FRACTAL FEATURES BASED ROLLER BEARING FAULT ANALYSIS USING MULTI SUPPORT VECTOR MACHINE

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Abstract: *In induction motor, condition monitoring gathers much attention which improves the reliability and requires lesser cost of maintenance. There is significant research space for improvement in algorithms and techniques for analyzing the condition of an induction motor. In induction motor failures distribution, around 40% of the failures is due to roller bearing faults. In this work, roller bearing faults such as outer race faults and inner race faults are analyzed using multi support vector machine. The vibration signals of outer and inner race faults along with normal bearing for various loads are considered for this analysis. The 3 dimensional (3D) images are plotted using the data obtained from the vibration signals. Fractal features like fractal dimension, fractal average, fractal standard deviation and lacunarity are extracted from these images using four types of filters namely sobel, prewitt, roberts and canny. These features are fed as input for multi support vector machine (MSVM) for the identification of different types of roller bearing faults using four types of kernel known as Gaussian, RBF, polynomial and sigmoidal. MSVM is operated in two approaches and are one versus one and one versus all. The performance of the MSVM with two different approaches is compared with other methods like Linear discriminant classifier (LDC), Quadratic discriminant classifier (QDA), Decision tree, K-nearest neighbour classifier. RBF kernel based MSVM with one versus all approach using roberts filter in box counting method provides better performance compared to other methods due to its gain flexibility and good sample-out-of generalization.*

Keywords: *Roller bearing faults, fractal features, box counting method, multi support vector machine(MSVM), and Kernels.*

1. Introduction

Bearing components in induction motor (IM) plays a critical role in operational performance and reliability of the system. Therefore, it necessitates the development of a condition monitoring and fault diagnosis system to reduce the malfunctioning of the ball bearing. Vibration analysis is commonly used in the detection of roller bearing failures [1]. The fault diagnosis method comprises of pattern recognition and classification paradigms in which feature extraction is the crucial role. The effective and accurate classification of roller bearing faults depends on the salient feature extraction and reducing the dimensionality [2].

In roller bearing fault diagnosis, a large amount of data is collected from the operating machinery. Extraction of feature is difficult as the relevant information might be submerged inside the large data pool. Principal component analysis [3], multi-dimensional scaling [4] and linear discriminate analysis [5] were used for reduction of redundant data. But, these feature extraction methods work effectively only in linear data with gaussian distribution whereas vibration signal of IM is nonlinear in nature.

The roller bearing faults can be predicted both in time domain and in frequency domain response of the system. Numerous feature extraction methods have been proposed based on time domain analysis and in frequency domain analysis [6]. Time domain features, namely, waveform length, slope sign changes, simple sign integral and wilson amplitude are used for the identification of roller bearing fault in IM [7]. Once fault occurs in roller bearing, it is followed by the occurrence of changes in the characteristic components of the frequency spectrum. The methods employing both time-frequency analysis are wavelet analysis [8], empirical mode decomposition (EMD) [9], envelope analysis [10], symbolic transformation [11], cepstrum analysis [12], the kurtogram [13], nonlinear features [14], etc. The feature extraction based on empirical wavelet transform and multiscale entropy is used for analyzing the vibration signals [15].

Sammon mapping [16] and neuroscale method [17] are the traditional techniques used for non linear mapping. Yang [18] proposed a time series principal manifold learning based noise reduction method. However, this traditional non linear method is an unsupervised learning method and does not yield accurate results for supervised learning problems.

For classification of faults, many types of classifiers are used by the researchers. For a decade, support vector machine (SVM) has been used for the binary fault classification in condition monitoring and fault diagnosis of machines [19]. SVM and artificial neural network (ANN) for fault and no-fault recognitions were improved by the use of genetic algorithm (GA) based feature selection process [20]. SVM with radial basis function (RBF) kernel and the weighted SVM along with GA were also used for the binary classification [21] [22]. C-SVC parameters and feature subset simultaneously with SVM classification was implemented using evolutionary algorithms [23]. A comparative analysis of proximal SVM using the Morlet wavelet was applied for the bevel gearbox [24]. SVM technique is used to detect and classify multiple gear-fault conditions using frequency domain vibration signals [25].

