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WAVELET CO-EFFICIENT OF THERMAL IMAGE ANALYSIS FOR MACHINE FAULT DIAGNOSIS

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ABSTRACT
The ultimate goal of this study is to introduce a new method of machine fault diagnosis using different machine conditions data such as normal, misalignment, mass-unbalance and bearing-fault from infrared thermography (IRT). Using thermal image, it is easy to obtain information about the machine condition rather than other conventional methods of machine condition diagnostic technique. Thermal image technique can be successfully applied in the field electrical and electronics system, mechanical system, energy system and medical diagnosis. To get information from the image many techniques of image processing such as discrete Fourier transformation, discrete cosine transformation, neural networks, wavelet transform and many others methods is being used. In this study, our main focal point is to analysis thermal image by discrete wavelet decomposition and tries to find out significant result of machine condition monitoring. In this work, decomposition level of 2 shows satisfactory result for machine condition diagnosis.

Keywords: Thermal image, Discrete Wavelet Decomposition, Fault Diagnosis, Machine Condition.

1. INTRODUCTION
The fault diagnosis of rotary machinery plays a great role in nondestructive preventive maintenance of rotating part of machine which could save the severe fault even catastrophic failure of machinery during the operating condition. Diagnosis of support bearing by analyzing thermal image signature is the new technique to distinguish machine condition that indicates healthy or unhealthy. Since the support bearing gives very useful information on the subject of machine condition. As typical rotating machinery, support bearing is being widely applied to evaluate machine health condition. Most of the cases, it is difficult to acquire signal from gear box because of its complex structure as well having convolution to evaluate the machine condition so that if the support bearings are examined then the useful information could be found. But more accurate information might be easily found by thermal image that should be processed because appropriate image processing does not create any new information moreover it gives more distinguishable feature [1]. Primarily, we have proposed and used desecrate wavelet decomposition (DWT) which gives some significant statistical feature that enable to get machine health condition.

Infrared (IR) imaging approach has been used in the industry as a part of nondestructive evaluation of machine condition especially to check misalignment, bend shaft and rolling element bearing fault. To evaluate electrical machine fault like cooling system, earth faults, circulating current, air leakage location, water pipe defect location and so on [2-5]. Some researchers have conducted experiment to evaluate the shallow delaminating in concrete bridge decks and they have developed some algorithm for detection that fault [6].

On the other hand, many researchers have been conducted experiment to acquire vibration signals are commonly used in the condition monitoring and diagnostics of the rotating machinery [7-9]. Generally, the vibration measurement of the bearing can be made by some accelerate sensors that are taken place on the bearing house. To analyze these signature usually different approach is been used. To date, some techniques such as envelope analysis, high frequency resonance technique, fast Fourier transformation, wavelet analysis are being used to machine condition diagnosis in bearing fault approach [10-12].

In fact, lots of samples are needed to obtain enough bearing signature because in this field of thermal image signal analysis the reference and sample data are not enough to investigate the machine condition monitoring.

In this study, thermo-cam has specially been used to obtain the thermal image data at the bearing housing of rotor kit and being measured the four condition of this rotor kit that are normal, misalignment mass unbalance and bearing fault. In these different conditions, the thermal image signature seems to be same it could not be identify what kind fault has occurred. In this paper, DWT has chosen because of complexity of thermal image data that is not conventional vibration signal data. The purpose of this current study is to demonstrate how to extract useful condition indicators (covariates) from raw thermal image signature by using DWT. Primarily, we proposed and used desecrate wavelet decomposition which gives some significant statistical feature that enable to get machine health condition.

2. THEORETICAL BACKGROUND

2.1 Wavelet Transforms

All wavelet transforms (WT) may be considered forms of time-frequency representation for continuous time (analog) signals and so are related to harmonic analysis. However, in the case of image signal analysis we should be considered the discrete wavelet transformation that might be appropriate tool. Almost all practically useful discrete wavelet transforms (DWT) use discrete-time filter banks. These filter banks are called the wavelet and scaling coefficients in wavelets nomenclature.

The definition of the continuous wavelet transform for a 1-dimensional signal f(x)∈L2(R), given by Morlet and Grossmann [13] the space of all square integrable functions, is

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(x)\, \psi^{*}\left(\frac{x-b}{a}\right) dx \qquad (1)$$

Where, W(a, b) is the wavelet coefficient of the function f(x), ψ(x) is the analyzing wavelet, a (> 0) is the scale parameter, b is the position parameter.

