Fault diagnosis of electric motors using vibration signal analysis

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ABSTRACT

In industrial applications, especially in manufacturing environments, electric motors are employed practically everywhere. They are necessary for many different sectors, which can sometimes make it challenging to prevent malfunctions and keep them operating at their best. Numerous defects can affect how well they work, but bearing-related errors are the most frequent reasons for motor failures. This research uses temporal and frequency domain analysis of vibration signals to identify motor faults. A public domain database has been used for the investigation and analysis. The findings show that electric motor problems, including inner raceway, outer raceway, and rolling element fault, can be identified and diagnosed using the time and frequency domain features extracted from the vibration signals. The effectiveness of the proposed technique is shown by comparing it with both the time domain and frequency domain techniques. The accuracy of the time domain and frequency domain techniques is 85.4% and 91.6% respectively. However, the proposed hybrid technique has a far better accuracy of 95.8% as compared to the two techniques.

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1. INTRODUCTION

Vibration spectrum analysis is a method that helps in the detection and diagnosis of faults in electric motors. The bearing-related faults are among the most common faults found in electric motors. In this study, time domain statistical features such as standard deviation, root mean square value, kurtosis, clearance factor, shape factor, impulse factor, peak value, and crest factor were extracted to detect any bearing fault. Whereas, in the frequency domain, cepstrum analysis of the vibration signal was done to detect and diagnose the existence of any bearing fault.

Iorgulescu *et al.* [1] used the fast Fourier transform (FFT) of vibration signals to detect motor faults. They presented a comparison between the amplitudes of spectrums under different operating conditions. However, they did not specify the type of fault present. Chaudhari *et al.* [2] proposed that wavelet analysis provides more prominent amplitudes of fault frequencies as compared to FFT. Shrivastava and Wadhwani [3] used time features to distinguish bearing conditions. Ágoston [4] observed that phase and amplitude monitoring of vibration signals can identify a fault; however, this approach cannot detect the fault location. Korkua *et al.* [5] predicted the severity level of imbalance in the rotor using vibration signals. Still, the analysis was limited to a few features, i.e., root mean square value, crest factor, and amplitude of the spectrum. Ma *et al.* [6] presented fault detection of bearing based on wavelet packet-cepstrum; however, they only confined the study to the bearing's outer ring failure. Rauber *et al.* [7] presented performance scores based on different machine-learning vibration signal algorithms. They compared four distinct sets of classifiers to validate their results. Alameh *et al.* [8] proposed a fault detection technique based on vibration signals for a permanent magnet synchronous machine. Various simulations have been performed, and finally, for fault detection, a global diagnosis approach is presented. Yakhni *et al.* [9] presented the condition monitoring of the induction motor using the transient motor current signatures method and elaborated on the fault type and location in order to diagnose them quickly. The results have been compared using two different techniques, i.e. Adaptive observer and Adaptive notch filtering. Alameh *et al.* [10] also presented one vibration fault diagnosis technique in the case of a BLDC motor using MATLAB Simulink. The different scenarios of vibrations have shown that which the space harmonics are extracted under different fault conditions. The results are then tested on two different sets of noisy simulated data under different machine conditions. Delgado-Arredondo *et al.* [11] presented a fault detection technique by analyzing acoustic sound and vibration signals for detecting various faults in the case of induction motors under steady-state conditions. Zhang *et al.* [12] analyzed the faults of permanent magnet motors and presented a default identification method using the residual convolutional neural network (RCCNN) model. The accuracy of the model is verified using the RCCNN model, which improves the accuracy of the permanent magnetic motor by 13.1%. Niu *et al.* [13] presented a motor-bearing fault diagnosis approach under variable speed conditions using order analysis. The efficiency and effectiveness of the order analysis have been verified on a BLDC motor set-up. Park *et al.* [14] proposed a novel health current residue map for the fault diagnosis of a permanent magnet synchronous motor. The experimental validation of this residue map was demonstrated under different load torque and variable speed conditions. Gangsar and Tiwari [15] analyzed the vibration and current signals for various fault conditions in the case of induction motors using other artificial intelligence methods. Glowacz [16] proposed a fault identification method for the analysis of thermal images of single-phase induction motors and commutator motors. Different techniques were proposed, and the results were compared under other fault conditions. Bedida *et al.* [17] compared two different approaches of an induction motor under different faulty conditions to analyze the harmonics and torque ripples. Noussaiba and Abdelaziz [18] analyzed the unbalanced supply voltage effect using ANN based algorithm. The results have been shown by both simulations as well as hardware. Wang *et al*. [19] detected the gears fault of induction motor by using different AI techniques. The results have been shown using time domain analysis and lumped parameter models. Similar analysis of induction motor faults has been shown by using different AI techniques as presented in [20], [21].