In this paper, as a new attempt, non linear data handling difficulty is addressed by converting the vibration data into 3D images. Fractal features like fractal dimension (FD), fractal dimension average (FDavg), fractal dimension standard deviation (FDsd) and Lacunarity (Lac) are extracted using box counting algorithm. These features consist of geometry information and the class information of the data. Based on literatures, SVM has still very little efforts in multi-fault classification for electrical machineries. In this work, multi support vector machine (MSVM) is used for the fault classification of IM roller bearing. The training and testing data which comprises of fractal features have been selected at same rotational speed. Classification of faults is performed for different types of kernel functions. Recognition of MSVM based fault classification is greatly improved when compared with Linear discriminant classifier (LDC), Quadratic discriminant classifier (QDA), Decision tree, K-nearest neighbour classifier.

The article is organized as follows: Section 2 shows the characteristics of vibration signal of IM. Section 3 explains box counting method and feature classification. Section 4 describes the MSVM based fault classifier. Section 5 presents the results and discussion. Section 6 provides the conclusion.

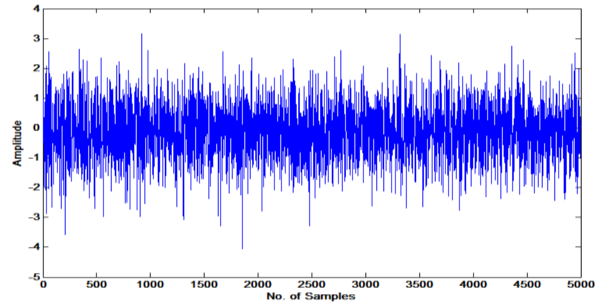
2. Characteristics of vibration signal

The ball bearing faults in IM is pronounced as fault frequencies in the machine vibrations. The magnitude of these frequencies depends on the surface of the bearings containing the faults. The components of vibration frequency are related to four basic fault frequencies, and are fundamental train frequency (FTF), ball spin frequency (BSF), ball pass outer race (BPFO) and ball pass inner race (BPFI) [19]. Table 1 gives the specifications of the test rig equipped with roller bearing.

Table 1 Specification of roller ball bearing

Parameter	Magnitude
Roller diameter	0.235
Pitch diameter	1.245
Number of elements	8
Contact angle	0
Number of balls	8
Ball diameter	5.97mm
Ball pitch diameter	31.62mm
FTF	0.5935*shaft speed
BPFO	3.245*shaft speed
BPFI	4.755*shaft speed
BSF	2.5564*shaft speed
shaft speed	25 Hz

Data sets used for analysis in this work are available in data-acoustics.com database. These data sets are capable of producing the required features for fault identification under various conditions. The vibration signal measured for 270 lbs load for normal, outer race and inner race conditions are shown in Figure 1.



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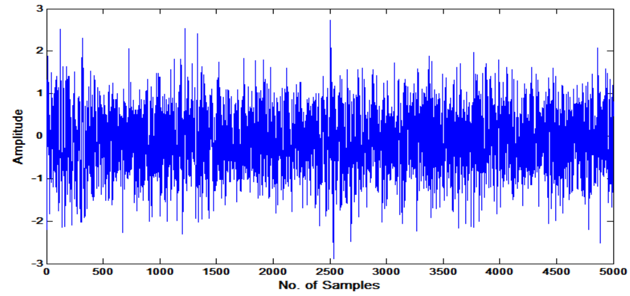

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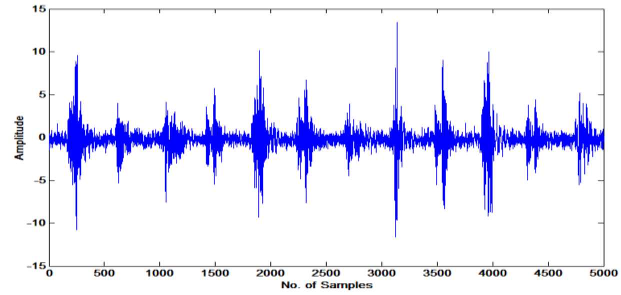
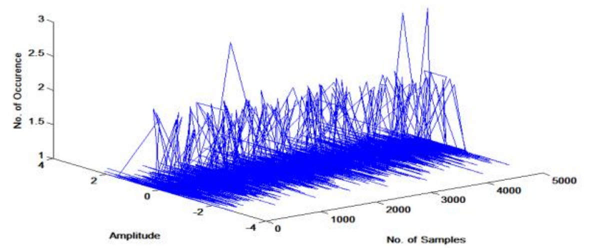