2.2 Discrete Wavelet Transform (DWT)

The 2D DWT is a very recent mathematical tool of two-dimensional data handling. A lot of meaningful and awful data is created after calculating the wavelet coefficients at every possible scale. If scales and positions based on powers of 2 called dyadic scales and positions- are chosen then analysis become more efficient and accurate. Such an analysis obtained from the discrete wavelet transforms (DWT) [14]. The analysis start from signal s and results in the coefficients C (a,b).

$$C(a,b) = C(j,k) = \sum_{n \in Z} s(n)\, g_{j,k}(n) \qquad (2)$$

From the above decomposition fundamental, low frequency and high frequency content signal is generated when original signal is passed through the high pass and low pass filter. For many signals, the low frequency content is the most important part whereas the high frequency content has less importance. The decomposition algorithm starts with signal s which is n by m dimensions, next calculates the coordinates of approximation (A1), horizontal detail (HD), vertical detail (VD1) and diagonal detail (DD1) then those of A2, HD2, VD2, and DD1 and so on. However, one-dimensional signal being decomposed into two components are approximation (A1) and detail coefficients (D1). The algorithm of 2D DWT is depicted in figure 1.

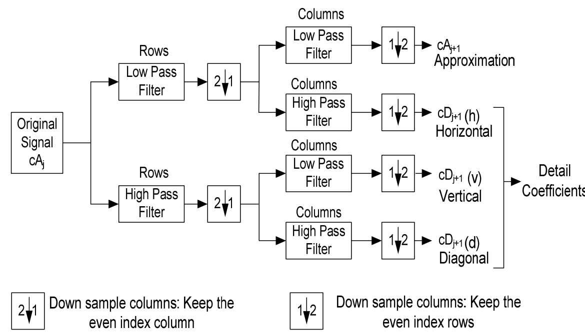


Fig 1. Algorithm of DWT

In this paper, the every level of decomposition and all coefficients have been consider to analysis for finding significant result of machine conditions. Among the huge data, obtained good features data is a great challenge for classify different class data. Primarily, to find out the decomposition level of coefficients is an objective as a part successful application in machine fault diagnosis.

3. EXPERIMENT AND MEASUREMENTS

3.1 Experimental Setup

Figure 2 shows the machine fault simulator with thermo-cam sensor that is apart. A short shaft of 30 mm diameter is attached to the shaft of the motor through a flexible coupling; this minimizes effects of misalignment and transmission of vibration from motor.

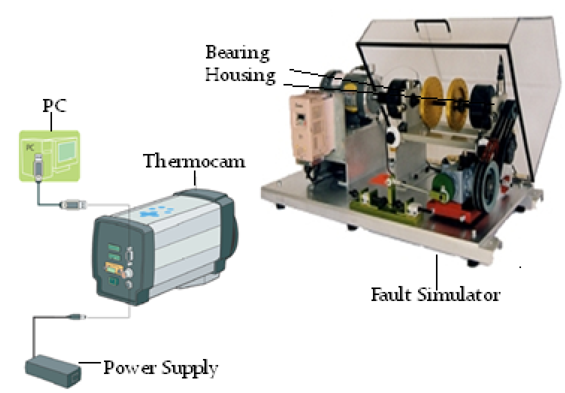


Fig 2. Experimental setup

Using coupling, we can set misalignment condition of the fault simulator. The shaft is supported through two ball bearings at its ends. Disks are attached on the shaft used to make balanced and unbalanced condition of fault simulator. To get unbalanced, extra mass is added on the disks. A variable speed DC motor (0.5 HP) with speed up to 3450 rpm was used as the basic driver. Table 1 shows the main specification of thermo cam and fault simulator. The sensor used in the experiments for this study is a long-wave IR camera from FLIR with a thermal sensitivity of 0.08 °C at 30.

3.2 Experimental procedure

In this experiment, the thermo-cam is the major key device that has some parameters is needed to set for data accusation. Some specifications of the thermo-cam have been given in the prior section where we can get some idea, regarding thermo-cam. There are some parameters of objects very important to obtain data that is especially for thermal image (signal) acquisition. However, those parameters are put automatically functioning of thermo-cam because all machine's materials are considered as similar. The most important parameter is emissivity and other parameters of object are relative humidity, scale temperature, focal length of camera and distance are set as our requirement of experiment in Table 1.

