Diagnosis of Bearing Fault Using Morphological Features Extraction and Entropy Deconvolution Method

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Abstract— It is observed that the bearing failure of rotating machinery is a pulse in the vibration signal, but it is mostly immersed in noise. In order to effectively eliminate this noise and detect pulses, a novel an image fusion technology based on morphological operators inference is proposed. The correctness of morphological operators lies in the correct selection of structural elements (SE). This report presents an effective algorithm for SE selection based on kurtosis, which makes the analysis free empirical method. When analyzing three different groups of faults, the results show that this method effectively and robustly generates impulse. It enables the algorithm to detect early faults too. Recently, minimum entropy deconvolution (MED) was introduced to the machine in the field of condition monitoring, to enhance the detection of rolling bearing and gear failures. MED analysis helps to extract these pulses and diagnose their source, namely defects bearing components. In this research, MED will be reviewed and reintroduced, Application in fault detection and diagnosis of rolling bearings. MED parameters are selected and its combination with pre-whitening. Test cases are presented to illustrate benefits of MED technology. The simulation has been done on MATLAB and a graphical user interface has been created for analysis of bearing and detection of bearing faults using morphological features.

Keywords— Morphological Features, Bearing Faults, Inner Cage, Outer Cage Fault, Kurtogram.

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I. Introduction

Since abnormal vibration of rotating machinery is the first sensorial effect of component failure; vibration analysis is widely used in the industry. The fault signal, vibration generated by the interaction between a damaged and a rolling surface area occurs regardless of the type of defect. Consequently, a vibration analysis can be used to diagnose all types of failures, either localized or distributed. In addition, low cost sensors, precise results, simple installation, specific information on damage location and comparable rates of damage are the other benefits of vibration measurement method. Very often the damage in bearings typically occurs in the laminate element, indoor track and outdoor track. The difficulty of detecting faults in bearings It lies in the fact that the signature of a defective bearing is spread over a wide frequency band and it can be masked by the noise. There are several techniques that can be used to support fault detection and these techniques can be classified in three areas, namely the frequency domain analysis, frequency domain time analysis and time domain analysis. The frequency domain methods often involve frequency analysis of the vibration signals and regards frequency of high frequency transients. In these processes, the frequency domain search methods of a train ring occur in any of the frequency characteristic defects. This procedure is complicated considering the fact that the frequency can be suppressed. These frequency domain techniques include frequency averaging technique, the adaptive noise cancellation and technique of high-frequency resonance (HFRT), to name a few. The HFRT is the most popular technique for bearing fault detection and the diagnosis but the disadvantage of the technique is that it requires HFRT several impact tests to determine the resonance frequency of the bearing. Therefore, It becomes computationally expensive. Another frequently used technique for the detection and diagnosis of bearing failures is envelopment analysis as it presented by McFadden and Smith (1984). The main disadvantage of the analysis of frequency domain is that it tends to average transient vibrations therefore it becomes more sensitive to background noise. To overcome this problem analysis time-frequency domain, showing how the frequency content of the signal change over time, is used. [9] In the recent year condition monitoring based on vibration rotating machinery has been studied mostly from a signal processing view. But little attention has been paid to the effects of failure bearing vibration behavior. Therefore, the first step in success the implementation of health monitoring support is to establish the behavior of the baseline a healthy bearing. Furthermore, although a number of rotating machines operate under varying speed and load conditions, very few researchers have robust techniques proposed for fault diagnosis and prognosis of such systems. This research also proposes a new algorithm for this SE selection based on kurtosis.Bearing faults of rotating machinery are observed as impulses in the vibration signal, but it is mostly immersed in noise. In order to effectively remove this noise and detect the impulses, a novel technique with morphological operators is proposed in this research. Rolling device laying, antifriction bearing and roller bearing are known as rolling elements, where load is borne over by rolling, not sliding and contact elements. The covers are designed for pure radial loads, pure thrust loads or two kinds of loads combinations [43], respectively. This thesis concentrates on radial load support rolling element rolling stock. The photo. 1.3 illustrates the rolling element bearing structure. A bearing has four important sections which are internal race, external race, roller or ball part and cage (separator). [12]

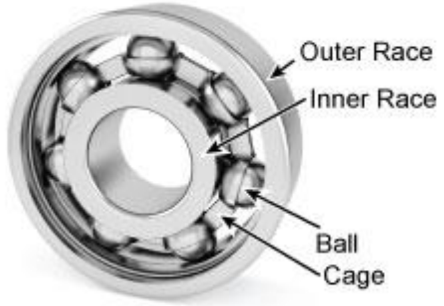

Figure 1.1 (Structure of Rolling Element Bearing)

