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Feature Extraction in a Diesel locomotive Starter Motor with Wavelet Transform method

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A B S T R A C T

Nowadays, due to the increasing growth of the railway industry and the need to increase safety in trains, component failure must be predicted and identified before it occurs. The direct current motor is one of the most important pieces of equipment in today's industries, especially in the rail transportation industry, and is used in various parts of electric and diesel electric locomotives, such as traction motors, train starters, cooling systems, snow wipers, etc. This article aims to categorize healthy and faulty motors and provide a method to separate them. For this purpose, a number of locomotive starter motor starting current data points have been used. The collected data, half of which are healthy and half of which are defective, are decomposed into nine levels by discrete wavelet transform with the Debuchies4 function, and the detail and estimation coefficients of each data point are calculated by MATLAB software. Unique features of the data were identified to represent it and separate the healthy and defective classes. Before the wavelet transformation, skewness, kurtosis, and root mean square parameters were extracted from all the data. The features showed that the data were intertwined, making it difficult to separate them, and a more complex classifier was needed. However, after applying wavelet transformation, the data was separated at different levels and could be separated from each other with a simple linear classifier.

1. Introduction

One of the most important factors for the commercial, cultural, and economic progress of a country is the existence of transportation infrastructure, especially rail transportation. With the development of the railway industry and the increasing attention of passengers to the use of the railway industry, attention should be paid to the higher and more reliable efficiency of this industry. Direct current motors are one of the most essential components of today's industry, especially in the rail industry, and are used in traction systems due to their robustness, cost reduction, and low maintenance requirements. Failure of these motors can lead to reduced performance, stoppages, or even accidents. Therefore, diagnosing the faults in these motors is one of the most important things to do to increase the performance and safety of trains. Feature extraction is one of the most important parts of data-driven fault diagnosis of motors. Instead of using high-volume time

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series data, features of that signal are used that can separate data classes as much as possible while preserving information. Much research has been done on fault detection in DC motors using machine learning and pattern recognition methods. Depending on the type of selected features, detection can be done in the time, frequency, and time-frequency domains [1]. The use of the common fast Fourier transform (FFT) method to identify the frequencies related to the failure requires the signal to be intermittent and at the same time static, which, in cases of violation, such as increasing the load on the motor, causes the loss of important frequency and spectral information. The short-time Fourier transform (STFT) was able to overcome some problems of the Fourier transform, but others remained unsolved, such as the use of a fixed window, which results in the same resolution for frequency and time. In contrast, the wavelet transform can use a short window at high frequencies and longer windows for low frequencies, which will have a better time and frequency output for non-stationary signals.

In [2], a model of a DC motor with an eccentric rotor and a modified equation to show the presence of rotor gap harmonics in DC motor flow are presented. To detect the eccentricity fault, a pattern detection technique utilized that works in a steady state and uses the armature current as input.

The paper [3] presented an efficient preprocessing of vibration signals to provide informational features in order to detect multi-bearing faults in induction motors for fault classification. The vibration signals are first analyzed by wavelet packet transformation to extract the frequency characteristics. The dimensions of the extracted feature set are reduced by resorting to LDA analysis to provide a set of small-sized informative features for decision making.

In the study [4], the author analyzes the induction motor current signal with multi-resolution analysis (MRA), extracts features, and uses feature selection approaches (Relief, CFS) to reduce the number of features and maintain the accuracy of induction motor fault detection.

In the paper [5], Lu and Wang developed the basis of fault diagnosis for permanent magnet direct current motors (PMDCM), with time domain features extracted from several consecutive segments of current signals and creating a feature vector. Experimental results show that multi-part features have a better diagnostic effect than single-part features.

Research [6] introduces fault diagnosis based on motor current analysis. A fast Fourier transform is applied to the obtained signals. A significant difference in the current spectrum between healthy motors and faulty motors is observed. High-frequency spectral analysis of current provides a method for detecting bearing faults, rotor bar failures, and commutator short circuits.

In the paper [7], Cunha and Silva describe an algorithm that uses discrete wavelet transform (DWT) for multi-resolution analysis (MRA), statistical features, and machine learning techniques to detect primary short-circuit faults in IM using the induced voltage signal. It is described from the axial leakage flux signal that after applying MRA at five levels to the signal, the statistical features of MAD, skewness, kurtosis, as well as the relative energy of the wavelet are applied at different levels of the decomposed induced voltage and finally they are classified by the machine learning algorithm.

