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Bearing Fault Diagnosis Using Weighted K-Nearest Neighbor

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***Abstract*—The rolling element bearings are essential components in rotating machines. Their condition can directly affect the machine operations. In this paper a new methodology for bearing fault diagnosis is proposed using weighted K nearest neighbor Classifier (WKNN). In WKNN, a squared inverse feature weighting technique is used to improve the performance of K-NN classifier. The proposed method uses simple time domain features to classify bearing condition using vibration signal. Multiple WKNN based classifiers are tested for optimizing the classification accuracy and computation complexity. Principle component analysis (PCA) is used to reduce the dimensionality of data set. Performance of WKNN for different K values and different distance metrics are compared with PCA and without PCA. Three bearing conditions, namely healthy, inner race fault and outer race fault were classified. The experimental results indicate that this method enables the fault detection in bearings with high accuracy. An accuracy of 100% was achieved using Mahalanobis distance metric.**

Keywords—induction motor, bearing faults, condition monitoring, fault detection, weighted K-nearest neighbor.

I. Introduction

Induction motors are most widely used energy converting devices in modern industries. More than 60% of electrical energy consumption in industrial applications is due to IM. Therefore the maintenance aspects of these machines become vital. Generally, these motors are considered robust, however due to environmental stresses, improper application and overloading can make them fail earlier than expected.

Rolling element bearing forms critical component in machinery operation. A major cause of machinery failures can be blamed to bearing failures [1][2]. Faults related to rolling bearing are around 30 to 40% of the total motor failures. These faults diagnosed in time can prevent accidents [3]. In the past bearing fault diagnosis have tried using different methods such as acoustic [4], vibration [5], current [6], thermography [7] etc.

In [8] a method is proposed to diagnose bearing fault in IM using adaptive noise cancellation. The stator currant signatures are analyzed for bearing fault components by cancelling the non bearing fault components. In [4] author used microphone sensor of a hand held mobile phone for recording acoustic signals to study bearing faults. However, the method suffers the limitation of poor frequency response of embedded mobile microphone in low frequency bands, especially for low voltage motors.

Among various diagnostic methods vibration based diagnostics is the most widely used technique for early fault detection in induction motors [9]. Artificial neural network (ANN) has been used for bearing condition estimation [9]. It is observed that using appropriate measurement and processing motor vibration signal can be applied for effective bearing diagnosis. In [10], bearing fault detection based on hidden Markov modeling (HMM) is proposed using vibration signal. Amplitude demodulated signal is used for feature extraction and training HMMs for estimating normal and faulty bearings.

Most acknowledged frequency domain technique for bearing fault diagnosis is envelope analysis, also commonly known as high frequency resonance technique (HFRT). The method is explained in [11] for bearing fault detection. However, the technique suffers from low signal to noise ratio and presence of a large number of frequencies because of mechanical components. Moreover the method requires pre-estimation of bearing defect frequencies.

K-nearest neighbor (K-NN) [12][13] classifier is a widely used classifier due to its simplicity and ease of implementation. It is a non parametric method for classification and regression. KNN is also known as lazy learning technique which does not require off line training. In this paper the vibration signal is collected from bearing under healthy and defective conditions. Feature extraction is applied to extract different time domain features from the data. These extracted features are used to categorize different conditions of bearing using weighted K-nearest neighbor (WKNN) classifier.

II. WKNN

One of the most successful statistical classifier studied widely in various pattern recognition problems is the K-NN. This classifier has been popularly used as the base line classifier in different problem domains [14][15]. The K-NN classifiers have advantages such as robustness to noisy training data, no training phase and learn complex models easily. However K-NN also suffers from disadvantages such as need for determination of K value, also the type distance metric to use. If the dimensionality of the data is high than problems such as low computational efficiency, data sparsity, false intuition and need for large amount of data storage requirement arises.