Internal clearance is one of the main influences on the efficiency of the bearing. When moved in the opposite direction they allow relative movement between the external and the internal races. Radial clearance allows for movement in diametric direction and axial clearance for movement in the longitudinal direction of the shaft. This investigation focuses on radial load bearings. The level of clearance affects the distribution of load in a bearing It extends to approximately 120 ° C. Q(along) denotes the unit length load magnitude at Newton position along. Deficiencies of bearing may occur at the external, inner, cage or roller surface. Bearing errors have an effect on another surface when they are in contact with the load field.

II. RELATED WORKS

Xiangjin Song et al. 2019 [10] showcased that bearing deterioration is the most well-known defect type in induction motors. As of late, bearing fault revelation based on engine current mark examination (MCSA) has been picked up broad consideration. Be that as it may, the adjustments in the stator current signal which is brought about by the bearing flaw are normally very powerless. distinguish bearing flaw utilizing stator current mark investigation.

Kaiwen Lu, Tianran Lin et al. 2019 [2] presented an automated Bearing Fault Diagnosis Using a Self-Normalizing Convolutional Neural Network. A Self-normalizing ConvolutionalNeural Network (SCNN) calculation can have an a lot quicker united rate than that of a conventional Convolution Neural Network (CNN) as the previous doesn't require a Batch

XueSen Lin et a. 2018, [3] showed Fault Diagnosis of Aero-engine Bearing Using a Stacked Auto-Encoder Network. As a significant piece of the rotor arrangement of the air motor, the bearing has consistently been the key site of shortcoming. In any case, it is difficult to screen and analyze the bearing's wellbeing state. In this paper, the creators utilized a profound learning techniques for Stacked Auto-Encoder Network (SAE) to analyze and group the bearing issues, which have various assortments and unique levels, basing on the bearing disappointment information getting by the bearing disappointment proving ground. In this paper, the exactness and intermingling rate of SAE calculation are concentrated by changing the example length of the gathered information and changing the first run through area signal into recurrence area signal by quick Fourier change (FFT). On account of equivalent info, it is contrasted and Deep Trust Network (DBN), which is another technique for profound learning. The outcomes show that with the expansion of the example length, the demonstrative precision is likewise expanded. Furthermore, the demonstrative precision of calculation which input information is recurrence space boundary is higher than the one which input information is by unique time space boundary.

Wang Kai et al. 2019, [4] have represented Bearing issue signal is mind boggling and non-fixed, this makes issue include extraction exceptionally troublesome. Through examination of delicate edge work and hard limit work, a wavelet denoising technique dependent on improved edge work has been proposed. By this strategy the component of flaw signal is featured and the issue conclusion impact was improved. This paper takes the estimated bearing deficiency signal as the examination object, the flaw signal element recurrence part has been found by this strategy. This paper gives another plan to blame element extraction and bearing deficiency finding. Actual analysis results show that the improved denoising method can effectively highlight the fault signal features. The proposed method provides a new idea for fault diagnosis of rolling bearings. it tends to be discovered that the greatest incentive in the range diminished from 1300mv to 450mv, which is more helpful for watch the sign with little abundance.This clamour decrease impact is equal to intensify the issue signal with a little sufficiency, which makes it simpler to discover the flaw include sign of 162.19Hz.

Jun-Hyuk Im et al. 2019, [5] recommended the strategy for discovery of earing issue which set off by electrical pressure. Average PWM-based inverter driven engine endures bearing current which causes harm on the heading. This harm increments vibration and flaw music in stage flows. These flaw signals contain highlighted low recurrence segments which is lower than the basic recurrence, due to the mathematical normal for bearing. In this examination, the bearing issue discovery strategies dependent on low-recurrence complete segments is introduced, which requires current sensor signal as it were. bearing deficiency recognition technique dependent on LFTC is introduced. Deficiency recognition utilizing LFTC can be led by estimating a stage current. To confirm the secret of the demonstrative technique utilizing LFTC, both harmed by electrical pressure and sound bearing examples are analyzed in the abundancy of vibration and LFTC. In spite of the fact that the LFTC can't speak to correct vibration sufficiency, course which are harmed by electrical pressure can be distinguished. This technique doesn't require outer sensor nor the adjusted engine nook which increment the expense. In expansion, the calculation can be handily executed distinctly with a current sensor sign and essential recurrence esteem contributions from engine driver. This technique can be applied to the engine which introduced in fixed spot, for example, a fan.The conducted review process in implemented only to specific fault of bearing using different approach. The comprehensive approach of bearing data health monitoring and fault diagnosis is yet to be explored significantlyFurthermore, although a number of rotating machines operate under varying speed and load conditions, very few researchers have robust techniques proposed for fault diagnosis and prognosis of such systems. This paper also proposes a new algorithm for this SE selection based on kurtosis.Bearing faults of rotating machinery are observed as