Lee and Cheng in [8] introduce an induction motor fault diagnosis method based on discrete wavelet transform in five levels to analyze the current signals of a healthy motor, bearing fault, stator short circuit, and broken rotor bar, and the energy of each level as a feature. It is used to separate the signals, and finally, it is combined with a back propagation neural network to classify the classes.

The paper [9] introduces multi-rate signal processing techniques that improve FFT-based methods by reducing spectral leakage with fractional resampling. This method is applied to experimental signals to demonstrate the improvement of FFT-based methods for fault detection in IM.

In the research [10], the proposed method uses time-frequency features extracted from motor current by DWT as machine health indicators and predicts the future state of fault severity using hidden Markov models (HMMs) in order to predict gear faults in DC machines.

This study [11] presents a comparison of two FFT and wavelet methods for detecting broken bars in induction motors with squirrel cage rotors. The FFT method allows for the detection of fractures in the rotor bar when the motor is working under load. But if the device is disconnected from the mechanical load, the side frequencies associated with the broken bars will not appear. Therefore, the wavelet transform will be a more appropriate choice and can be used to diagnose the fault of a broken rotor bar.

In [12], the stator current signal is used to detect the electrical faults of an IM motor. For signal processing, the discrete wavelet transform method with the db44 function has been done in 10 levels; then, for feature extraction, threshold and signal energy features are taken from all levels, and the signal threshold will have more effect in detecting signal faults.

To detect the broken rotor bar of an IM motor, a discrete wavelet transform is taken from the motor vibration data at three levels. Then, the signal is taken on all levels to extract the important features of the signal, i.e., rms and kurtosis, to finally classify the healthy and defective motors by the neural network [13].

In the article [14], Zuhaib uses a feature extraction method based on discrete wavelet transforms to detect the rotor fault of an IM. To find the specific features for fault detection, the data is decomposed into nine levels, and then the RMS features as well as the average of the data are taken from the 5th, 7th, 8th, and 9th levels and then used by the neural network as a classifier.

The article [15] investigates the use of different wavelet families in wavelet decomposition to extract the acoustic characteristics of DC motor sounds recorded in the production environment. In the following, discrete wavelet transformation with various wavelet functions is applied to the audio data collected at eight levels, then detail and estimation coefficients, absolute value characteristics, the average and standard deviation of the signal are extracted from each level, and finally their results are compared.

This article is organized as follows: In Section (2), the issues of motor fault detection and the need to use feature extraction are discussed, followed by the discrete wavelet transform, and the MRA algorithm and its related equations. In Section (3), the aforementioned wavelet transformation is applied to the data at nine levels, and the features of skewness, kurtosis, and root mean square (rms) are extracted before and after the wavelet transformation, and the results are compared. Section (4) includes the conclusion and suggestions of this article.

2. Fault detection

Fault diagnosis in the motor includes the current state of the sensor readings and the interpretation knowledge available in the motor. Early fault detection while the system is still controllable, before it leads to instability, can help prevent the growth of faults and prevent system failure. A fault detection system in general can be considered as follows: (1). After the current signal is received from the motor and pre-processed, in the next step, the special features of the signal that can make the most separation between the two defective and healthy classes are extracted. This step is called feature extraction, and finally, the extracted features are provided to the classifiers. This will increase the performance and speed of the classifiers, resulting in higher accuracy in the classification step.

Figure 1: data driven fault detection system

2.1. Feature extraction

In the past, when a motor failed, experienced maintenance engineers had to make an initial judgment before repairing the motor. The motor is often affected by the harsh working environment and noise interference, causing maintenance engineers to make mistakes. Therefore, in recent years, many studies have been conducted in the field of signal analysis for fault diagnosis of electric machines. Common methods include fast Fourier transforms based on frequency and energy and wavelet transforms based on frequency, energy, and time, which serve as a reference for maintenance engineers to determine types of failures.

Feature extraction in general can include temporal or statistical features (mean, variance, skewness, etc.), frequency features (harmonic analysis, frequency peak, etc.), as well as time-frequency features. Sometimes it is necessary to have time and frequency features simultaneously. For example, in non-stationary signals whose frequency changes with time, the Fourier transform cannot extract its relevant features correctly and will not detect the change in time, so the wavelet transform, which is a time-frequency transform, will be used [1].

