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Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs)

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ABSTRACT

Condition monitoring of induction motors is a fast emerging technology in the field of electrical equipment maintenance and has attracted more and more attention worldwide as the number of unexpected failure of a critical system can be avoided. Keeping this in mind a bearing fault detection scheme of three-phase induction motor has been attempted. In the present study, Support Vector Machine (SVM) is used along with continuous wavelet transform (CWT), an advanced signal-processing tool, to analyze the frame vibrations during start-up. CWT has not been widely applied in the field of condition monitoring although much better results can been obtained compared to the widely used DWT based techniques. The encouraging results obtained from the present analysis is hoped to set up a base for condition monitoring technique of induction motor which will be simple, fast and overcome the limitations of traditional data-based models/techniques.

1. Introduction

Induction motors known as workhorse of modern industries are subjected to some undesirable stresses during their operating lifetime, causing some faults to develop leading to failures [5,16]. Heavy reliance of industry on these machines in critical applications makes catastrophic motor failures very expensive. Thus, finding an efficient and reliable fault diagnostic technique, especially for induction motors, is extremely important due to widespread use of automation and consequent reduction in direct man–machine interface to supervise the system operation. During the last decade different kinds of data-based models such as Neural Networks (NNs) have established a firm position in condition monitoring of electrical machinery.

Vibration analysis has been used in rotating machines fault diagnosis for decades [2–4,19,22]. In [4], it is claimed that vibration monitoring is the most reliable method of assessing the overall health of rotor system. Each fault in a rotating machine produces vibrations with distinctive characteristics that can be measured and compared with reference ones in order to perform the fault detection and diagnosis.

Traditional techniques like Fast Fourier Transform (FFT) used for analysis of the vibration signal is not appropriate to analyze signals that have a transitory characteristic. Moreover, the analysis is greatly dependent on the machine load and correct identification of very closed fault frequency components requires a very high-resolution data [10]. Wavelet a very powerful signal-processing tool can be used to analyze transients signal and thus eliminating load dependency. Variable window size allows the possibility to extract both low frequency as well as high frequency information as per requirement. Keeping these points in mind the investigation aims to design and develop an on-line monitoring and incipient fault detection scheme of induction motors by assessing the signature of the motor frame vibrations (g_{frame}) signals during start-up [4,11].

Continuous wavelet transform (CWT) used to extract the local information content of the data has several advantages over the more commonly used DWT [28,29] which uses a set of orthogonal wavelet bases to obtain the most compact representation of the data mainly useful for image compression. The CWT on the other hand uses a set of non-orthogonal wavelet frames to provide highly redundant information that is very good for detection of various types of faults. Wavelet coefficient at each analysis scale can be obtained allowing us to characterize the local information content. Moreover, CWT is easier to interpret since its redundancy tends to reinforce the traits and makes all information more visible which is especially true for very subtle information. Thus, CWT analysis gains in “readability” and in ease of interpretation, what it losses in terms of saving space, which is immaterial in signal processing technique where very important distinct informative feature extraction is the most important.

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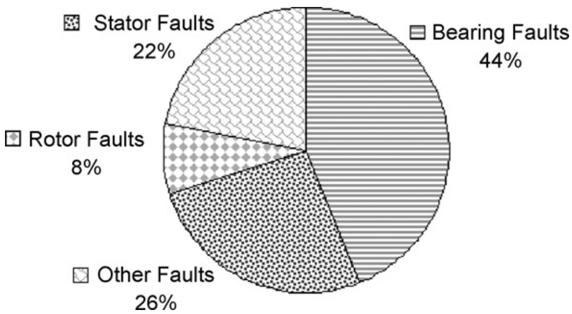

Fig. 1. Percentage occurrence of induction motor faults [1].

Among various motor faults the proposed investigation has been restricted to *bearing faults* only since motor reliability studies shows that bearing faults accounts for 44% of the faults occurring in an induction motor as shown in Fig. 1.

In recent years, Support Vector Machines (SVMs) have been found to be remarkably effective in many real-world applications. SVMs have been successfully applied in various classification and pattern recognition tasks, but in the area of fault diagnostics they have not been widely studied. SVMs are based on statistical learning theory and they specialize for smaller number of samples [13]. As it is hard to obtain sufficient fault samples in practice, SVMs have been applied for machinery fault diagnosis. It is believed that these techniques along with advanced signal processing tools like instantaneous power FFT, Park's transformation, bispectrum, wavelets will have significant role in electric drive system diagnosis. The current research works have obtained encouraging results by using Support Vector Machine (SVM) [18] as a fault classifier to identify the machine faults.

2. Proposed method

The schematic representation of the work is shown in Fig. 3. The scheme consists of four major parts, namely (i) simulation of different induction motor faults, (ii) data acquisition, (iii) signal processing and (iv) Post Processing and Diagnosis using SVM. For identifying the faults motor frame vibration (g_{frame}) signals at start-up are monitored and diagnosed.

Photograph of the experimental setup is presented in Fig. 2.

2.1. Simulation of faults

Machinery Fault Simulator (MFS), a tool for simulating various types of induction motor faults initially fitted with a healthy motor and a motor with faulted bearings of same specification has been used for the fault simulation [24].

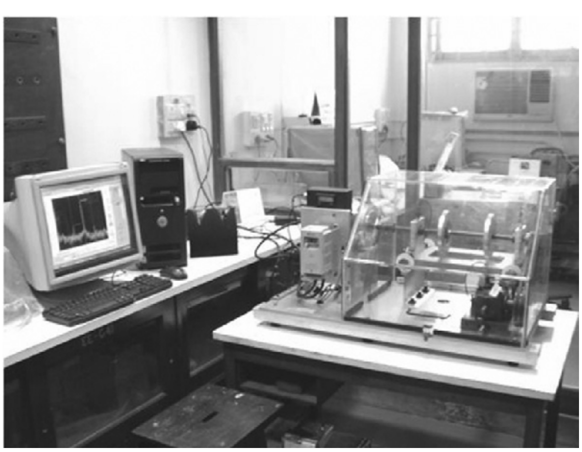

Fig. 2. Photograph of Machinery Fault Simulator (MFS).