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impulses in the vibration signal, but it is mostly immersed in noise. In order to effectively remove this noise and detect the impulses, a novel technique with morphological operators is proposed in this research. In this research, MED will be reviewed and reintroduced, Application in fault detection and diagnosis of rolling bearings. MED parameters are selected and its combination with pre-whitening. Test cases are presented to illustrate benefits of MED technology. The simulation has been done on MATLAB and a graphical user interface has been created for analysis of bearing and detection of bearing faults using morphological features.

III. ENVELOPE DETECTION

The Envelope Analysis, which can extract the related characteristics of signals from high frequency modulation signatures, is generally used as frequency analysis technique for the detection and diagnosis of induction motors and electromechanical systems faults. The principle of signatures analysis of Envelope Analysis is using wavelet analysis to find fault signal band and envelope spectrum analysis in the signal band by Hilbert transformation. Envelope Analysis is signatures demodulation method as theoretically based on the Hilbert transformation. The major steps are showed in Fig. 1.2.

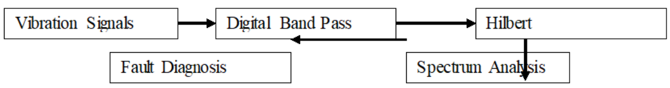


Figure 1.2 Steps of Envelope Analysis diagnosis

Firstly, Envelope Analysis, which is the high frequency resonance method, extracts the resonance frequency band of the natural frequency of fault signal using wavelet packet transform filtering, and reconstructs this signal to filter out the interference of other signatures frequency component. Then, Envelope Analysis implements envelope demodulation by using Hilbert transform to extract the reconstructed signal, removes high frequency natural vibration components, and finally finds the fault band and diagnoses defect information of fault induction motors and electromechanical systems.

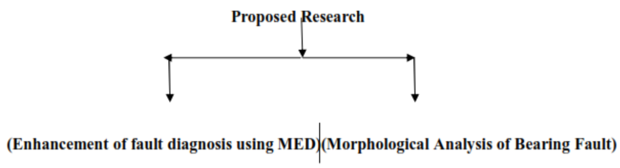
Envelope analysis consists of the following three steps.

- Selecting a frequency band for envelope analysis
- Building the analytic signal or pre-envelope
- Analyzing the spectrum of the envelope signal

It is very important to select a frequency band to effectively include the fault induced response for the envelope analysis. Sensitivity of the envelope analysis is improved by this means [11, 38]. Since the envelope signal is an approximation of the modulating signal, we know that the spectrum of the envelope signal is shifted and centred at plus and minus the resonance frequency ωr based on discussion about amplitude modulation. The transmission path from the bearing fault to the vibration transducer is a continuous mechanical system. Theoretically, there exist infinite vibration modes in this system. Depending on the modal damping properties and excitation condition, there may be several vibration modes excited in a specific machine under specific operating conditions. It is unlikely that a suitable centre frequency can be determined beforehand. This fact also speaks for the need of a reliable automated band selection process. Vibration signals from an operating bearing indicate whether or not bearing is undergoing resonance. Any frequency band encompassing one or more resonance can be used for envelope analysis. Obviously, the frequency band with the highest resonance energy would be the best. In Fig. 4.2 we circled two vibration modes. The spectral magnitude indicates that they have similar energy. Thus, either one can be used for the envelope analysis with no appreciable difference. [25]

IV. METHODOLOGIES

The work is split into two main sources. We tried in the first part to improve bearing fault diagnosis with MEDs integrating spectral curtogram and autoregressive techniques. The second aspect involves morphological analysis as the same fault signal bears the identification of fault bearing frequencies.