The wavelet transform uses a wavelet function to scale and transform to match the signal being decomposed. This method can transform the signal into different parts with different frequencies, which are divided into discrete wavelet transforms and continuous wavelet transforms. Discrete wavelet transforms are usually used for fault diagnosis. In this transformation, the resolution of the signal at high frequencies will be increased due to the rapid change of the signal in time, and at lower frequencies, it will increase the quality of the signal at a higher frequency.

2.1.1. Discrete wavelet transform

The wavelet transformation of a signal $x(t)$ can be done through a convolution operation between the signal x(t) and the complex conjugate of a family of wavelets, which is expressed as Equation (1). ψ^* is the complex conjugate function of ψ that has been scaled and shifted. Equation (1) shows that the wavelet transform is similar to the Fourier transform, with the difference that the wavelet family is used as basis functions instead of sine and cosine functions [16].

Performing a continuous wavelet transform on a signal will result in the generation of additional information because the scale parameter and the transfer parameter are continuously changing. This redundancy due to more calculations will increase the delay time parameter and, as a result, increase the fault detection time [16].

$$dwt(j,k) = \frac{1}{\sqrt{2^j}} \int x(t) \psi^* (\frac{t-k2^j}{2^j}) dt \qquad (1)$$

Practically, the discrete wavelet transform can be done with a pair of low-pass and high-pass filters, which are respectively denoted by $h(k)$ and $g(k) = (-1)k\, h(1-k)$. These filters are mainly known as quad mirror filters, which are constructed through the selected wavelet function ψ as well as the corresponding scale function φ. The MRA algorithm implements DWT using a pyramidal structure where down-sampling time dilation is performed for each step of the wavelet transform [17].

$$\begin{cases} \varphi(t) = \sqrt{2} \sum_k h(k) \varphi(2t-k) \\ \psi(t) = \sqrt{2} \sum_k g(k) \varphi(2t-k) \end{cases} \qquad (2)$$

Using this method, the signals are divided into a subset of high-frequency and low-frequency signals, which are defined by Equation (3):

$$\begin{cases} a_{j,k} = \sum_k h(2k-m)a_{j-1,m} \\ d_{j,k} = \sum_k g(2k-m)a_{j-1,m} \end{cases} \tag{3}$$

In Equation (3), $a_{j,k}$ are the estimation coefficients that represent the low frequency components of the signal, and $d_{j,k}$ are the detail coefficients that represent the high frequency components of the signal [16]. As shown in Figure (2), H is the low-pass filter and G is the high-pass filter.

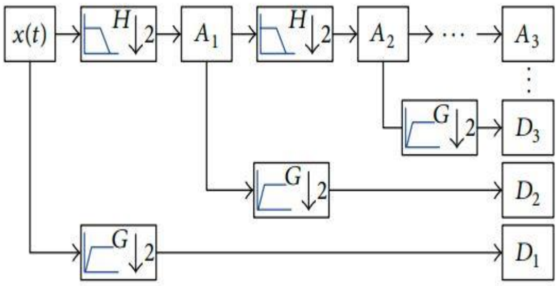


Figure 2: How discrete wavelet transform works in j step [18]

Regarding the applications of wavelet transforms in motor fault diagnosis, the most common wavelets in this field are Haar and Daubechies. Although other functions such as Coiflets and Symlet have been used for this purpose [15], choosing the right function is not an easy task, especially for some applications. For example, the Daubechies family contains 45 different types of functions. The proper selection of these functions will be an optimization problem. Choosing the level of signal decomposition is one of the most important influencing parameters in the discussion of the wavelet transform. By increasing the level of decomposition of a signal in the wavelet transform, the resolution of the signal decreases and the estimation coefficient deviates from the original signal. In other words, the initial level of decomposition has the closest resolution to the original signal. But in the meantime, some articles such as [11] refer to signal decomposition at high levels, i.e., levels 8 and 9, and others such as [19] point out that favorable results can be achieved at 4 or 5 levels of analysis. Due to the uncertainty of industrial conditions, the existence of noise, and the non-stationary nature of industrial signals, the time and frequency characteristics may not be able to solve the need to extract the desired characteristic. In the following, the current signal is decomposed into nine levels using discrete wavelet transformation, followed by feature extraction on each part.