From the available literature, it has been observed that faults in motors have been explicitly detected. Still, there are research gaps like the inability to locate the type of fault present or restricting the analysis to observe the amplitude difference of vibration spectra under normal and faulty conditions. In this paper, authors have tried to detect the faults using time domain analysis, and then the location of the fault is obtained using cepstrum analysis of vibration data. This provides an efficient method to find the fault location and rectify it to reduce the machine's downtime.

2. NOTATION

There are some critical parameters used throughout this paper, which are outlined to ensure clarity and consistency. The bearing ball diameter influences load capacity, while the pitch diameter defines the path of rolling elements during rotation, affecting kinematics and load distribution. The contact angle determines the direction of forces between the rolling elements and raceways, impacting axial and radial load handling. The number of rolling elements affects stability and load capacity, and the rotation speed influences wear and lubrication. Bearing size is defined by its width, inner diameter, and outer diameter, with pitch diameter and contact angle playing key roles in load dynamics and overall performance. The key notations used throughout the paper are: d is bearing ball diameter; D_m is pitch diameter; α is the contact angle of the rolling element; Z is the number of rolling elements; and f is the rotation speed.

The bearing size is usually calculated by identifying three parameters: width, inner diameter, and outer diameter. Pitch diameter refers to the circle diameter through which the center point of a ball travels when the bearing rotates. The contact angle of a rolling element, such as a ball bearing, is the line of contact through which the rolling element traces the channels of the assembly unit.

3. DATABASE AND METHODOLOGY

This research work uses the ball bearing test data provided by Case Western Reserve University Bearing Data Centre. The experimental acceleration data of the 2 hp electric motor were recorded at different locations around the mearings of the motor. At the inner raceway, outer raceway, and rolling element, faults had been introduced ranging from 0.007-0.040 inches in diameter. Then at a motor speed ranging from 1797-1720 rpm and at a load of 0-3 hp, the reinstallation of faulted bearings was done into this test motor, and experimental analysis of vibration data was obtained from the Case Western University dataset [22].

3.1. Time domain analysis

The time domain vibration signals were obtained at a sampling frequency of 12,000 (12k) samples per second. These signals were obtained for different operating conditions of various faults in the motor i.e. at normal operation as well as with inner raceway, outer raceway, and rolling element faults in the motor. The statistical features were obtained with a fault diameter of 0.007 inches, at no load and a speed of 1797 rpm. The complete statistical features are shown in Table 1 [23], [24].

Table 1. Time domain features extracted and their formulae

Feature	Formula	Feature	Formula
Peak value	$max(X_i)$	Skewness	$\frac{\frac{1}{N}\sum_{i=1}^{N}(X_i - X_m)^3}{(\text{Standard Deviation})^3}$
Mean ($\boldsymbol{X_m}$)	$\frac{1}{N}\sum_{i=1}^{N} X_i$	Clearance factor	$\frac{\text{Peak Value}}{\left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{\lvert X_i\rvert}\right)^2}$
Standard deviation	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - X_m)^2}$	Kurtosis	$\frac{\frac{1}{N}\sum_{i=1}^{N}(X_i - X_m)^4}{(\text{Standard Deviation})^4}$
Root mean square (RMS)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i)^2}$	Impulse factor	$\frac{\text{Peak Value}}{\frac{1}{N}\sum_{i=1}^{N}\lvert X_i\rvert}$
Crest factor	$\frac{\text{Peak Value}}{\text{RMS Value}}$	Shape factor	$\frac{\text{RMS Value}}{\frac{1}{N}\sum_{i=1}^{N}\lvert X_i\rvert}$

