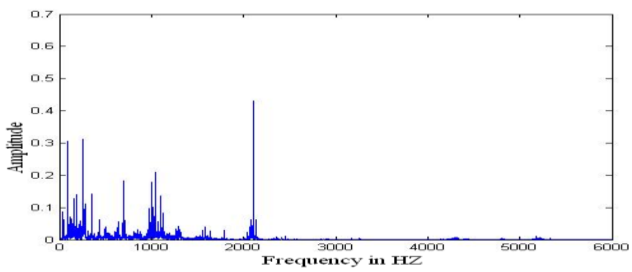

Fig. 4: Normal condition motor vibration signal in frequency domain

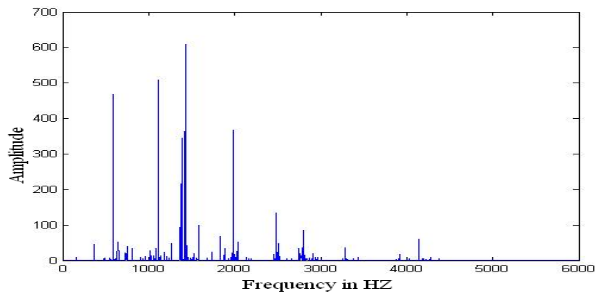

Fig. 5: Faulty condition motor vibration signal in frequency domain

2.1.2 Normalizing

The second step in preprocessing is the Normalization, which changes the amplitude range of raw signals values. This process normalizes the signals to have common maximum amplitude, but does not change the relative magnitudes of these signals. The frequency domain signal from the above step after normalization is as shown in Fig. 6 and Fig. 7 respectively.

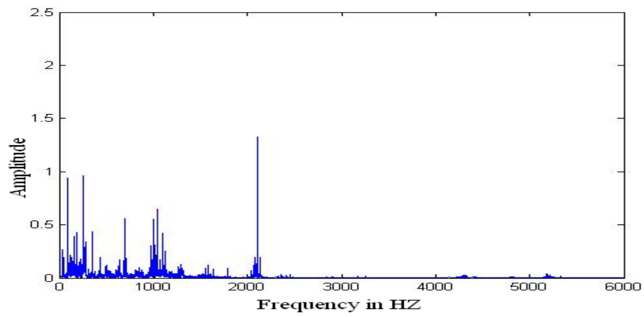

Fig. 6: Normalized normal condition motor vibration signal in frequency domain

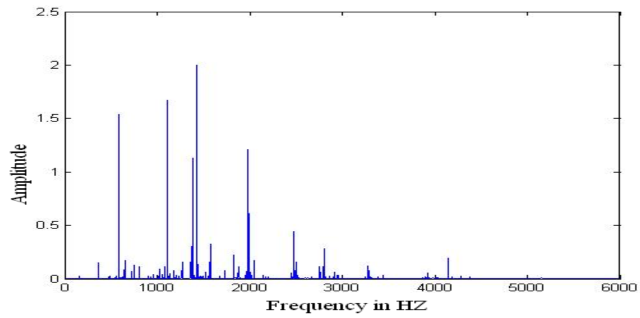

Fig. 7: Normalized faulty condition motor vibration signal in frequency domain

2.1.3 Removing Low Amplitude Frequency Components

The study of frequency spectrum of vibration signals from a good and faulty induction motor revealed that the spectrum of vibration signals of a normal and faulty induction motor contains low amplitude frequency components.

Hence, next step in preprocessing of data for ICA was to remove the low amplitude frequency components using thresholding of 0.1, keeping only the high amplitude frequency components above 0.1 amplitude values as shown in Fig 8 and Fig. 9.

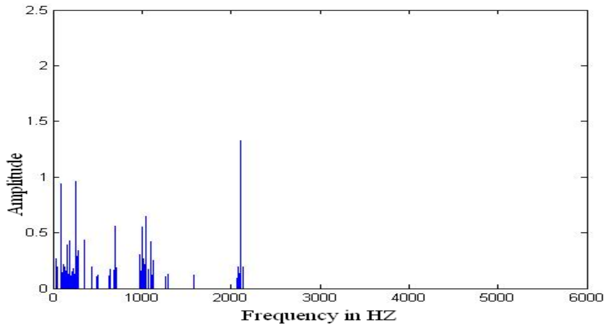

Fig. 8: Normal condition motor vibration signal in frequency domain after removing low amplitude frequency components

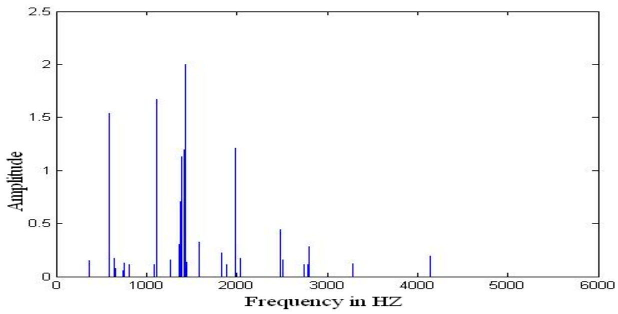

Fig. 9: Faulty condition motor vibration signal in frequency domain after removing low amplitude frequency components

2.1.4 Centering

Centering is the next step in pre-processing where the input signatures are transformed to zero-mean variable. This results into all independent components having zero means. This processing involves subtracting mean (E{x}) from the observed variable x.