The system condition monitoring area has recently been implemented to improve fault detection at rolling element bearings and gears. Minimum Entropy Deconvolution (PED). MED proved a great help in the extraction and diagnosis of such impulses, that is to say the faulty bearing part. MED is updated and reintroduced in this paper with more details on its use for error detection and diagnosis in rolling element roller bearings.. The MED technique originated from Ralph Wiggins[17] and has demonstrated its effect on the de-convolution of impulsive excitations from a mix of response signals[18,19]. It was efficiently used by In order to boost impulses resulting from spalls and crashes in gears, Endo and Randall[20]. MED's objective is to find the optimal set of philtre coefficients for the x[n] output signal that has the highest kurtosis value. The envelope spectrum is a very efficient diagnostic tool for the aforementioned faults, as the information about the fault is extracted from the spacing between impulses but not from the excited frequencies. The process of obtaining the envelope spectrum is often named as signal demodulation. However, the quality of the demodulated signal depends on the frequency band selected for the demodulation, which requires two parameters bandwidth and central frequency [12]. SK is a powerful tool for detecting the presence of transients in a signal, even when they are buried in strong additive noise, by indicating in which frequency bands they are taken place. The Kurtogram optimization considers a variety of bandwidths and central frequencies. It is basically a cascade of SK obtained for different values of the Short Time Frequency Transform (STFT) window length. It analyzes the shapes and forms of objects, and this analysis is based on set theory, integral geometry, and lattice algebra [13]. The basic concept of morphological signal processing is to modify the shape of a signal, by transforming it through its intersection with another object, the SE. Morphological filter with functional SE for 1-D time series data was first presented by Maragos and Schafer [14]. The basic operators of include dilation, erosion, opening, and closing [13]. The erosion of an image f by a SE B is denoted by δB(f) and is

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defined as the minimum of the translation of f by the vectors −b of B. In other words, the eroded value at a given pixel x is the minimum value of the image in the window defined by the SE when its origin is at x

$$[\varepsilon B(f)]\,(x) = \min_{b\in B} f(x + b) \quad (1.1)$$

The dilation of an image f by a SE B is denoted by δB(f) and is defined as the maximum of the translation of f by the vectors −b of B. In other words, the dilated value at a given pixel x is the maximum value of the image in the window defined by the SE when its origin is at x

$$[\delta B(f)]\,(x) = \max_{b\in B} f(x + b) \quad (1.2)$$

The dilation operation can be considered as a "stamp" operation on the original set A, using the set B as a "stamp." The eroded set can be morphologically considered as the "region marked" by the object B, if it translates but always has tonremain in a confined area defined by A [9]. Based on then dilation and erosion operators, two other basic morphological operators, the opening and the closing, can be further defined. The opening γ of an image f by a SE B is denoted by γB(f)

and is defined as the erosion of f by B followed by the dilation with the reflected B_

$$\gamma B(f) = \delta B'\,[\varepsilon B(f)] \quad (1.3)$$

The closing of an image f by a SE B is denoted by φB(f) and is defined as the dilation of f with a SE B followed by the erosion with the reflected SE B'

$$\varphi B(f) = \varepsilon B'\,[\delta B(f)] \quad (1.4)$$

The effect of closing operation is practically to fill small holes in the signal, whereas the effect of opening is to eliminate sharp and thin parts from the signal. It is to be noted that further operation of closing or opening will not change the final result.
According to the theory , two factors are determinative for morphological analysis: the morphological operator and the SE. In practice, morphological operators are chosen based on different application scenarios of signal processing. Gradient: In the case of vibration signal fault analysis, to easily detect peaks, the variations in the signal density are to be enhanced which is done by gradient operators. Morphological gradients are operators enhancing pixel intensity in a neighborhood defined by the SE. Beucher gradient: It is a basic morphological gradient defined as the arithmetic difference between the dilation and the erosion operators by the SE B and is denoted by ρ
This gradient outputs the maximum variation of the gray-level intensities within the neighborhood defined by the SE rather than the local slope. Kurtosis criterion is proposed for the selection of length of SE. The obtained signal was morphologically filtered with ten different SEs of different lengths spaced by 10% of the pulse repetition values. The pulse repetition value (T) is the pulse period from either the IR or OR fault. The kurtosis of the morphologically filtered signals was calculated. The kurtosis values give an approximate estimate of the peaks present in the signal. Hence, the maximum value denotes the signal with more number of peaks, which is an indication that a fault is present. Hence, the signal with the maximum kurtosis value is selected for further analysis. It is to be noted that, if two kurtosis values are equal, any SE can be taken, as the maximum kurtosis has more peakedness information. The length of SE, which gives the maximum kurtosis value, will change with the signal, the morphological operation, and the fault frequency. Hence, the kurtosis criterion is to be done separately for every signal, for both the operators that are being used for analysis in this paper and for both IR and OR faults that are to be detected.
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V. Simulation & Result