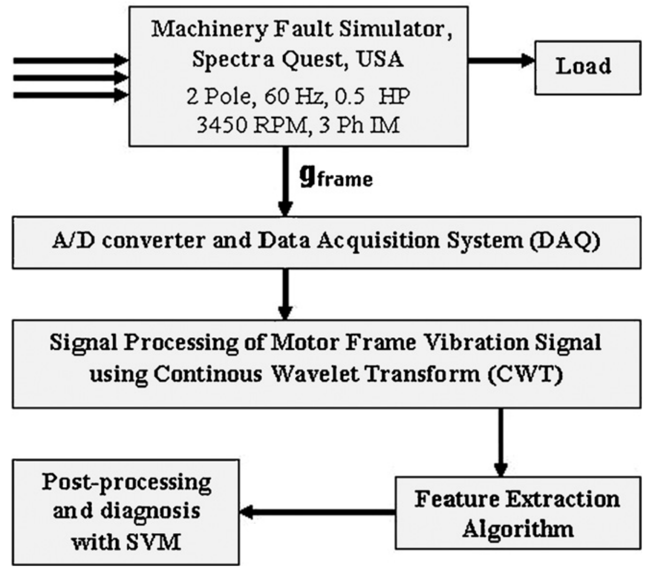

Fig. 3. Schematic diagram of the work.

2.2. Data acquisition

The generated data corresponding to a particular motor condition were collected using an accelerometer probe, recorded and stored using a computer with four-channel data acquisition system (DAQ) [24]. The collection was done for both healthy motor and a motor with faulted bearings under the same running conditions. Time domain frame vibration signal for healthy motor and faulty motor with faulted bearing are shown in Fig. 4(a) and (b).

2.3. Signal processing

2.3.1. Continuous wavelet transform (CWT)

The *wavelet transform* or *wavelet analysis* is probably the most recent solution to overcome the shortcomings of the traditionally used Fourier transform [17,20,21]. Wavelets are well suited for approximating data with sharp discontinuities. Motor starting vibration contains numerous non-stationary or transitory characteristics: *drift*, *trends*, *abrupt changes*, and *beginnings and ends of events.* These characteristics are often the most important part of the signal, and traditional tools like Fourier analysis are not suited for analyzing non-stationary or transitory signals. Fourier analysis is only suitable for steady state analysis consisting of stationary signals – where only the signal's frequency content is needed. When looking at Fourier transform of a signal, it is impossible to tell when a particular event took place, since in transforming to the frequency domain, time information is lost. While in short time Fourier transform (STFT) compromises between time and frequency information can be useful, the drawback is that once a particular size time window is chosen, that window is the same for all frequencies. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In wavelet analysis, the scale plays a special role. Wavelet algorithms process data at different scales or resolutions. If we look at a signal with a large "window", we would notice gross features. Similarly, if we look at a signal with a small

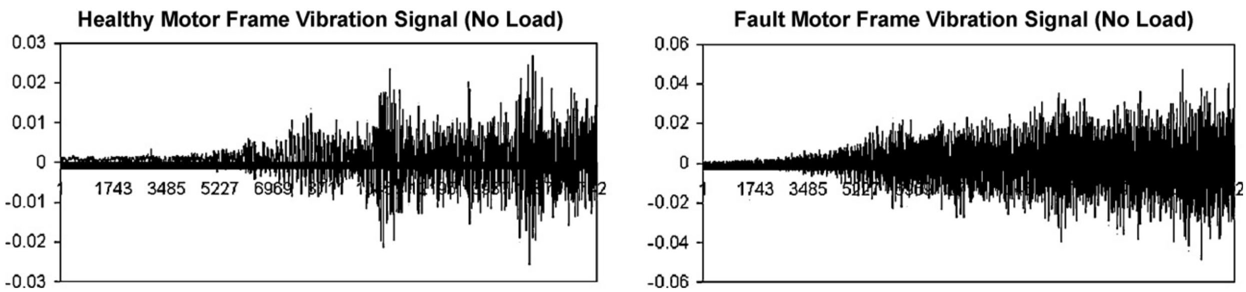

Fig. 4. Time domain waveform of frame vibration signal of (a) healthy (b) faulty motor.

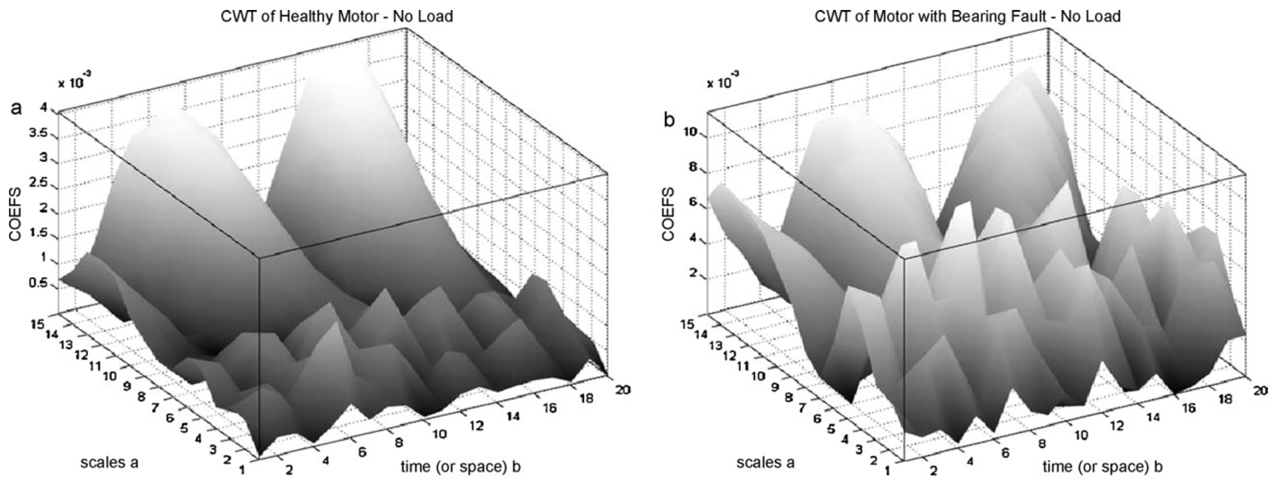

Fig. 5. A typical CWT plot of frame vibration signal of (a) healthy, (b) faulty motor.