(c)

Fig. 1. Vibration signal
(a) Normal bearing condition (b) Outer race fault (c) Inner race fault

1.1 Extraction of 3D data

In the data acquisition system, of vibration signal in IM, the no. of samples and amplitude are measured. From the measured signal, 3D distribution plot has been drawn between no. of samples, amplitude and the number of occurrence of every sample. The data acquisition is sampled at a rate of 97,656 samples per second, for 6 seconds. But only 5000 samples are considered for analysis. Figure 2 shows the 3D plot for normal bearing condition, outer race and inner race roller bearing faults of IM.



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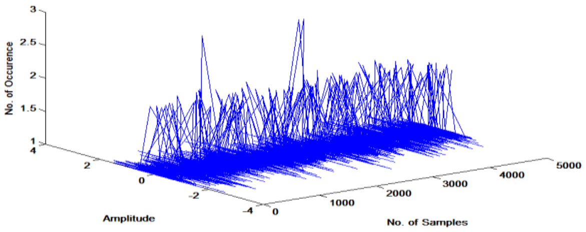

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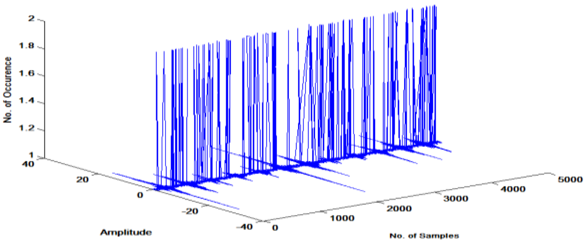
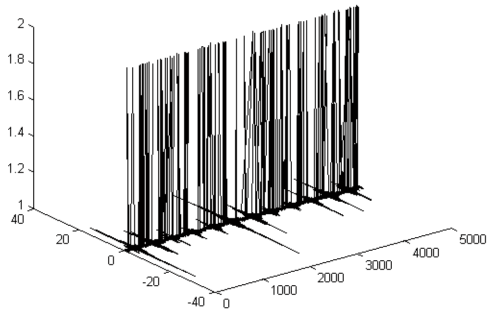


(c)

Fig. 2. 3D plot
(a) Normal (b) Outer race fault (c) Inner race fault

3. Box Counting Method

The box counting analysis is an appropriate method of fractal dimension estimation for images with or without self-similarity. Fractal dimension is due to its ability to summarize the whole dataset in one value [ios paper]. A famous technique to calculate fractal dimension is the grid dimension method popularly known as box-counting method. In this method, initially 3D image is converted to black and white image known as fractal. Then the edges of the fractal are detected using four types of filters namely Sobel, Prewitt, Roberts and Canny. Edge detected 3D fractal is then covered with square boxes and then the number of boxes (m) needed to cover image is calculated. This process is repeated with different box sizes. Then the logarithmical function of box sizes (x-axis) and number of boxes needed to cover fractal (y-axis) is plotted. Then the best fit is evaluated for this plot. The slope of this plot referred to as the fractal dimension.



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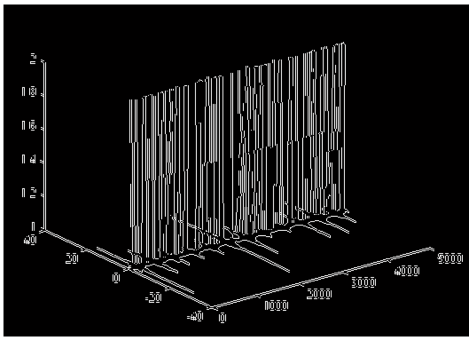

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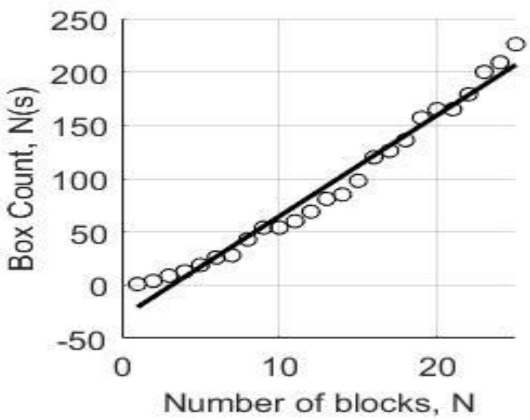