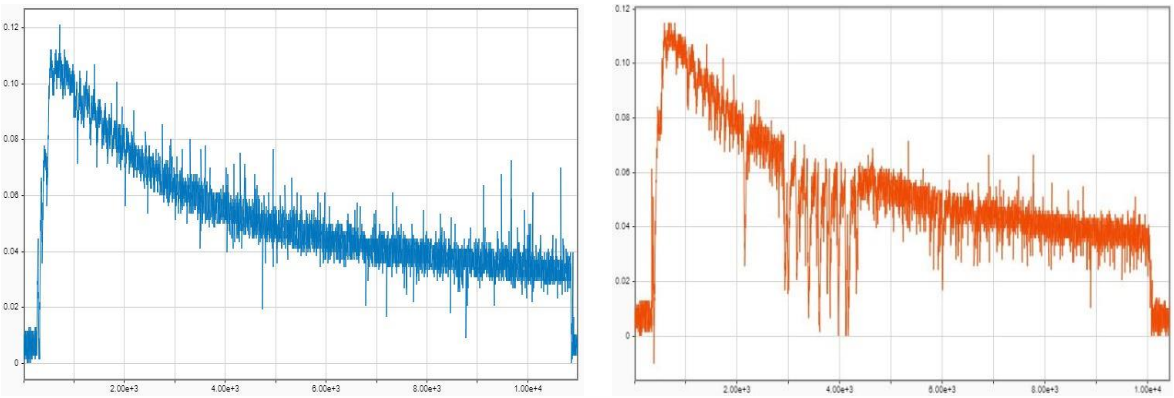
Choosing the number of decomposition levels for a signal is a key step in discrete wavelet transform analysis. The total number of N_{LS} decomposition steps is calculated by Equation (4):

$$N_{LS} = int\left(\frac{log\left(\frac{f_s}{f}\right)}{log(2)}\right) + 2 \tag{4}$$

f_s is the sampling frequency of the stored signals (in this research, the sampling frequency is 10 kHz). And f is the base frequency (60 Hz), while 2 means two more decompositions. Equation (4) will finally reach nine levels of decomposition.

3. Implementation of Discrete Wavelet Transform method

In this article, a diesel locomotive direct current starter motor is used. The starter motor is an electrical device that is used to start the internal combustion motors in such a way that when the starter motor starts to work, it causes the flywheel and crankshaft to rotate, which ultimately leads to the pistons moving. As soon as the diesel motor starts working, it is disconnected, and the diesel motor continues to work. The feature extraction process has been done on twenty motor starting current data points. Of these, ten are healthy and ten are broken, as shown in Figure (3) of a healthy and faulty motor current signal.



(a) (b)

Figure 3: a. faulty motor starting current signal b. Healthy motor starting current signal

Then, using the Signal Multi Resolution Analyzer toolbox in Matlab software, the current signals are analyzed by DWT into nine levels. At these nine levels, the signal retains its basic information, and at the same time, the behavior of the signal at different frequency levels can be studied. The wavelet function used in this article is the db4 function, which provides finer detail with lower harmonics [12] and is closer to the current signal. In Figure (4), the faulty and healthy data are divided into nine levels, where each level represents the detail coefficients in a frequency range of the signal. Figure (4-a) shows the faulty data, and Figure (4-b) shows the healthy data. As it is evident in Figure (4), important information is available from the healthy and defective signals. The defective data coefficients have more extreme fluctuations, which is evident in levels 4 to 9 of the difference between the healthy and defective data coefficients, which can be used to extract the features and finally used to diagnose the motor fault.

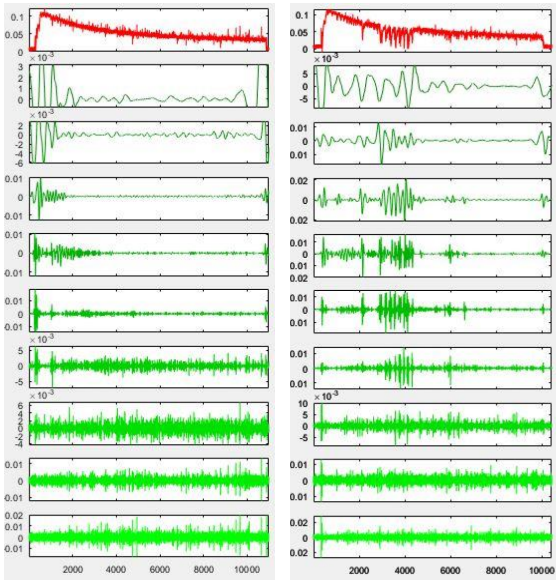
3.1. Feature extraction on wavelet coefficients