The vibration data used for analysis were collected from the Bearing Data Figure of the Case Western Reserve University. Experimental vibration surveillance system. The test setup is a two-hp motor of Reliance Electric, along with a torque transducer, a dynamometer and control electronics. Image. 2 displays the experimental configuration. The specifications of the deep-groove ball bearing 6205-2RS-JEM SKF (BB) are specified in Table I. Failures in sizes 0.177 mm (0.07 in) are used for electrostatic discharge machining.
The size is 0.533 mm (0.21 in). The data was obtained by means of three-o'clock accelerometers. The frequency of rotation is 29 Hz (Fr).

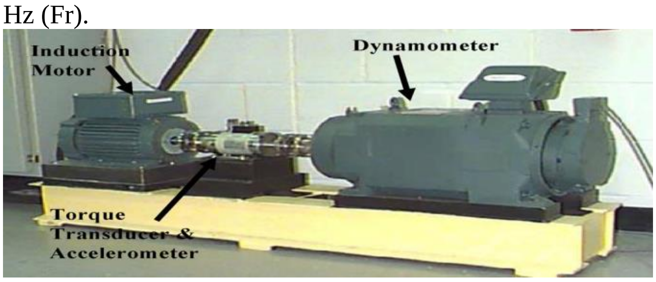

Fig. 1.3 Experimental setup for vibration monitoring.

TABLE 1.1
BEARING DETAILS (6205-2RS-JEM SKF)

Parameter	Values(mm)
Inner Race Diameter	25.001
Outer Race Diameter	51.998
Thickness	15.001
Ball Diameter	7.940
Pitch Diameter	39.039

Sample Signal of collected bearing data has been given below.

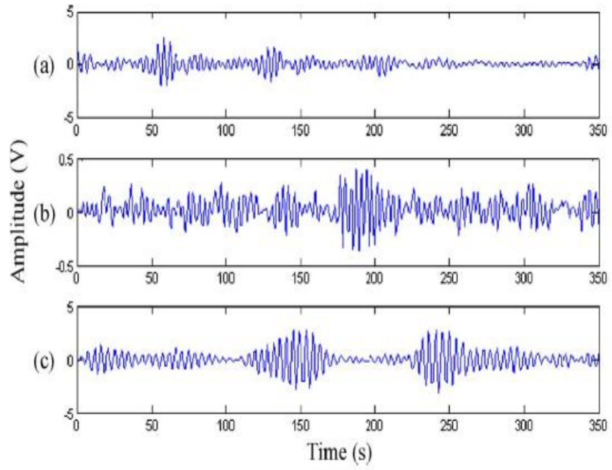

Figure 1.4 Vibration signals for (a) IR fault, (b) OR fault, and (c) BB fault.

When a defect occurs in a bearing, vibrational impulses are The simulation has been done on matlab R2013 a for applying these algorithms. Simulation has been done by creating a graphical user interface for interactive execution of the program. Figure 1.5 is the snapshot of the generated GUI in matlab for execution of our algorithm.

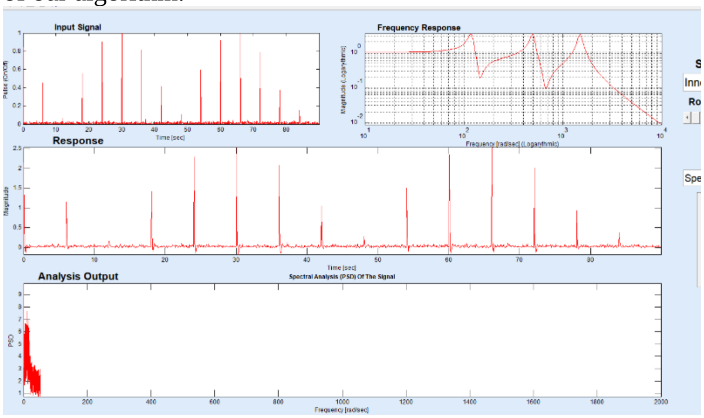

Figure 1.5 Layout of GUI

Minimum entropy deconvolution has been implemented along with autoregressive correlation to remove redundancy in faulty signal and to efficiently find out peaks in the database.