"window", we would notice small features. The result in wavelet analysis is to see both the forest and the trees, so to speak [6,23].

Continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function Ψ [9]

$$L_{\Psi}f(s,\tau) = \int f(t)\psi^{*}_{s,\tau}(t)dt \tag{1}$$

$f(t)$ is decomposed into a set of basis function $\psi_{s,\tau}(t)$, called wavelets generated from a single basic wavelet $\psi(t)$, the so called mother wavelet, by scaling and translation:

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right) \tag{2}$$

s is a scale factor, τ is the translation factor and the factor $|s|^{-1/2}$ is for energy normalization across the different scale. Scaling a wavelet simply means stretching (or compressing) it.

Typical CWT plots for healthy motor and faulty motor with faulted bearing are shown in Fig. 5(a) and (b).

2.4. Post Processing and Diagnosis of faults

Post Processing and Diagnosis of faults was done by using Support Vector Machines (SVMs) as a classifier and then with artificial neural network (ANN) for a comparative study.

2.4.1. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a modern computational learning method based on statistical learning theory presented by Vapnik [12] and specializes for a smaller number of samples for training. SVM is developed from the optimal separating plane under linearly separable condition. Its basic principle can be illustrated in two-dimensional way as represented in Fig. 6. Fig. 6 shows the classification of a series of points for two different classes of data, Class I (white squares) and Class II (black dots). The SVM tries to place a linear boundary represented by a bold line between the two classes and orients it in such way that the margin is maximized, namely, the distance between the boundary and the nearest data point in each class is maximal. The nearest data points are used to define the margin and are known as support vectors [15,25,28].

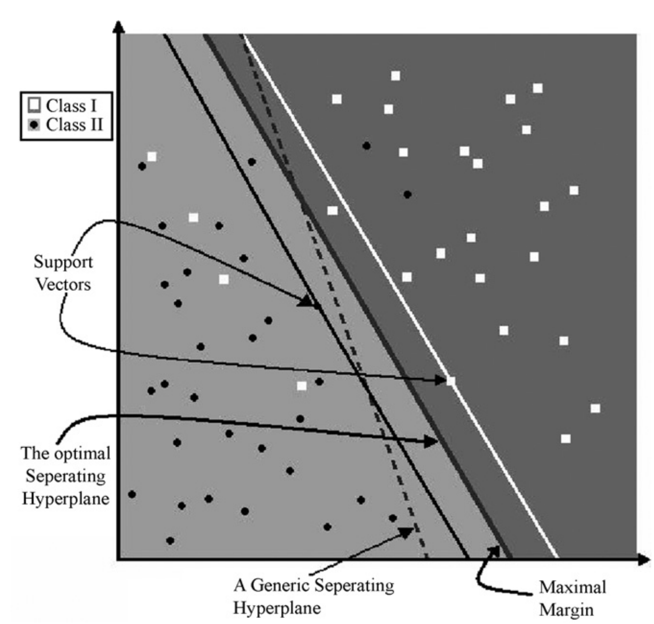

Fig. 6. The optimized separating hyperplane in classification.

Let $\mathbf{X}_i = (x_{1i}, x_{2i},\ldots,x_{ni})^T$, $i = 1,\ldots,M$, be a sample of $x \in \mathbb{R}^n$ and belong to Class I or Class II. For linearly separable data, it is possible to determine a hyperplane that separates the data leaving one class on each side of the hyperplane. This plane can be described by the equation [18]:

$$f(x) = \mathbf{w}^T x + b = \sum_{j=1}^{n} w_j x_j + b = 0 \tag{3}$$

where $\mathbf{w} \in \mathbb{R}^n$ is a weight vector and b is a scalar. The vector $\mathbf{w}$ and the scalar b determine the position of the separating hyperplane.

Let us define the label $\mathbf{y}_i$ associated to $\mathbf{x}_i$ as $\mathbf{y}_i = 1$ if $\mathbf{x}_i$ belongs to Class I, $\mathbf{y}_i = -1$ for Class II. A separating hyperplane satisfies the constraints $f(\mathbf{x}_i) \geq 0$, if $\mathbf{y}_i = +1$ and $f(\mathbf{x}_i) < 0$, if $\mathbf{y}_i = -1$. If this inequality condition holds that is for linearly separable case optimal hyperplane is found by solving the following convex quadratic optimization problem:

$$\begin{aligned} &\text{minimize} \quad \gamma = \frac{1}{2}||w||^2 \\ &\text{subject to} \quad y_i(\mathbf{w}^T \mathbf{x}^i + b) \geq 1 \end{aligned} \tag{4}$$

For non-linear classification problem, the linear boundary in the input space is not enough to separate the two classes properly. Non-linear mapping is used to generate the classification features from the original data. The non-linearly separable data to be classified is mapped by using a transformation $\boldsymbol{\varphi}(\mathbf{x})$ onto a high-dimensional feature space, where the data can be linearly classified or separated [12]. A kernel function is used to perform the transformation. Among the kernel functions in common use are linear functions, polynomials functions, radial basis functions multi layered perceptron and sigmoid functions.

2.4.2. Artificial neural network (ANN)

Artificial neural networks (ANNs) are among the widely studied data-based model which has generated considerable interest in the engineering field as a problem solving tool. In engineering, neural networks serve two important functions: as pattern classifiers and as nonlinear adaptive filters. At present, artificial neural networks are emerging as the technology of choice for many applications, such as pattern recognition, prediction, system identification, and control. An artificial neural network is a system based on the operation of biological neural networks, in other words, is an emulation of biological neural system [26,31,32].