3.2. Frequency domain analysis (cepstrum analysis)

A cepstrum is obtained by taking the inverse Fourier transform of the logarithm of a spectrum, i.e. cepstrum is given by (1).

$$F^{-1}\{log|\{F[x(t)]\}|\} \tag{1}$$

Cepstrum has quefrency (sec) as the independent variable, which is the reciprocal of frequency spacing in the original frequency spectrum. Cepstrum analysis can detect repeated patterns in a spectrum, making it helpful in differentiating various faults that are difficult to see in the different primary spectra. The peaks in the cepstrum plot can be used to find the bearing fault peaks in the original spectra. Significant peaks in the cepstrum correspond to possible fundamental bearing frequencies, which are given by the following expressions [25]:

$$\text{For inner raceway defect, } f_{ir}(Hz)\text{: } \frac{Z}{2}\frac{f}{60}\left[1 + \left(\frac{d}{D_m}\right)cos\,\alpha\right] \tag{2}$$

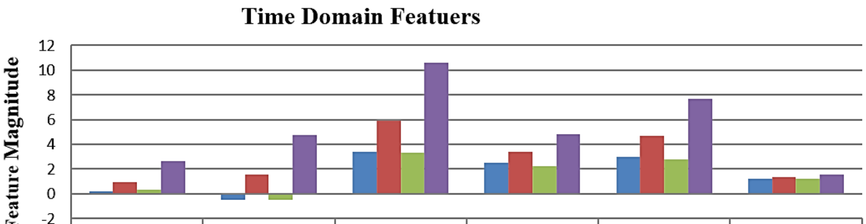
$$\text{For outer raceway defect, } f_{or}(Hz)\text{: } \frac{Z}{2}\frac{f}{60}\left[1 - \left(\frac{d}{D_m}\right)cos\,\alpha\right] \tag{3}$$

$$\text{For rolling element defect, } f_{re}(Hz)\text{: } \frac{D_m}{d}\frac{f}{60}\left\{1 - \left[\left(\frac{d}{D_m}\right)cos\,\alpha\right]^2\right\} \tag{4}$$

4. ANALYSIS AND RESULTS

4.1. Time domain analysis results

A significant difference in the magnitudes of extracted time domain features was observed between the vibration signal recorded under normal operating conditions and the ones with bearing faults introduced in the motor, which depicts an increase in the vibration signal amplitude in case of faulty bearings, as shown in Figure 1. Different features of the time domain analysis have been presented in terms of six different parameters: peak value, kurtosis, crest factor, clearance factor, impulse factor, and shape factor. The clearance factor has the highest magnitude in the case of outer raceway fault, followed by inner raceway fault, and thus, these can be used to distinguish an outer raceway fault from other operating conditions. The crest factor, clearance factor, and impulse factor, also being lowest in case of rolling element fault, can help to identify it. Therefore, only time-domain analysis of vibration data helps in fault detection but does not precisely diagnose the fault present. Therefore, better classification of faults can be achieved using frequency domain analysis of the vibration signal after the time domain analysis. It can be observed from Figure 1 that the peak value is significantly different for normal operations versus inner raceway faults and outer raceway faults.