2.1.5 Whitening

Whitening is the next preprocessing algorithm in ICA to de-noise the measured data vector x by linearly transforming it into a new Vector x_w, where all its components are mutually uncorrelated and have equal unity variance. The purpose of whitening is to simplify the procedure of ICA by reducing the dimension of parameters, which are estimated after whitening. Furthermore, this preprocessing not only reduces the complexity of ICA, but also avoids over-learning in ICA.

2.2 ICA Algorithm Model

Details of ICA algorithm are as follow[5]:

Assume that there are n linear mixtures, $x_1(t)$, x_2 (t),… x_n (t) measured by n transducers and n independent source signals $s_1(t)$, s_2 (t) , …, s_n (t) . Then each linear mixture can be expressed as,

$$X=AS \quad (1)$$

Generally, these independent source components are latent variables and cannot be measured directly. Therefore, only the vector X is observed, and both the matrix A and the vector S are estimated through X. If the matrix A and the vector X are available, the inverse of A, namely W and the vector S can be computed by,

$$W=A^{-1} \quad (2)$$

$$S=WX \quad (3)$$

FastICA is an efficient and robust method for independent component analysis. The algorithm is based on a fixed-point and iteratively maximizes non Gaussianity to measure the statistical independence. This algorithm, also can be called as "approximated negentropy", is a quantitative measure of non Gaussianity. Negentropy is defined as:

$$J(y) = [E\{G(y)\}-E\{G(v)\}]^2 \quad (4)$$

Here, G is any non-quadratic function, and v is Gaussian variable, which is zero mean and unit variance.

2.2.1 ICA Steps

1) Choose an initial (e.g. random) weight vector W having $||W|| =1$.
2) $W^+=E\{Xg(W^TX)\}- E\{Xg^{'}(W^TX)\}W$.
3) $W=W^+/ ||W^+||$.
4) If not converged, go back to 2.

2.2.2 A Novel Method of Feature Extraction using ICA

The aim of feature extraction generally is dimensionality reduction without loss of the important information in the observed signal. A novel approach of feature extraction using ICA algorithm has been proposed by us and can be used to obtain statistically independent components before feature extraction. The concept behind this novel approach can be implemented in following two steps.

Step 1: Divide observed signal of 12000 time slots into 4 equal parts with 3000 time slots in each part as below,

$$\mathbf{X}_{(1\times12000)} = X_{1(1\times3000)} +X_{2(1\times3000)} +X_{3(1\times3000)} +X_{4(1\times3000)} \quad (5)$$

By ICA model and Eq. (1), X can also be written as

$$\mathbf{X} = a_1s_1+a_2s_2+a_3s_3+a_4s_4 \quad (6)$$

where,

s_1, s_2, s_3, s_4 are Independent Components and a_1, a_2, a_3, a_4 are mixing matrices.

Step 2: Obtain the feature vectors by linearly transforming the measured signals into independent components as below.

$$\begin{aligned}
\mathbf{F}_{\mathbf{1}(1\times4)} &= X_{1(1\times3000)} \cdot (IC_1\ IC_2\ IC_3\ IC_4)_{(3000\times4)} \\
\mathbf{F}_{\mathbf{2}(1\times4)} &= X_{2(1\times3000)} \cdot (IC_1\ IC_2\ IC_3\ IC_4)_{(3000\times4)} \\
\mathbf{F}_{\mathbf{3}\,(1\times4)} &= X_{3(1\times3000)} \cdot (IC_1\ IC_2\ IC_3\ IC_4)_{(3000\times4)} \\
\mathbf{F}_{\mathbf{4}\,(1\times4)} &= X_{4(1\times3000)} \cdot (IC_1\ IC_2\ IC_3\ IC_4)_{(3000\times4)} \quad (7)
\end{aligned}$$

where, (IC_1, IC_2, IC_3, IC_4) are the independent components.

Step 3: Apply any classifier on these feature vectors to detect and classify the fault.

It may be noted that the original signal can be divided into more number of segments to get more number of feature vectors to increase the accuracy of fault detection and classification. An effort to optimize on number of feature vectors in our study of detecting bearing fault of induction motors will be taken up as future scope of this idea. This method was applied to detect fault in induction motor shaft and classification accuracy found to be more than 90% using artificial neural network.

3. CONCLUSION

This paper has introduced an extension of ICA algorithm for feature extraction to be used in pattern recognition applications. ICA is simple and reliable to extract the relative features from the signals and does not require any prior knowledge of the objects under study. In industries, ICA can monitor the condition of machines by collecting the time domain signals and guides to take appropriate remedial action, if required, before catastrophic failure takes place. Vibration data sets studied in this work were collected from bearings of an induction motor. However, there are still some other common faults in induction motors, such as gear faults, mechanical looseness, imbalance in motor load, and so on. In the future, these types of induction motor faults should be established on laboratory motors, and be detected and diagnosed by ICA algorithm.

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