The K-nearest neighbor classifier is a non parametric classifier usually used to classify an unknown new feature vector, where computation is performed online. For an unknown vector the K-NN classifier computes distances between the new vector and training data set using one of the distances metric such as Euclidean distance, in order to identify the nearest neighbor and compute the output class. It assigns new vector a class among one of the classes of its k nearest neighbors, where k is an integer value which represents the number of nearest points considered. Fig.1 explains the methodology of KNN classifier, a testing point is shown (as a triangle) surrounded by a number of training vector points (as squares and circles) representing two different classes. For K=1, the test point belongs to 'class A' because of minimum distance and if K=5, the test point belong to 'class B' which is the majority class in 5 nearest points.

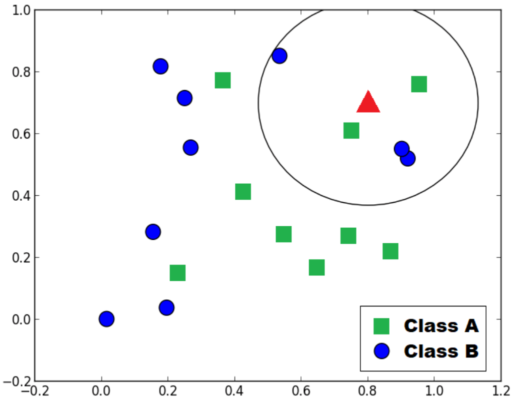


Fig.1 Classification of new data point using k nearest neighbour

For measuring distance between two points in feature space, different distance function have been reported, such as Minkowsky, Correlations, Manhattan, Chi-square and Euclidean distance in which Euclidean distance function is the most extensively used in the literature. For calculating the distance between points A and B in feature space different types of metrics used are:

$$Eulicidean(A,B) = \sqrt{\frac{\sum_{i=1}^{m}(x_i-y_i)^2}{m}} \tag{1}$$

$$Minkowsky(A,B) = \left(\sum_{i=1}^{m}|x_i - y_i|^r\right)^{1/r} \tag{2}$$

$$Correlation(A,B) = \frac{\sum_{i=1}^{m}(x_i-\mu_i)(y_i-\mu_i)}{\sqrt{\sum_{i=1}^{m}(x_i-\mu_i)^2 \sum_{i=1}^{m}(y_i-\mu_i)^2}} \tag{3}$$

$$Mahalanobis(A,B) = \sqrt{(x-y)^T S^{-1}(x-y)} \tag{4}$$

$$Hamming(A,B) = \sum_{i=1}^{m}|\mathrm{x_i} - y_i| \tag{5}$$

where points A and B are represented by the feature vectors A = (x_1, x_2, x_3, x_4,....x_m), B = (y_1, y_2, y_3, y_4,.....y_m), m represents the dimensionality of the feature space and S is the covariance matrix.

The WKNN is an improved version of conventional K-NN technique (where all features are given equal weight). In WKNN, features in the feature space are assigned weights according to their position [16][17]. The distance weights are assigned to neighbors using 'squared inverse' method.

III. EXPERIMENTAL SETUP

Experimental set up for data collection is shown in Fig. 2. A 3-phase, 0.5 hp, star connected induction motor is used with a single axis accelerometer (sensitivity 100mV/g) is mounted on the motor housing at the drive end of the motor to acquire the vibration signals from the bearing. In this setup bearing 6204 having 8 balls, with ball diameter 7.93mm and contact angle 0 degree is used with inner and outer race defects created by producing 2mm diameter hole through electron discharge machining. Measurements from motor were obtained using data acquisition system comprising of NI-cDAQ-9178 and NI-9234 vibration sensing module. The complete experimental setup is shown in the Fig. 2(a) and the defective bearings used in Fig. 2(b) below.