To extract features in this article, three statistical parameters, i.e., skewness, kurtosis, and root mean square, are used, which are applied to all the decomposed levels of the signal. Skewness and kurtosis measures are often used to describe the shape of the distribution. In the science of statistics, skewness and kurtosis are two very important parameters, where skewness represents the asymmetry and kurtosis represents the rise from the peak in the distribution. Their mathematical relationships are given in Table (1) [20]. The effective value actually calculates the average power in a signal.

Table 1: Mathematical equation of skewness, kurtosis and RMS

Feature	Description
Kurtosis	$\boldsymbol{x}_{\boldsymbol{kurt}} = \boldsymbol{E}\{[(\boldsymbol{x_i} - \mu)/\boldsymbol{\sigma}]^{\boldsymbol{4}}\}$
Skewness	$\boldsymbol{x}_{\boldsymbol{skew}} = \boldsymbol{E}\{[(\boldsymbol{x_i} - \mu)/\boldsymbol{\sigma}]^{\boldsymbol{3}}\}$
Root Mean Square	$\boldsymbol{x_{RMS}} = \{\boldsymbol{E}(\boldsymbol{x_i}^{\boldsymbol{2}})\}^{\frac{1}{2}}$

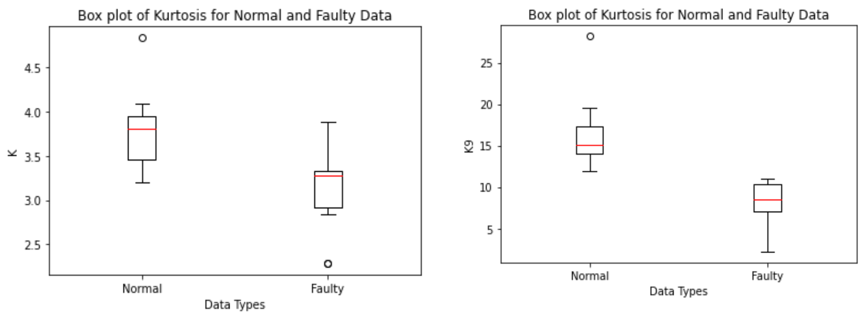
In the equations mentioned in Table (1), x_i represents the data, μ is the average of the data, and σ is the standard deviation of the data.



(a) (b)

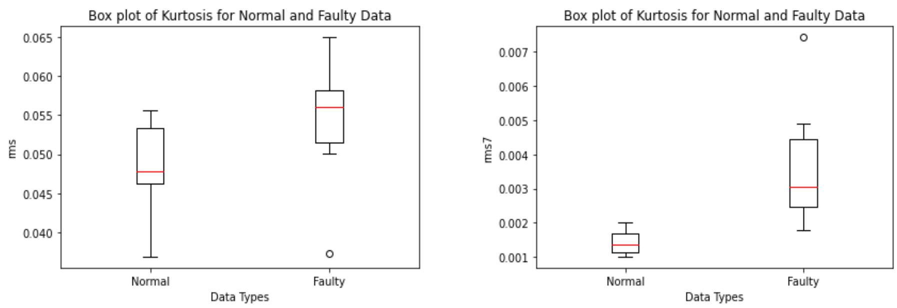
Figure 4: detail signal coefficients of two healthy (a) and faulty (b) motor

First, the features of skewness, kurtosis, and root mean square are applied to the raw data without a wavelet transform. A box plot is used to find the dispersion of features in each class. In this diagram, the middle line indicates the median, and the upper and lower lines indicate the minimum and maximum values of the features. As can be seen in Figures (5-a) and (6-a), the mentioned features cannot separate healthy and defective classes from each other, and there is a lot of overlap. Then a wavelet transform is applied to the data at nine levels. As shown in Figures (5-b) and (6-b) for the two kurtosis features at the 9th wavelet level and the root mean square for the 7th wavelet level, the mentioned features do not overlap and can be used to separate the classes.A scatter plot is used to see the separation of data in two dimensions and the integration of features in two dimensions.