	Peak Value	Kurtosis	Clearance Factor	Crest Factor	Impulse Factor	Shape Factor
Normal Operation	0.2178	-0.5132	3.3768	2.5186	2.9918	1.1879
Inner Raceway Fault	0.9504	1.5678	5.876	3.3939	4.6702	1.3761
Rolling Element Fault	0.3281	-0.5036	3.3525	2.2628	2.8054	1.2398
Outer Raceway Fault	2.6375	4.7730	10.5598	4.8435	7.7041	1.5906

Figure 1. Statistical features extracted in time domain

4.2. Cepstrum analysis results

At no load operation of the motor, i.e. at 1797 rpm, inner raceway fault frequency=5.4*running speed in Hz = 161.73 Hz; which corresponds to $6.2*10^{-3}$ or 0.0062 sec on the quefrency axis. Similarly, outer raceway fault frequency=3.5848*running speed in Hz corresponds to 0.0093 sec, and rolling element fault frequency=4.7135*running speed in Hz corresponds to 0.0071 sec. When cepstrum analysis was performed, the plot peaks were obtained, corresponding to fault frequencies calculated theoretically. This confirms the existence of the respective bearing fault in the electric motor. The Case Western Reserve University (CWRU) bearing dataset is widely used for bearing fault diagnosis research. This dataset provides vibration data for various bearing fault conditions, including inner race faults, outer race faults, and ball faults at different fault sizes and loads.

As per the (2), for the given one sample of data the inner race frequency is fr = 1797 RPM = 1797/60 = 29.95 Hz; Contact angle of rolling element of 0 degree i.e. $cos\alpha$ = 1; Rolling element = 9; d = 7 mm; D_m = 35 mm. The inner race frequency f_{ir} = 4.5*(1+(7/35))*29.95 = 161.73 Hz (as per (2)). Now if we analyze the FFT or the cepstrum plot of the vibration signal, then there will be a peak at the frequency of 161.73 Hz which corresponds to 0.0062 sec on the quefrency axis. This shows that there is definitely an inner race fault. The cepstrum analysis of the inner and outer raceway fault in the bearing is shown in Figures 2 and 3 respectively. However, the cepstrum analyze of rolling element fault in the bearing is shown in Figure 4. The above-said parameters have been used to analyze all the existing motor faults available.