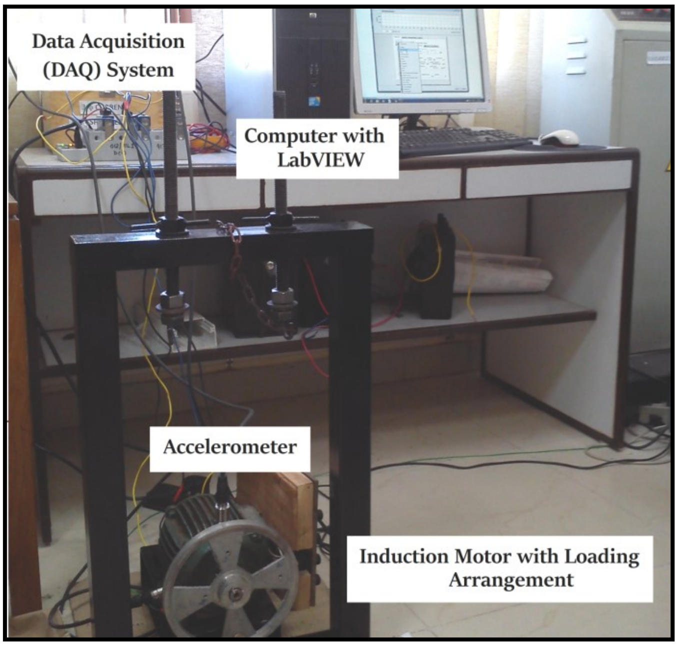


Fig. 2. (a) Experimental setup

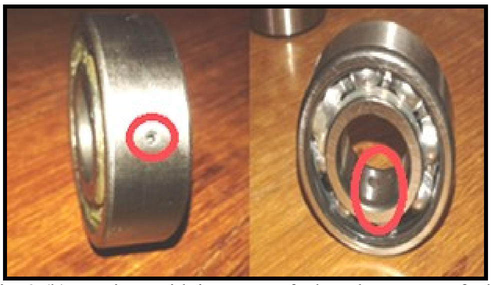
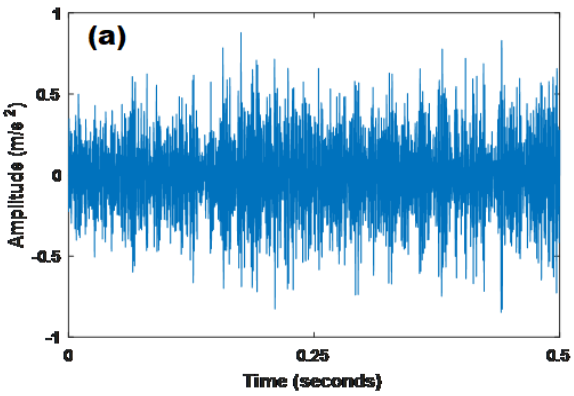


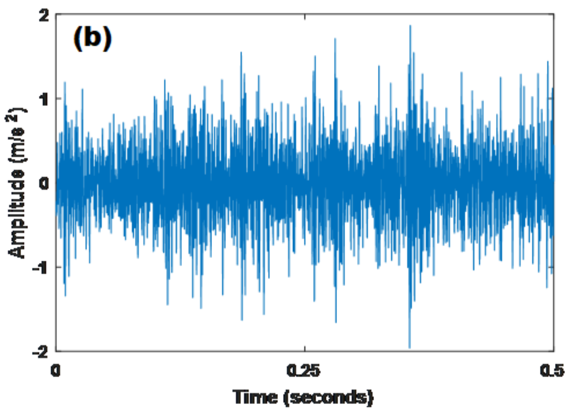
Fig. 2 (b) Bearings with inner race fault and outer race fault.

The data was acquired from motor for different condition of ball bearing with motor running at 75% of rated load. Samples of data are obtained at a sampling rate of 12800 samples per second with a scan length of 96000 samples. The experiment was performed 5 times for each condition and each repetition data was divided into 10 equal non-overlapping sections comprising of 9600 samples. Thus, 50 subsets of data were produced, which were further used for feature extraction. These sections were chosen such that each section contains data of at least 10 revolutions of motor. A total of 8 time domain features were extracted from these 50 sections for each healthy, inner race and outer race defect conditions.

IV. FEATURE EXTRACTION

Fig. 3 (a) to Fig.3 (c) shows the time domain vibration signal obtained from healthy bearing, bearing with inner race defect and outer race defect respectively.