(a) (b)

Figure 5: Applying kurtosis to the data (a) on the raw data (b) on the level of 9 detail coefficients after wavelet transformation



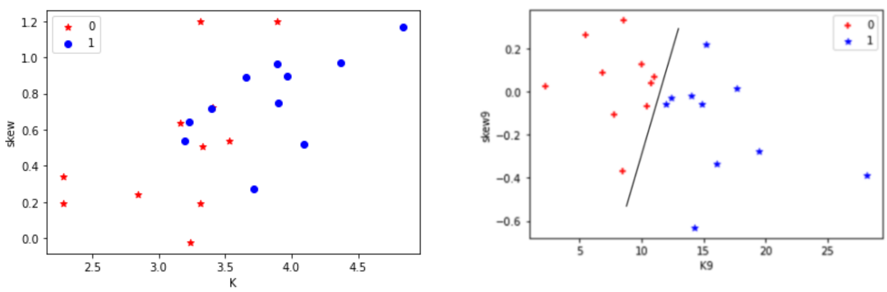
(a) (b)

Figure 6: Applying the root mean square to the data (a) raw data (b) on level 7 detail coefficients after wavelet transformation

Different features from different levels of the wavelet transform are used as separate features. They are drawn relative to each other so that the distribution of features in two dimensions and relative to each other can be seen in each class. The said statistical features are applied to all the wavelet-decomposed surfaces so that the difference between two classes in all frequency ranges can be extracted. As shown in Figures (7) and (8), as an example of data kurtosis, they are drawn with respect to skewness and root mean square, in part (7-a) on the raw signal without applying wavelet, and in part (7-b) on Level 9 details done. In parts (7-a) and (8-a), where the feature extraction is done on the raw data, the classes are not separated and are intertwined, which is not suitable for the discussion of fault detection and will require more complex classifiers for fault detection. And it greatly reduces accuracy. But in Figure 8, the data are separated to a good extent and can be easily separated with a linear classifier. If more features and higher dimensions are applied, the entanglement of the two classes can be further removed and separated with a simple linear classifier.

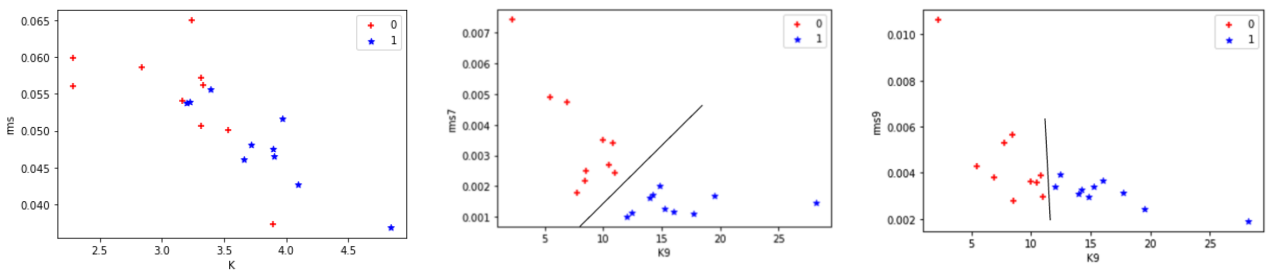
4. Conclusion

This study extracted features from diesel locomotive starter motor current data using a 9-level discrete wavelet transform in MATLAB. The skewness, kurtosis, and root mean square (RMS) features were extracted from the wavelet transform detail coefficients. The extracted features were more separated after the wavelet transform, which will enable better classification accuracy in subsequent studies using machine learning methods such as support vector machines. Due to the limited dataset, only a limited number of features could be studied. This paper focused on feature extraction and its effect on data separation. It also captured appropriate feature selection methods to select the appropriate features and reduce dimensions, such as PCA and LDA.



(a) (b)

Figure 7: Scatter plot of two healthy and faulty classes with twofeatures of skewness and kurtosis (a) Raw data (b) Applying wavelet to the data



(a) (b) (c)

Figure 8: Scatter plot of two healthy and faulty classes with two features of rms and kurtosis (a) on raw data (b) after wavelet transform on levels 7 and 9 (c) After wavelet transformation on level 9

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