An artificial neural network is an adaptive, most often nonlinear system that learns to perform a function (an input/output map) from data and does not need to be reprogrammed once it is completely trained. A *neural network* is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. Knowledge is acquired by the network through a learning process. The interconnection strengths known as synaptic weights are used to store the knowledge. A model of a neuron is shown in Fig. 7. A single neuron consists of synapses, adder and an activation function. Bias is an external parameter of neural network. Each node in a layer (except the ones in the input layer) provides a threshold of a single value by summing up their input value x_i with the corresponding weight value w_i. This weighted value $\Sigma w_i x_i$ is added up with the bias term b to form the net input which goes into transfer function f to produces the neuron output a [28].

$$\alpha = f\left(\sum_{i=}^{r} w_i . p_i + b\right) \tag{5}$$

In this study, multilayer feed-forward back-propagation NN (FFBPN) is used as shown in Fig. 8 [27]. This is a supervised learning method where an input (x_i) is presented to the neural network and

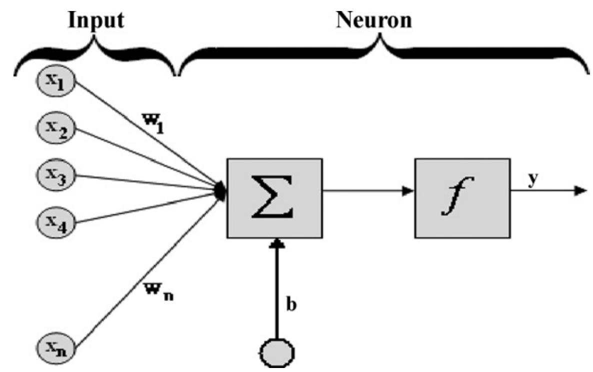

Fig. 7. A neuron.

a corresponding desired output or target (t_n) response set at the output:

$$\{x_1, t_1\}, \{x_2, t_2\}, \ldots, \{x_n, t_n\}$$

where x_n is an input to network and t_n is the corresponding output target.

The resultant outputs produced by the network are compared with that of the desired ones (targets) and normalized mean square error (MSE) is calculated and propagated backwards to adjust the value of the weights on the neural connection in the multiple layers. The process is repeated until the MSE is reduced to an acceptably low value suitable to classify the test set correctly [28].

For supervised learning the performance of the network hinges heavily on the training data. If one does not have data that cover a significant portion of the operating conditions or if they are noisy, then neural network technology is probably not the right solution. On the other hand, if there is plenty of data and the problem is poorly understood to derive an approximate model, then neural network technology is a good choice.

3. Results and analysis

The frame vibrations signal of the healthy and the faulty motors at the time of starting were collected through DAQ at a sampling frequency of 7680 Hz. The supply frequency was set to 50 Hz. The experiments were carried out under three different loading conditions: *no-load*, *half load* and *full load*. The recorded data were decomposed using CWT [6,8]. In this investigation '*morlet*' and '*daubechies10*' have been used as mother wavelet for all CWT operations and implemented in MATLAB 6.5 environment [14]. The CWT coefficients thus obtained were prepared and analyzed with the help of SVM/ANN as a fault classifier.

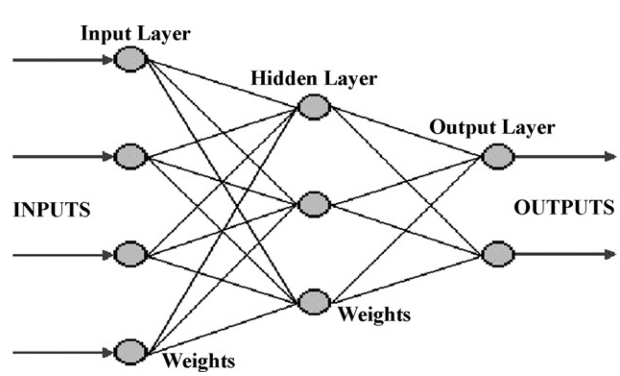

Fig. 8. Artificial neural network.

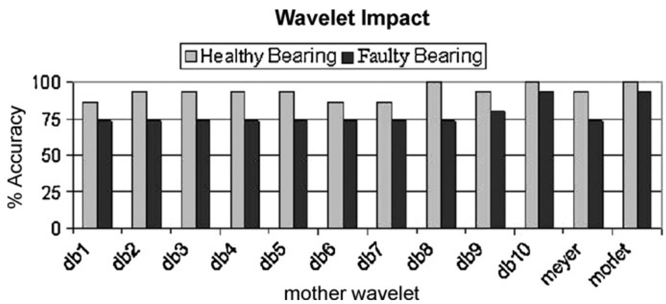

Fig. 9. The impact of mother wavelet selection in faulty motor detection.

3.1. Data preparation

Training and testing data files were created for analysis of start-up frame vibration signal. 50 (25 + 25) feature samples were taken from each motor condition and each loading situation (in total: $50 \times 3 = 150$ samples). 60 (20×3) of the samples from both healthy and faulty motors were used in training the classifier (120 samples) and 30 (15 + 15) remaining samples left were used to test the classifier's generalization ability.

Each of the 150 feature samples was decomposed using CWT. From the results presented in Fig. 9, it is obvious that the choice of mother wavelet is crucial to the development of a good fault detection algorithm. Analysis was carried out with different wavelets with a scale range of (1–15), to account for the high frequency information, while selecting the best wavelet. A wavelet scale range of (1–8) was also taken to study the effect of scale. From Fig. 9 '*morlet*' and '*daubechies10*' wavelets were found to be the best choice and used for further study. Three types of statistical data: *root mean square* (*RMS*), *crest* and *kurtosis* values were evaluated from the CWT coefficients for each loading condition and treated as attributes.