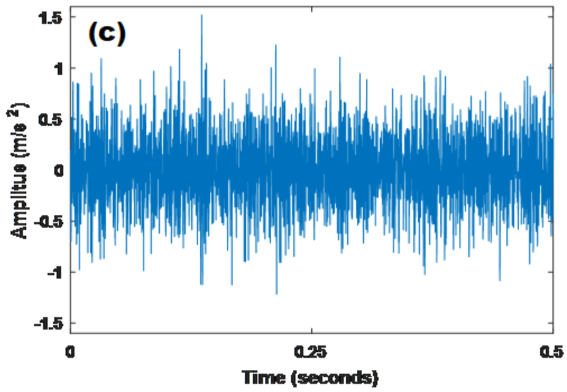


Fig. 3. Vibration signal of (a) Healthy; Fig. 3 (b) Inner Race Fault; Fig. 3 (c) Outer Race Fault.

The time domain vibration signal looks similar for all three cases except for change in the vibration magnitude. The magnitude of faulty bearing, i.e. bearing with inner and outer race defects is more than a healthy bearing vibration signal. To diagnose bearing condition time domain features were extracted from vibration data. The time domain vibration signal was split into sub-sections before feature extraction. The extracted time domain features include root-mean-square (RMS), variance (VAR), kurtosis (KUR), peak value (PV), skewness (SKW), median (MED), rms*kurtosis (F1) and rms*peak (F2). The mathematical expression for the same is given as under (where, N = total number of observations):

$$Root\ Mean\ Square\ (RMS) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2} \tag{1}$$

$$Variance\ (VAR) = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 \tag{2}$$

$$Kurtosis\ (KUR) = \frac{\sum_{i=1}^{N}(x_i-\bar{x})^4}{(RMS\ value)^4} \tag{3}$$

$$Peak\ Value\ (PV) = \frac{1}{2}[max(x_i) - min(x_i)] \tag{4}$$

$$Skewness\ (SKW) = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\overline{x_i})^3}{(Standard\ deviation)^3} \tag{5}$$

$$Median\ (MED) = \left(\frac{N+1}{2}\right)^{th} term \text{ in an ordered list} \tag{6}$$

$$F1 = RMS \times KUR \tag{7}$$

$$F2 = RMS \times PV \tag{8}$$

After feature extraction, the features were normalized individually for each class. The obtained features were normalized in the range [0, 1] (except skewness which was normalized in the range [-1, +1]). This was done in order to improve the accuracy and discrimination of any bias among features. Fig. 4 shows the normalized features for different fault conditions.

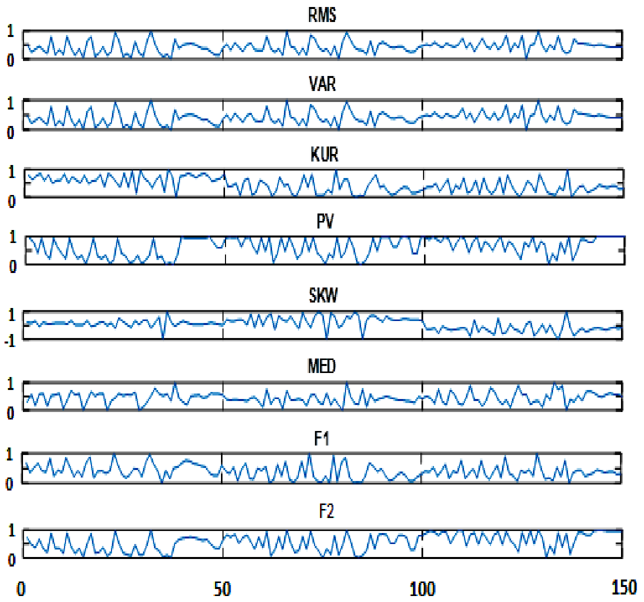


Fig. 4. Normalized features used as training data; Healthy (0-50 samples), Inner Race Fault (51-100 samples), Outer Race Fault (101-150).

These extracted and normalized features were used as input feature vectors (50 for each bearing condition) to classify motor conditions using WKNN classifier.

V. RESULTS AND DISSCUSSION

Classification results were obtained by selecting 25% holdout validation from training data using different number of features. In holdout method, two data sets are randomly assigned, typically called the training data set and the test data set. The size of testing data set is generally 25% of the total data, which is used to test the trained model.