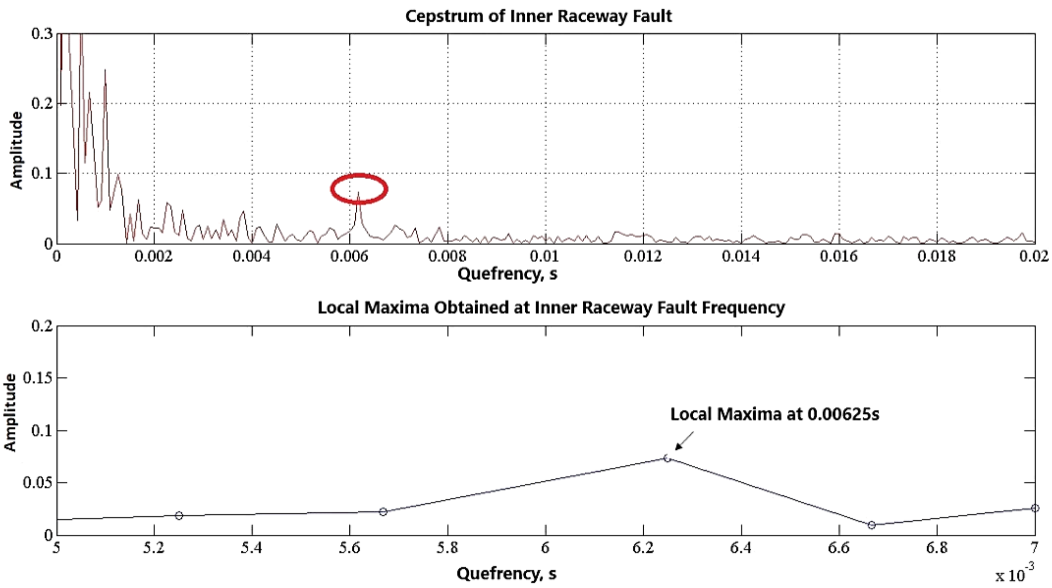


Figure 2. Cepstrum analyze of inner raceway fault in bearing

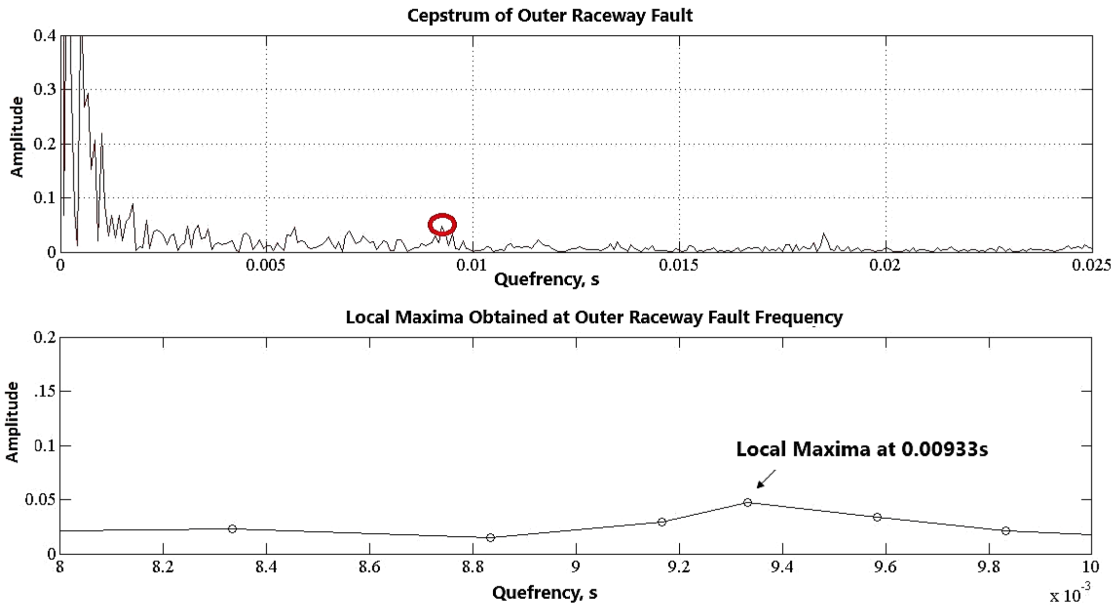


Figure 3. Cepstrum analyze of outer raceway fault in bearing

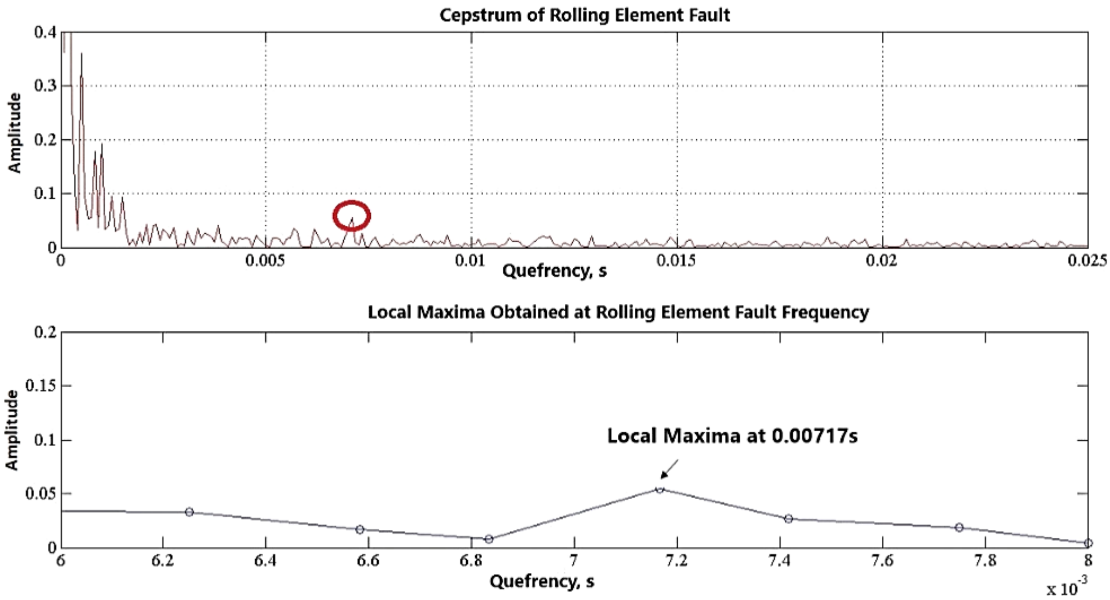


Figure 4. Cepstrum analyze of rolling element fault in bearing

In the available data, there were a total of 48 signals, 32 signals were taken from faulty motors (same fault), and 16 signals were taken from normal motors with no fault. All the signals have been evaluated using the above parameters, and a confusion matrix has been prepared to calculate the overall accuracy of the proposed features. A confusion matrix is a record of results against some hypothesis. When there is a fault in the motor, and the vibration signal gives the same information, it is called true positive (TP) and if the signal says the motor is normal, it is false negative (FN). On the other hand, if there is no fault in the motor and the vibration signal gives the same information, it is called true negative (TN), and if the signal says the motor has a fault, then it is false positive (FP). The confusion matrix of the detection of fault is shown in Table 2. A detailed comparison in terms of the accuracy of the two different domains is shown in Table 3. It has been concluded that the accuracy of the time domain technique is 85.4%, whereas the accuracy of the frequency domain technique is 91.6%. However, the proposed hybrid technique has a far better accuracy of 95.8% than the two domains.

The following performance parameters can be found from the confusion matrix, Table 2.

$$Sensitivity = \frac{TP}{(TP+FN)} \quad (5)$$

$$Specificity = \frac{TN}{(TN+FP)} \quad (6)$$

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (7)$$

As per (7), the accuracy of the proposed method has been calculated as 98.5%. This means that the correctly detected samples (TP+TN)/total samples: (31+15)/48=46/48=95.8%. Similarly, we can also calculate the specificity = (15)/(0+15)=1, which shows that all abnormal samples have been correctly detected by the proposed methodology.