3.2. Training

The training of the SVM model with real time data sets was implemented with the help of *LIBSVM* software [33]. In SVM classification, radial basis kernel functions (*RBF*s) were considered. The optimized model with minimum the number of SVs was considered, since lesser the number of SVs better the generalization [18]. The cost (c) gamma (g) parameters were varied for determining the optimized model. It was found the optimized model was obtained for cost value $c = 2$ and gamma value $g = 0.5$ (Fig. 10).

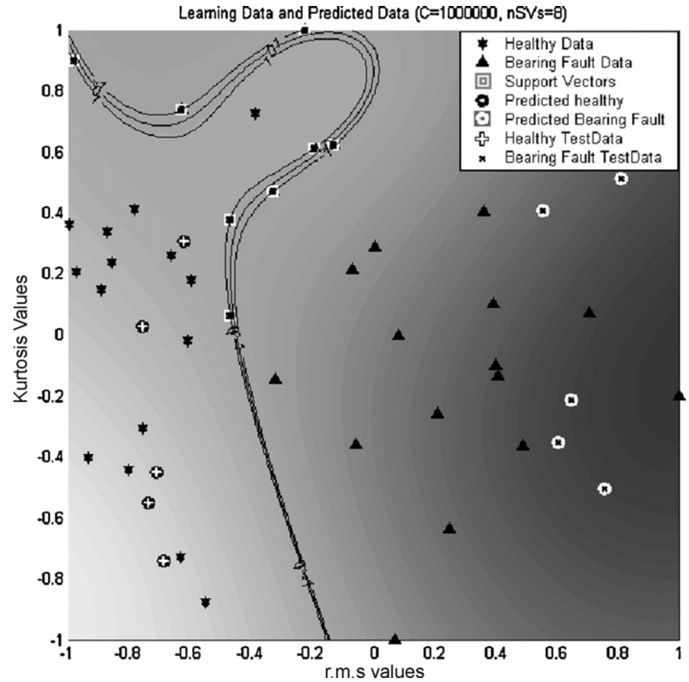

Fig. 11. The SVM model for Two Class Classification [$C = 10^6$, $g = 10^{-6}$].

The SVM models obtained (neglecting kurtosis attributes, since only two dimensional can be represented) for different values of cost (c) and gamma (g) after training for two-class classification are shown in Figs. 11–13. The models were obtained using KSVM Matlab toolbox [34] and implemented in Matlab 6.5. Fig. 11 shows the most optimized result for cost $c = 10^6$ and gamma $g = 10^{-6}$. All data which are on the left of the separating hyperplane were detected

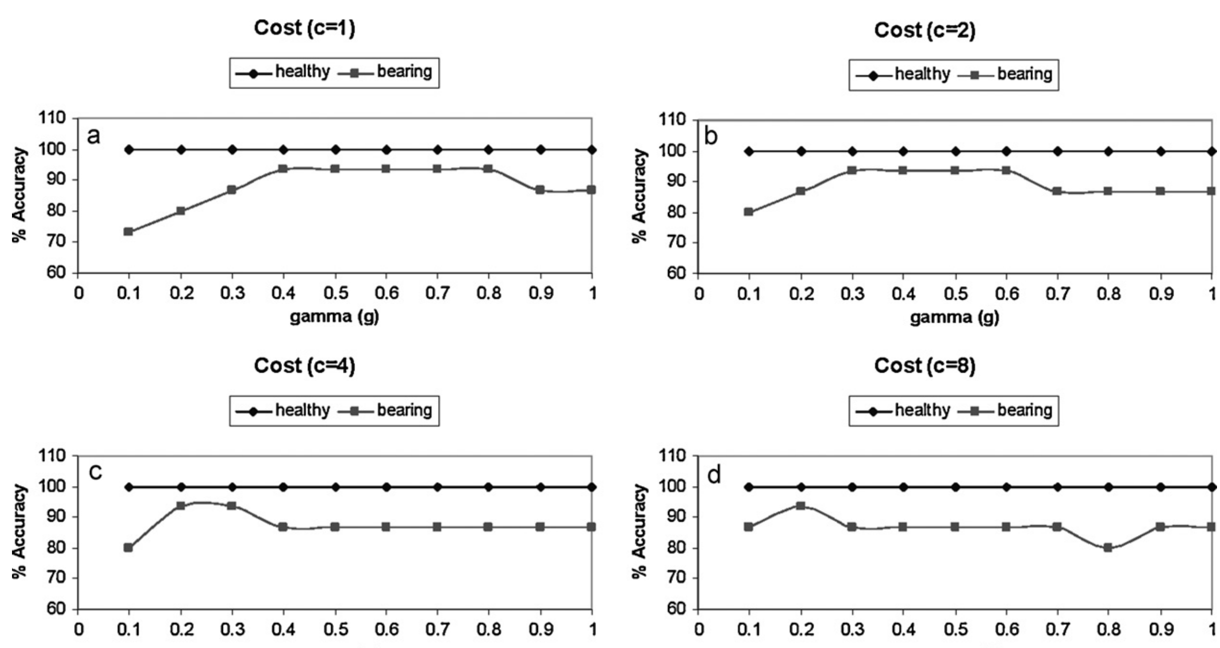

Fig. 10. Classification accuracy for different values of cost function (a) $C = 1$, (b) $C = 2$, (c) $C = 4$, (d) $C = 4$.