Feature reduction on extracted features was implemented using principal component analysis (PCA) technique and its effect on classification accuracy was observed. PCA is a mathematical technique used for transforming a number of variables which may be correlated, to a set of uncorrelated variables called principle components. The new set of a variables are linearly uncorrelated and are usually smaller in number which are used to bring out strong patterns in data. The following sections describe the results for different cases:

A. Classification Results Obtained Without PCA

The extracted features were tested for their ability to distinguish the different fault classes using individual (single feature) accuracies with weighted KNN model. Euclidian distance metric was used for calculating the output of model with value of K set as 10. Fig. 5 shows the accuracies obtained for different features.

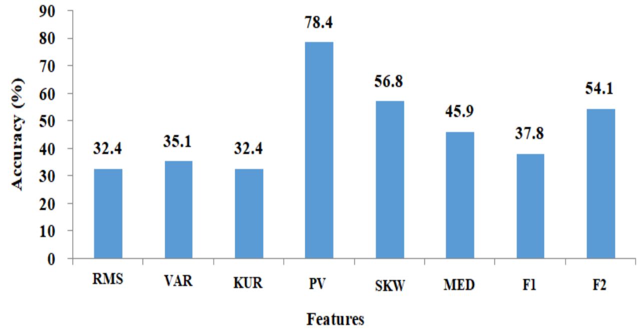


Fig. 5. Individual accuracies obtained for different feature using weighted 10-NN.

A combination of features with best accuracies were tried to maximize the classification rate. It is seen that best accuracy is obtained when all the features are combined together. Table 1 shows the results of various feature combinations for the model. Accuracies obtained for different combination of features.

Table 1 Output accuracies obtained for different combination of features.

Features	Accuracy (%)
PV, SKW	67.6
PV, F2	70.3
PV, SKW, F2	70.3
PV, SKW, MED	75.8
PV, SKW, MED, F2	83.8
PV, RMS, SKW, F2, KUR, VAR, F1, MED	86.5

B. Classification Results Obtained using PCA

To improve the results further and reduce the dimensionality of data set, the PCA based feature reduction was applied on the originally obtained features to generate new principal components. Fig. 6 shows the explained variance in percentage for each component.

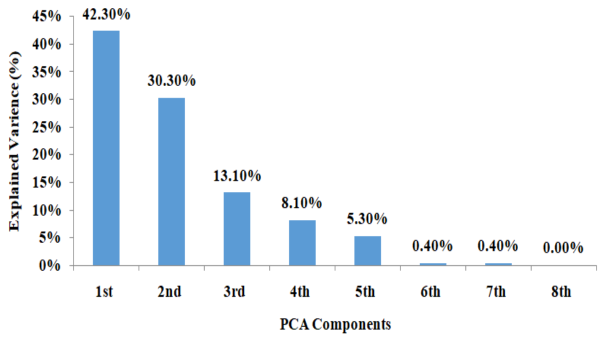


Fig. 6. Explained variance for PCA components

Different number of PCA components were used to find out the accuracies using WKNN (for K=10), with inverse squared distance weight and Euclidian distance metric. Fig. 7 shows corresponding results obtained:

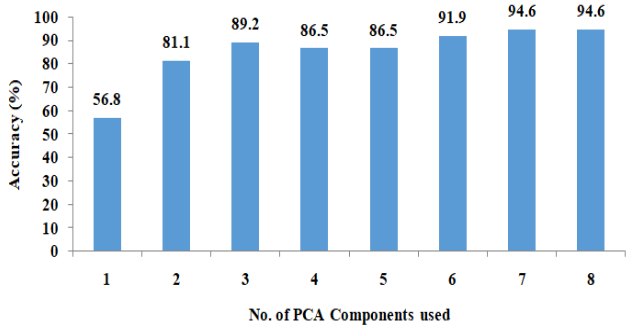


Fig. 7. Percentage accuracy obtained with different number of PCA components

C. *Effect of Variation of 'K' and Different Distance Metrics on Classification Accuracy.*

Using different K values and distance functions (metrics) are likely to produce different classification results. To find the optimal value of K (neighborhood parameter) different values of K were tried along with three different distance functions, namely Euclidean, Mahalanobis and Correlation. Fig. 8 shows the variation of classification accuracy for different values of K and distance metrics. To simplify the computation and ambiguity, only the odd values of K were selected to find the classification accuracies. Fig. 8 shows the accuracy obtained for different K values.