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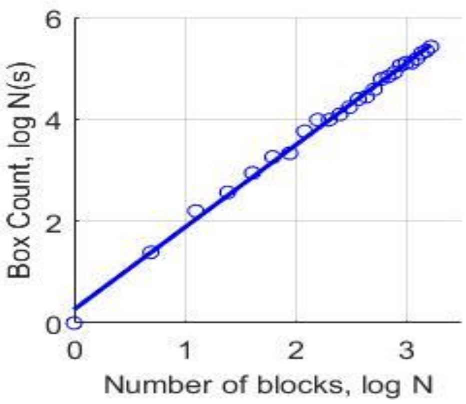

(d)

Fig.3**.** Box counting method for inner race fault
(a) blackwhite-3D image (b) edge detected image-sobel filter,
(c) plot for Fractal dimension (d) logarithmic fit curve

The features extracted in this method are Fractal Dimension (FD), Fractal Dimension Average (FDavg), Fractal Dimension Standard Deviation (FDsd) and Lacunarity (L). Lacunarity is a measure of how the data fills the space. It complements fractal dimension, which measures how much space is filled. L quantifies the denseness of the surface and calculated using Equation (1).

$$p(m,L)=\frac{\sum_{m=1}^{N} m^2 p(m,L)-\left[\sum_{m=1}^{N} mp(m,L)\right]^2}{\left[\sum_{m=1}^{N} mp(m,L)\right]^2} \quad (1)$$

where $p(m,L)$ is the probability having m boxes within a size of box L, and N is the number of possible points within the box. $p(m,L)$ is normalized for all L. For the sake of simplicity, box counting method with sobel filter applied to inner race fault is shown in Figure 3. Figure 3 shows the fractal image of inner race fault, edge detected fractal, logarithmic plot and best fit of inner race fault. Table 2 lists out the fractal features evaluated for normal bearing condition, inner race fault and outer race fault conditions for roller bearing faults in induction motor.

Table 2 Fractal Features extracted by box counting method

Ball bearing condition	FD	FDavg	FDsd	Lacunarity
Sobel filter				
Normal bearing	1.5488	0.9163	0.8945	0.4764
Inner race fault	1.6048	0.9262	0.9597	0.5368
Outer race fault	1.572	0.9122	0.9331	0.5232
Prewitt filter				
Normal bearing	1.5512	0.9162	0.8979	0.4802
Inner race fault	1.604	0.9262	0.9586	0.5356
Outer race fault	1.5754	0.9114	0.939	0.5307
Roberts filter				
Normal bearing	1.5389	0.9166	0.8801	0.461
Inner race fault	1.596	0.9272	0.9458	0.5203
Outer race fault	1.5633	0.9131	0.9195	0.507
Canny filter				
Normal bearing	1.5535	0.918	0.8987	0.4742
Inner race fault	1.6123	0.9264	0.9699	0.5481
Outer race fault	1.5797	0.9124	0.9436	0.5348

4. Ball Bearing Fault Classification

In this proposed work, identification of roller bearing faults is done by multi SVM classifier. Using the extracted fractal features, Gaussian, radial basis function (RBF), polynomial and user defined sigmoidal kernel function are used in MSVM for classifying three different conditions of ball bearing in IM. To prove the efficiency of the proposed classifier, the recognition rate is compared with Linear discriminant classifier (LDC), Quadratic discriminant classifier (QDA), Decision tree, K-nearest neighbour classifier and MSVM with two features as input.

4.1 Linear discriminant classifier

LDC uses training data to estimate the parameters of discriminant functions of the predictor variables. LDC searches with linear combinations of selected variables in order to provide the best separation between the measured classes. These linear combinations are called discriminant functions. Discriminant functions are used to find the the boundaries in predictor space between the three different types ball bearing conditions.

4.2 Quadratic discriminant classifier

QDA is a statistical-based classifier whose function based on normally distributed measurements. The covariance of each of the different ball bearing conditions need not be identical. It calculates the likelihood ratio, and make use of the quadratic decision surface to classify the different ball bearing conditions.

4.3Decision tree

Decision tree is a classifier in the form of a tree structure. It specifies test on single attribute. Leaf node denotes the target attribute value. This classifier finds the output responses based on a sequence of decisions. The maximum number split allowed in this decision tree classifier is training data -1 with minimum leaf size and maximum parent sixe as 10 respectively.