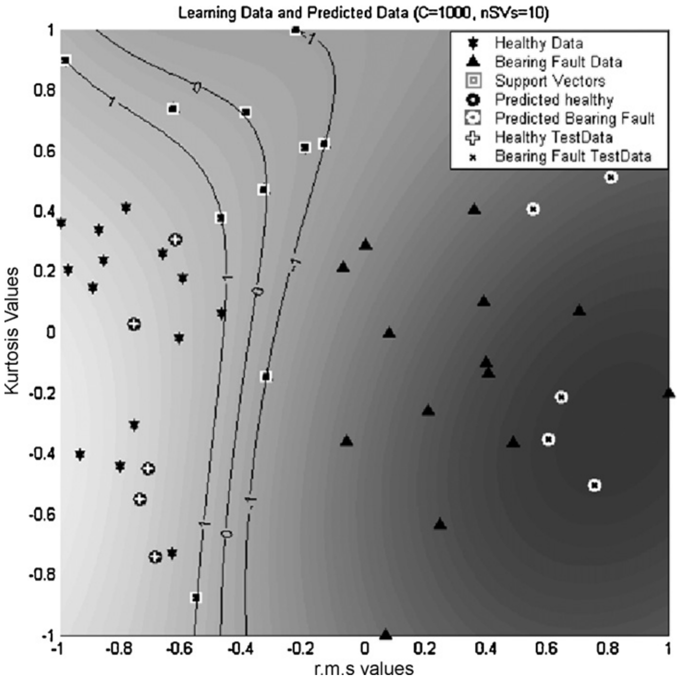

Fig. 12. The SVM model for Two Class Classification [$C = 10^3$, $g = 10^{-6}$].

as healthy and that on the right hand as faulty motor with faulted bearings.

It can be seen from Fig. 11 that the number of SVs for the most optimized two-class model is eight. Figs. 12 and 13 were obtained varying cost function (c) to 10^3 and gamma (g) to 10^{-3}, respectively. In both of this model the number of SVs increased and the optimized model could not be achieved. Thus it can be seen that the cost and gamma parameters should be selected in such a way so as to minimize the number of SVs.

The training of the NN with real time data sets was implemented in MATLAB (6.5) with the help of ANN toolbox [7]. A three layer feed

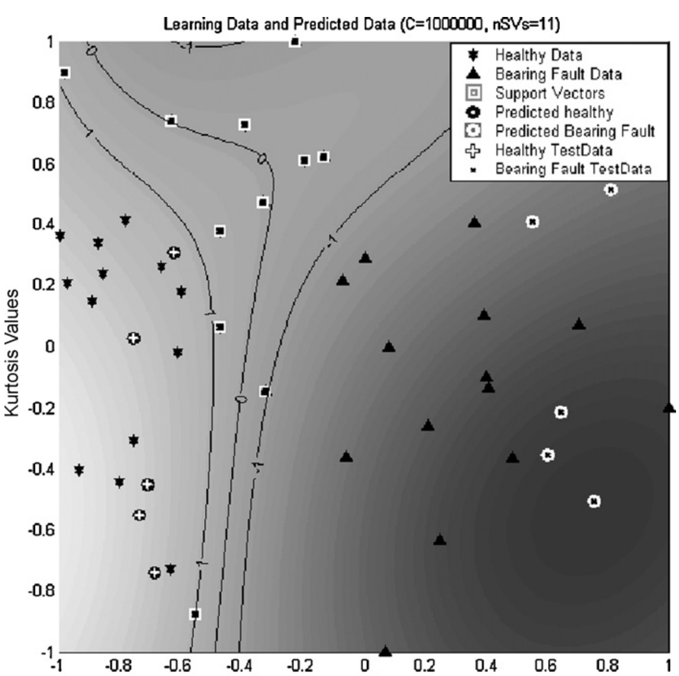

Fig. 13. The SVM model for Two Class Classification [$C = 10^6$, $g = 10^{-3}$].

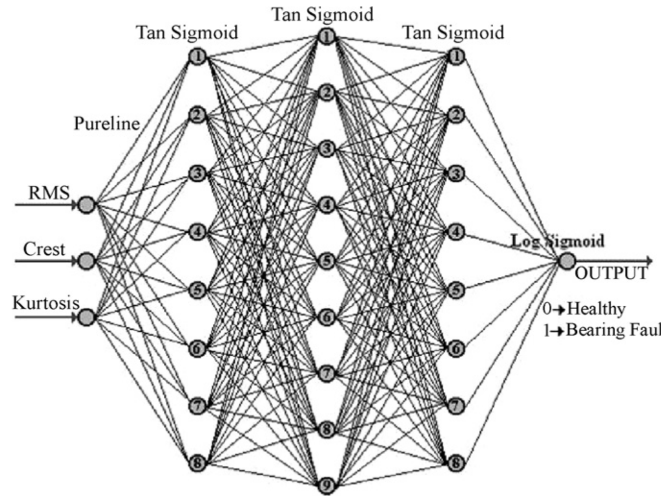

Fig. 14. ANN structure used in classification.

forward neural network was trained by back propagation training algorithm. Training has been tried with different number of layers and types of layers. The optimized results were obtained with three layer feed forward neural network as shown in Fig. 14. Back propagation algorithm has been implemented because this algorithm is most popular and successful neural network architecture for supervised learning. It is based on the weight error correction rules. It is considered a generalization of the delta rule for nonlinear activation functions and multilayer networks. The NN architecture used is presented in Fig. 14, the activation functions at the hidden layers and output layer in the network are tan sigmoid and log sigmoid respectively. The log-sigmoid transfer function is chosen because its output range (from zero to one) suits to output Boolean values. The number of neurons in a hidden layer has a strong impact on the performance of the network. With a large number of hidden neurons, it is possible to achieve excellent performance in the training set, but this does not necessarily lead to good generalization ability and high accuracy in the evaluation set. After a number trails the network with three ($8 \times 9 \times 8$) hidden neurons was selected as the most optimized model giving the best overall accuracy.

3.3. Testing

After successful training the optimized SVM model obtained was used to test the testing file to test the generalization ability of the classifier. The testing file consists of data points unknown to the SVM model. The classification ability of SVM for fault prediction using '*morlet*' and '*daubechies10*' are summarized in Tables 1 and 2 for a wavelet scale range of (1–15). The classification ability for scale range of (1–8) is presented in Tables 3 and 4. These results have been compared with ANN model [30]. The data distributions are depicted in Figs. 15–17.