Table 2. Confusion matrix

Fault status	Fault detected	Fault not detected
Actual fault	31 (TP)	02 (FN)
Actually no-fault	00 (FP)	15 (TN)

Table 3. Comparison of both techniques

S.No.	Method	Accuracy
1	Time domain	85.4%
2	Frequency domain	91.6%
3	Hybrid features(proposed)	95.8%

5. CONCLUSION

This study presents the techniques for analyzing the operating condition of a motor using time domain statistical feature analysis and frequency domain cepstrum analysis. As depicted by experimental results, time domain analysis of vibration data helps to differentiate between normal and faulty operating conditions but does not efficiently diagnose the fault. Whereas the cepstrum analysis technique, which includes the detection of peaks corresponding to different fault frequencies, is a reliable and efficient technique for fault diagnosis, locating the fault present in the motor bearings. Therefore, a hybrid method is proposed, where highly discriminating features from the time domain and frequency domain have been selected and used to classify the data for fault detection. It has been observed that the proposed hybrid method is working better than the previous methods. As compared to the existing methods, this combination of hybrid features has higher accuracy (95.8%) in detecting the raceway faults in motors.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Mandeep Singh	✓	✓		✓		✓	✓	✓	✓					
Tejinder Singh Saggu	✓	✓		✓	✓			✓	✓					
Arvind Dhingra					✓	✓				✓	✓	✓	✓	

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the Case Western Reserve University Bearing Data Centre at http://csegroups.case.edu/bearingdatacenter/pages/welcome-case-western-reserve-university-bearing-data-center-website, reference number [22].

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