4.3 K-nearest neighbour classifier

This classifier is based on unsupervised learning for each class in the dataset. Initially, it finds the number of neighbouring points in the training set nearest to new point. It also finds the neighbor point response values. Then it assign the new target based on largest posterior probability of neighbourhood response points.

4.4 Multi SVM Classifier

SVM is initially designed for binary classification. The learning is based on matrix pseudo inversion by diagonalization and the run time depends only on the training data size. In this work, MSVM is used in two approaches. In the first approach, one class is compared with another class. So, this type of MSVM needs a set of all possible pair wise classifiers. It evaluates and assigns class to predictor variable. The maximum number of label given to the predictor is finally assigned to the target class. In the second approach, it distinguishes all classes at a time and label is assigned using posterior values. In both approaches, Gaussian, RBF, polynomial and sigmoidal kernel function are used, as measured vibration signal data contains highly non linear data.

5. Results and discussions

The classification of different types of ball bearing conditions like normal, outer race fault and inner race faults in IM are recognized by using LDC, QDA, Decision Tree, K-nearest neighbor classifiers and MSVM with two approaches. For these classifiers, totally 90 samples with 30 samples for each ball bearing condition are taken. Out of these 90 samples, 60 samples are used for training and 30 samples are used for prediction.

The validation results of classifiers except MSVM are tabulated in Table 3. In these, LDC yields high recognition rate for the ball bearing conditions of IM when using Roberts filter. The higher recognition rate achieved is 86.67 by QDA for outer race fault in ball bearing but low recognition in other two ball bearing condition. Eventhough other classifiers yields high recognition for certain ball bearing conditions, LDC classifier has the capability to recognize all type of faults. Hence, the recognition rate of LDC is compared with MSVM based classifiers for subsequent comparison.

Table 3 Recognition rate of different classifiers

Ball Bearing Conditions	LDC	QDA	Decision Tree	K-nearest Neighbor Classifier
Sobel filter				
Normal	83.33	43.33	26.67	50.00
Outer race fault	46.67	83.33	43.33	43.33
Inner race fault	36.67	46.67	83.33	46.67
Prewitt filter				
Normal	56.67	36.67	23.33	26.67
Outer race fault	30.00	46.67	46.67	46.67
Inner race fault	56.67	83.33	73.33	43.33
Roberts filter				
Normal	**66.67**	46.67	50.00	36.67
Outer race fault	**66.67**	46.67	48.00	56.67
Inner race fault	**70.00**	76.67	46.67	26.67
Canny filter				
Normal	56.67	26.67	26.67	26.67
Outer race fault	43.33	86.67	56.67	56.67
Inner race fault	36.67	16.67	46.67	83.33

5.1 MSVM classifier

The fractal features extracted by box counting method is fed as input to MSVM classifier. In the first approach, one class is compared with other class and it continues with all possible pairs of classes. In this approach, all fractal features are taken into account. In the second approach, MSVM classifier works as one class versus all classes. Only two features are fed as input to the classifier. The features are selected in such a way that all possible two combinations of features are used to train the MSVM model. Predictive performances of each combination are compared and the best combination is used to train the MSVM.