Figs. 15–17 shows the 3D data distribution plots of the samples under study. As seen in Fig. 15 the training dataset of faulty samples with bearing fault were found to be scattered in the right half whereas the healthy motor data are scattered on the left half. The healthy data are represented by squares and bearing fault by bold circles.

In Figs. 16 and 17 the data distribution for training as well testing/predicted data are shown. Squares and bold circles show the training data. The triangles represent healthy test data and circles represent bearing fault test/predicted data.

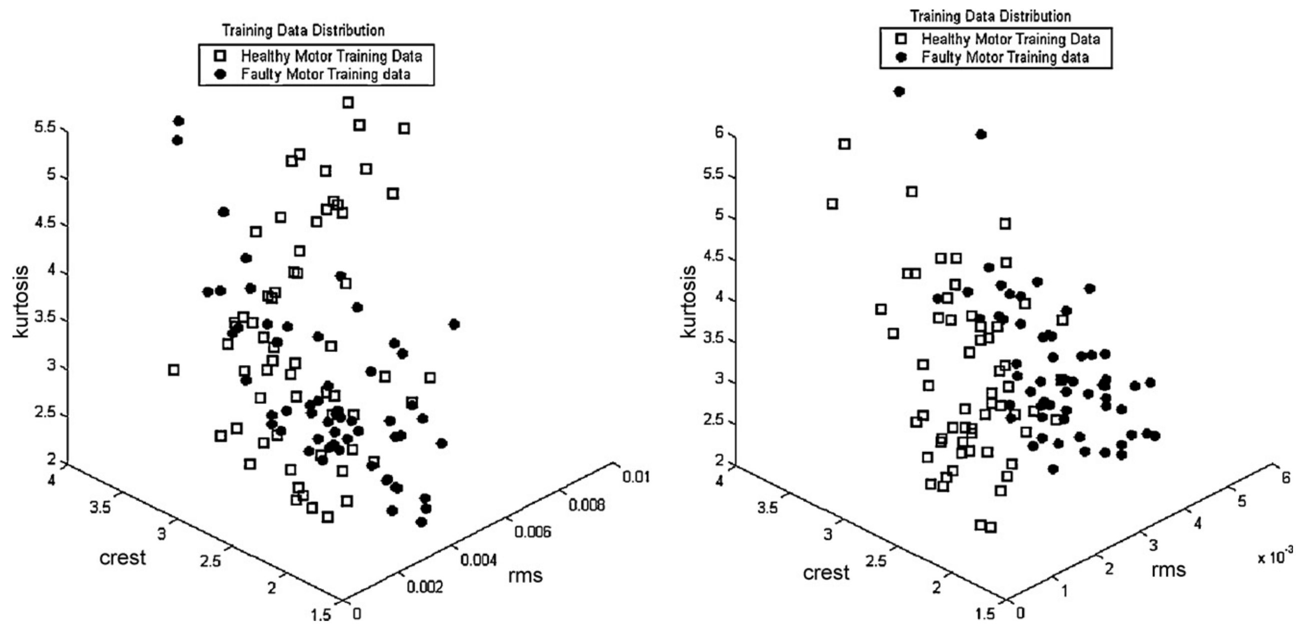

Fig. 15. The 3D plot showing training data distribution for morlet wavelet scale (a) 1–15, (b) 1–8.

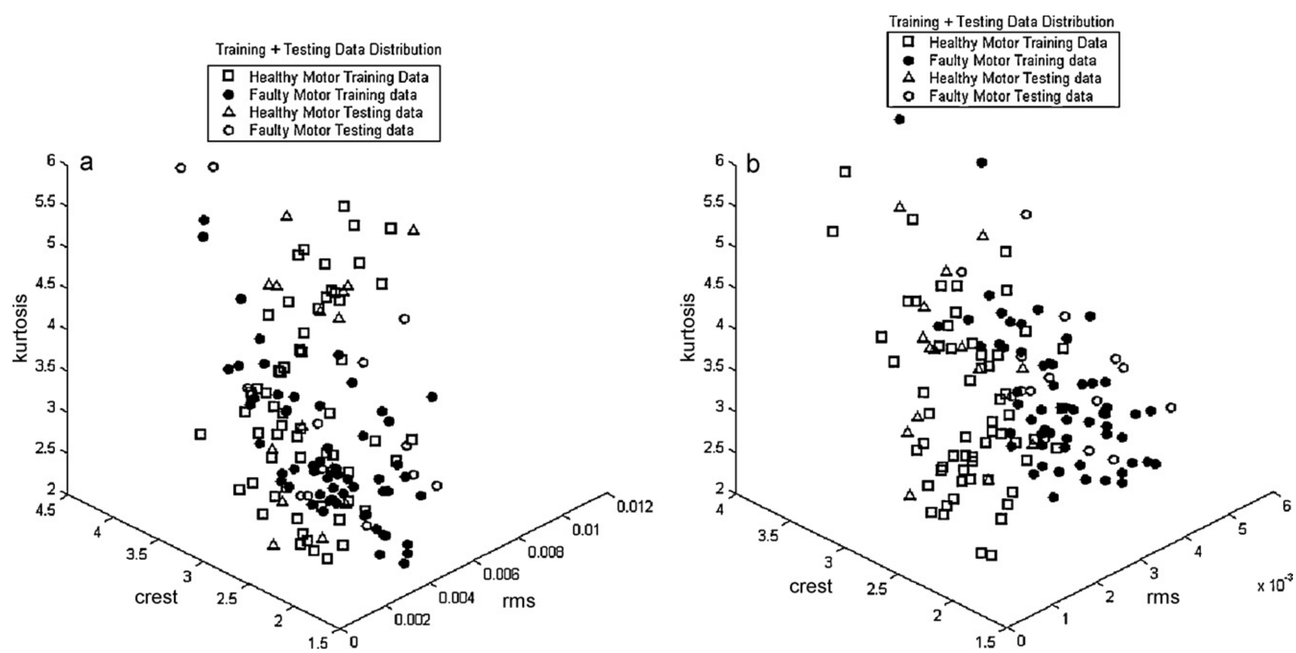

Fig. 16. The 3D plot showing training and testing data distribution morlet wavelet for scale (a) 1–15, (b) 1–8.