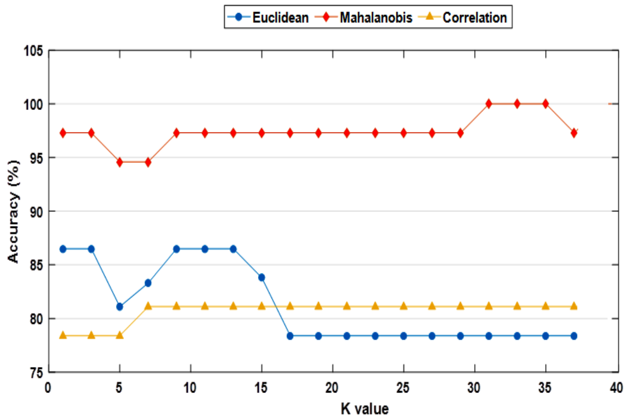


Fig. 8. Variation of classification accuracy for different distance metric and K values (without using PCA)

Different odd values of K (i.e. K = 1, 3, 5, ….) were tested for the classifier. It is observed that the accuracy becomes constant for Mahalanobis distance, after K = 9 (97.3%) and reaches 100% for K = 31, 33 and 35 and again decreases. For Euclidean distance the accuracy is maximum for K = 1, 3, 9, 11 and 13 and decreases and becomes constant for K > 17 (78.4%). For Correlation distance the accuracy for K=1 is 78.4% which increases at K=7 (81.1%) and becomes constant for higher values of K.

It is observed that the Mahalanobis distance metric produces best classification accuracies as compared to Euclidean and Correlation distance metrics. To improve the classification further, PCA was applied and all 11 components were used as input vectors for WKNN classifier. Fig. 9 shows the variation of accuracy with different K values, when PCA was used.

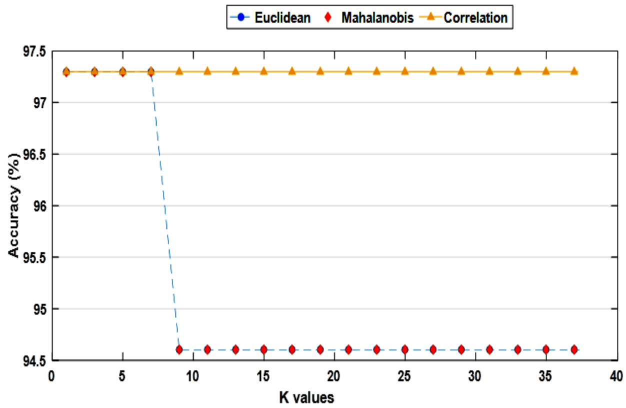


Fig. 9. Variation of classification accuracy for different distance metric and K values (with PCA)

For all the distances metrics using PCA (considering all components), the maximum achievable accuracy is 97.3% for K values lying between 1 and 7. Further, it is observed that for Correlation distance metric, accuracy was constant for all values of K. However, in case of other two distance metrics it decreases and becomes constant at a value of 94.6%.

VI. CONCLUSION

In this paper, a WKNN based bearing fault diagnosis method is proposed. The vibration data is collected for healthy and defective bearings for classification purposes. The effectiveness of proposed method was tested using different distance functions such as Euclidean, Correlation and Mahalanobis, with different number of nearest neighbors (K). Fig. 8 and 9 shows the accuracies obtained for variation of neighborhood parameter (K) values and different distance metrics. It is observed that Mahalanobis distance function performs best over the other functions for the same K values without using PCA. On the other hand, correlation function has higher classification rate than the other distance functions when PCA is used. However, 100% accuracy can be achieved only in case of Mahalanobis distance for K = 31, 33 and 35 without using PCA. The obtained results suggest the effectiveness of the proposed method for bearing fault diagnosis. For further improvement of classification accuracy, the results of multiple WKNN classifiers with different values of nearest neighbor parameter can be combined. The classification can also be improved by classifier-fusion using different other types of classifier such as Support Vector Machine (SVM), Decision Trees and Artificial Neural Networks (ANNs) etc.

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