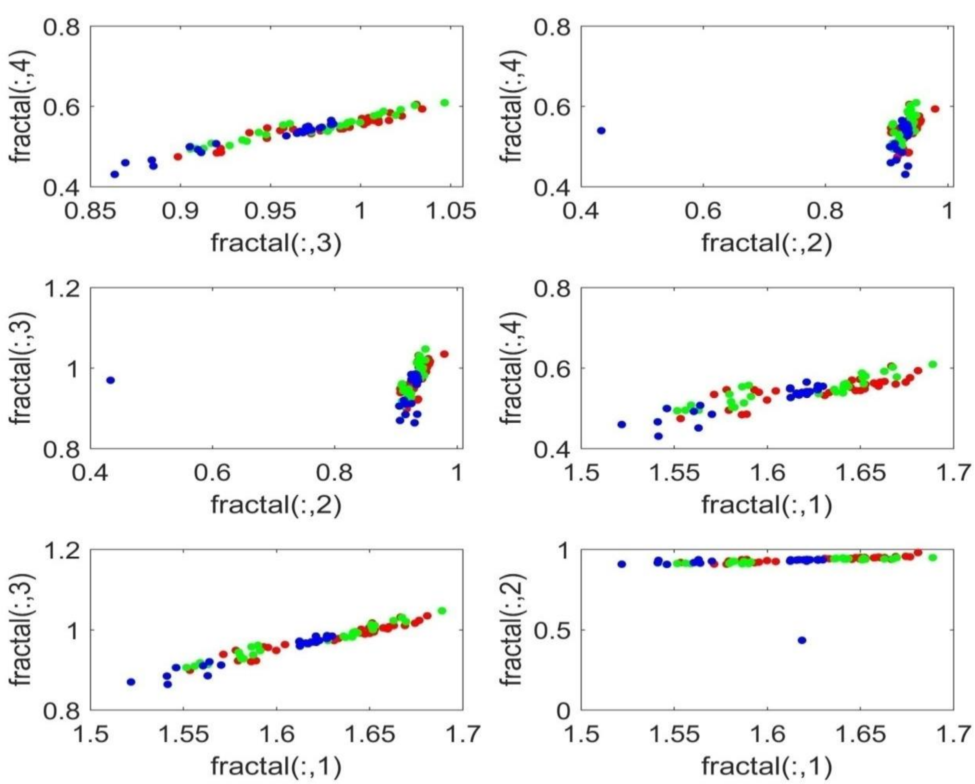

Fig. 4. Scatter plot of fractal features

For simplicity, all 2 dimensional combinations of fractal features extracted using Robert filter is alone shown in Figure 4. From figure, it is viewed that fractal 1 and fractal 4 combination scatter well which discriminates the ball bearing fault conditions clearly. Fractal 1 and fractal 4 are the fractal dimension and lacunarity respectively. These two fractal features are fed as input to MSVM for one versus all approach. The fault classification of ball bearing in IM along with posterior is shown in Figure 5. The recognition rate of MSVM of two approaches is listed in Table 4.