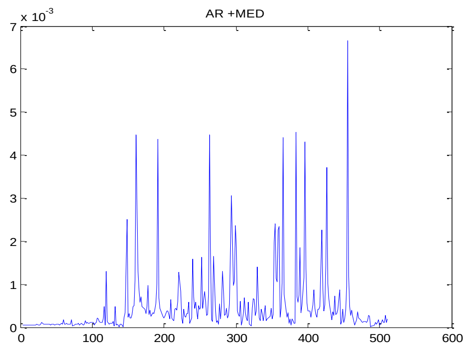

Figure 1.6 AR and MED Processed output

Figure 1.7 shows the output of AR-MED algorithm. It also illustrates the comparative analysis for the same database when we apply AR alone for detection of peaks in the faulty signal.

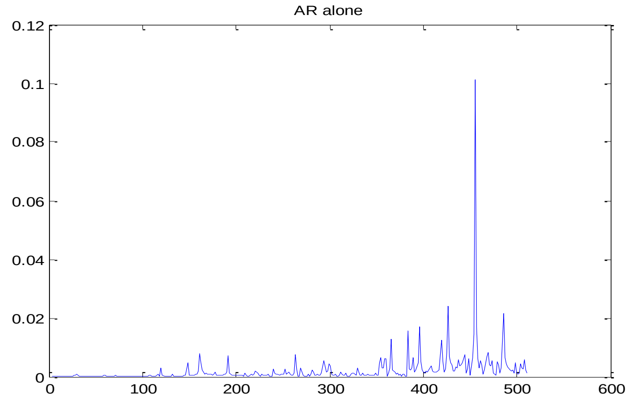

Figure 1.7 AR alone Processed output

We have implemented morphological analysis to detect the features of the signal along with correlation to remove redundancy in faulty signal and to efficiently find out peaks in the database.

Figure 1.8 shows the subplot of signal along with the morphological features which are further used to detect the fault in the bearing.

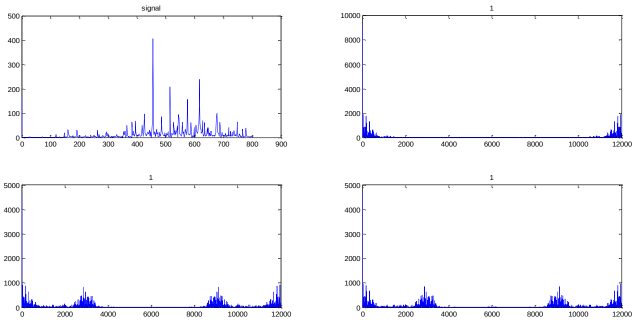

Figure 1.8 Morphological operators output signals waveform

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Table 1.2 Analysis of Accuracy of Methodology

Parameter	Accuracy
Detection of Fault	98 %

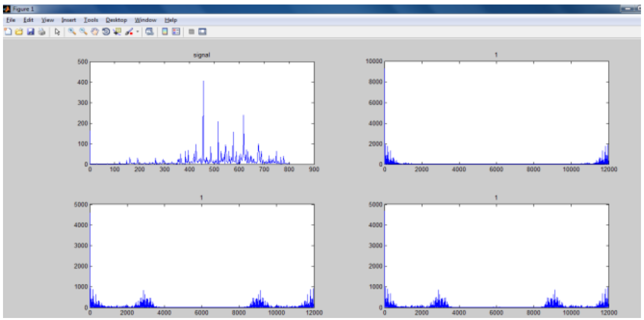

Figure 1.9 Snapshot of morphological analysis

Figure 1.9 illustrates the snapshot of morphological analysis. In this research a comprehensive analysis and design of bearing fault diagnosis sytem has been implemented and tested on the data to analyse the accuracy of the discussed system.

VI. CONCLUSION

The proposed analysis method for vibration data for bearing fault diagnosis has been discussed. The proposed new method with

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kurtosis criterion for SE's length selection and the two operators, Beucher gradient and self-complementary top hat, used forthe fault detection is proven to be effective for IR and OR faults. With the application of the method for BB fault, this method is validated for bearing fault detection. Minimum entropy deconvolution (MED) method to aid extracting faults in rolling element bearings. The MED technique was applied to signals with defective bearings taken from an experimental test .The residual signal was then pre-whitened to aid further the enhancement of the impulses by minimizing the variation between adjacent frequencies. The MED was then applied with the aim of removing the effect of the transfer path (decon-volution) and enhance the clarity of the impulses and then the detection and diagnoses of the bearing fault. MED significantly increase the peakedness of the vibration signals and the clarity of the impulses. This has been illustrated in both the time domain signals and further observed in the envelope spectra.

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