Table 1
Correct level of classification using frame vibration as the medium of fault detection. Wavelet scale: 1–15, classifier: *SVM*.

	Testing success (%) Mother wavelet: *morlet*			Testing success (%) Mother wavelet: *daubechies10*		
	Healthy motor (%)	Faulty motor (%)	Total (%)	Healthy motor(%)	Faulty motor (%)	Total (%)
No load	100	100	100	100	100	100
Half load	100	100	100	100	100	100
Full load	100	80	90	100	80	90
Total	100	93.33	96.67	100	93.33	96.67

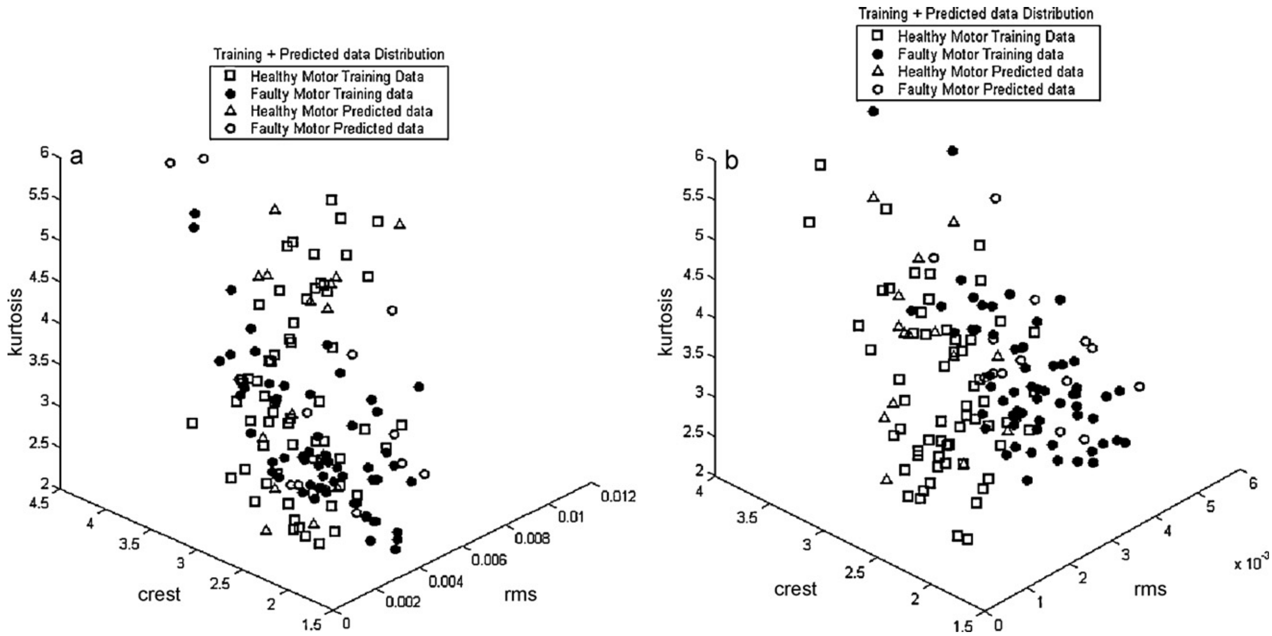

Fig. 17. The 3D plot showing training and predicted data distribution morlet wavelet for scale (a) 1–15, (b) 1–8.

Table 2
Correct level of classification using frame vibration as the medium of fault detection. Wavelet scale: 1–15, classifier: *ANN*.

	Testing success (%) Mother wavelet: *morlet*			Testing success (%) Mother wavelet: *daubechies10*		
	Healthy motor (%)	Faulty motor (%)	Total (%)	Healthy motor(%)	Faulty motor (%)	Total (%)
No load	80	80	80	60	60	60
Half load	100	100	100	80	60	70
Full load	100	80	90	80	100	90
Total	93.33	86.67	90	73.33	73.33	73.33

Table 3
Correct level of classification using frame vibration as the medium of fault detection. Wavelet scale: 1–8, classifier: *SVM*.

	Testing success (%) Mother wavelet: *morlet*			Testing success (%) Mother wavelet: *daubechies10*		
	Healthy motor (%)	Faulty motor (%)	Total (%)	Healthy motor(%)	Faulty motor (%)	Total (%)
No load	100	100	100	100	100	100
Half load	100	100	100	100	100	100
Full load	100	100	100	100	100	100
Total	100	100	100	100	100	100

Table 4
Correct level of classification using frame vibration as the medium of fault detection. Wavelet scale: 1–8, classifier: *ANN*.

	Testing success (%) Mother wavelet: *morlet*			Testing success (%) Mother wavelet: *daubechies10*		
	Healthy motor (%)	Faulty motor (%)	Total (%)	Healthy motor(%)	Faulty motor (%)	Total (%)
No load	80	100	90	100	100	80
Half load	100	100	100	80	100	100
Full load	100	100	100	100	80	100
Total	93.33	100	96.67	93.33	93.33	93.33

4. Conclusion

In this paper bearing fault detection algorithm of an induction motor using CWT as an advanced signal-processing tool is presented. With scale variation excellent results were obtained as compared to widely studied DWT based fault detection techniques [28–30]. CWT can be applied with higher resolution to extract information with higher redundancy, that is, a very narrow range of scales can be used to pull details from a particular frequency band. The choice of mother wavelet also plays a crucial role in the fault detection algorithm. The results obtained are very encouraging and there is a great scope for extending this technique in identifying other types of induction motor faults.

As a classifier SVM gives excellent result, which is very simple and easy to implement, compared to ANN based approach, which requires an exhaustive task of trial and error process for determining the most optimum model. Hence, a hybrid CWT–SVM approach can definitely be used as a better alternative to DWT/ANN based fault classification algorithm, which will be quite fast and efficient.

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