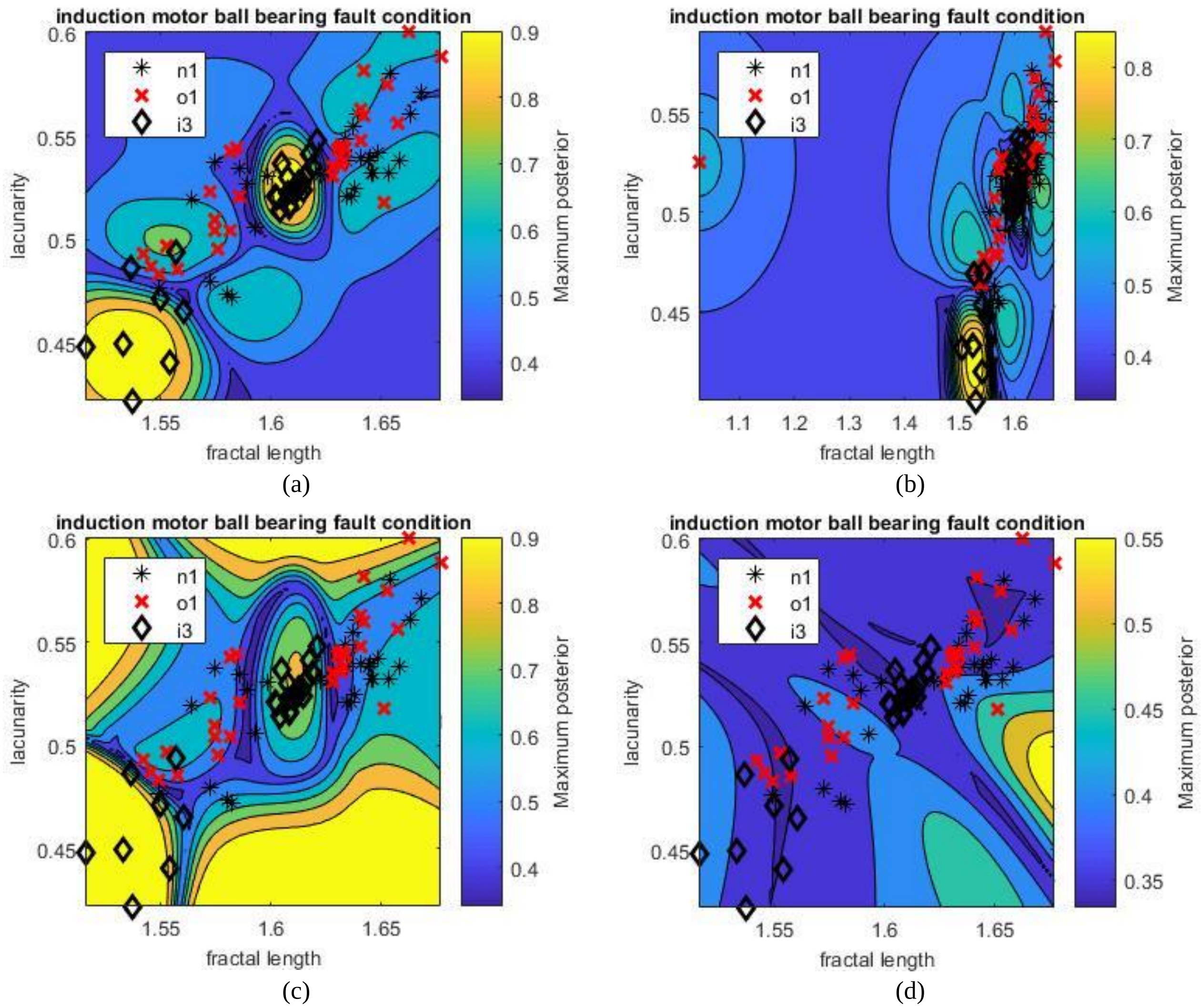

Fig. 5. Induction motor ball bearing fault classification
(a) gaussian kernel (b) RBF kernel (c) polynomial kernel (d) sigmoidal kernel

Table 4 Recognition rate of ball bearing fault condition by proposed MSVM classifier

SVM (first approach)																
Kernel Types	Gaussian				RBF				Polynomial				Sigmoidal			
Filter	Sobel	Prewitt	Roberts	Canny	Sobel	Prewitt	Roberts	Canny	Sobel	Prewitt	Roberts	Canny	Sobel	Prewitt	Roberts	Canny
Normal	73.33	76.67	63.33	76.67	76.67	76.67	**86.67**	75	66.67	76.67	70.00	70.00	73.33	66.67	66.67	70.00
Inner race fault	66.67	63.33	76.67	66.67	70.00	73.33	**70.00**	66.67	60.00	73.33	66.67	73.33	66.67	46.67	46.67	46.67
Outer race fault	70.00	86.67	66.67	70.00	66.67	73.33	**73.33**	80.00	66.67	66.61	73.33	46.67	70.00	66.67	73.33	66.67
SVM (second approach)																
Kernel Types	Gaussian				RBF				Polynomial				Sigmoidal			
Normal	76.67	76.67	86.67	70.00	93.33	90.00	**96.67**	73.33	73.33	66.67	73.33	73.33	80.00	66.67	80.00	66.67
Inner race fault	73.33	80.00	80.00	66.67	80.00	86.67	**80.00**	66.67	93.33	80.00	66.67	80.00	76.67	76.67	76.67	76.67
Outer race fault	70.00	76.67	76.67	76.67	66.67	66.67	**76.37**	76.67	80.00	76.67	73.33	66.67	93.33	66.67	66.67	66.67

MSVM model trained with two fractals features performs better than the MSVM trained using four features which are shown in table 8. It is clear that number of features taken should be less than the number of classes to be identified. As there is three set of ball bearing conditions in IM, MSVM can have the number of input fractal features less than two. MSVM using one against all with RBF kernel, works well for ball bearing fault classification as it yields higher recognition compared to other classifier for fractal feature extracted through Roberts filter.

6. CONCLUSION

In this work, Multi Support Vector Machine based ball bearing fault classification is carried out using fractal features which are extracted through box counting method. In box counting method, four types of filters namely sobel, prewitt, roberts and canny are employed for edge detection. The performance evaluation of the MSVM with two different approaches namely one versus one and one versus all is analyzed using the fractal features extracted from vibration signal of induction motor. In both the approaches, four different kernels namely Gaussian, RBF, polynomial and sigmoidal functions are used. RBF kernel based MSVM with one versus all approach using roberts filter in box counting method provides outer performance compared to other methods due to its gain flexibility and good out-of-sample generalization. The future research will be focused towards multiple faults in ball bearing recognition. This method addressed the challenge issues related with ball bearing fault classification in induction motor.

7. References

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