Table 1: Specification of thermo-cam and fault simulator

Thermo-cam (FLIR-A 40 series)	• Solid state, uncooled micro bolometer detector, 7.5 to 13 µm • -40 °C to +70 °C storage temperature range • Solid object materials and emissivity: 0.1 to 0.95. • For short distance, humidity is default value of 50 %. • 0.08 °C at 30 °C thermal sensitivity
Fault simulator	• Shaft diameter: 30 mm • Bearing: Two ball bearings • Bearing housings: Two bearing housings, • Bearing housing base: Completely movable using jack bolts for easy misalignment in all three planes • Rotors: Two rotors, 6" diameter with two rows of tapped holes at every 20°.

All of these parameters are chosen according to our experiment condition. For all four normal, mass unbalance, misalignment condition and bearing fault, we have put same parameters for accomplished the experiment.

In the current study, we try to analyze different types of faulty condition machine by this experiment. Firstly, we set the normal condition of machine, afterward speed of the motor been increased gradually up to 900 rpm. And then, machine was run for five minutes to get its stable condition then data acquisition was lunched. We conducted experiment of normal, misalignment, mass unbalance condition and bearing fault of machine successively. Data from thermo-cam was saved directly to the notebook or PC.

The original thermal imaging shows in Figs. 3 and 4 the gray level value at each pixel in the thermal image. Fig. 5 presents the temperature value at each pixel of thermal image. The reduced data size 158 by 25 is shown in Fig. 3 by black rectangular marks that have been extracted from original raw images that were 320×240 array.

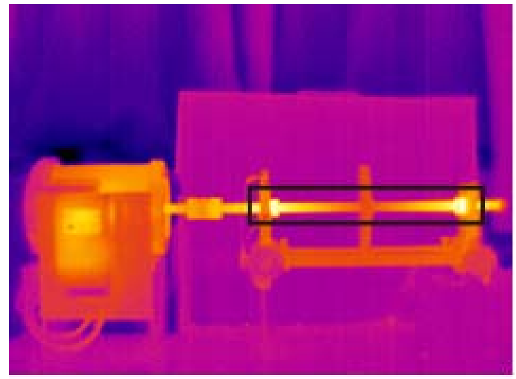


Fig 3. Original thermal image

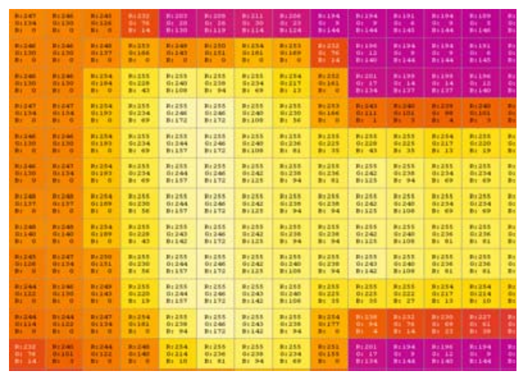


Fig 4. Gray level value at each pixel in thermal image

….	….	….	….	…	….	…
….	….	….	…	…	….	…
….	….	315.58	315.39	315.12	….	….
….	….	315.72	315.87	315.51	….	…
….	….	316.51	316.05	315.69	….	….
….	….	316.45	316.41	316.13	….	…
….	….	316.22	316.32	316.44	….	…
….	….	315.89	316.49	316.60	….	…
….	….	315.36	315.90	316.15	….	…
….	….	315.67	315.72	315.82	….	…
….	….	315.10	315.72	315.74	….	…
….	….	315.21	315.95	315.84	….	…
….	….	….	….	…	….	…
….	….	….	…	…	….	…

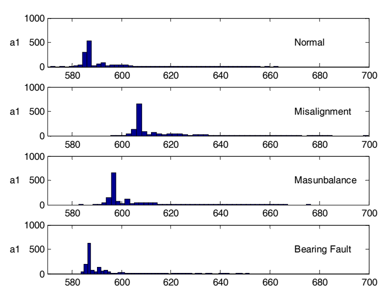
Fig 5. Temperature at each pixel of thermal (Kelvin scale)

4. RESULTS AND DISCUSSION

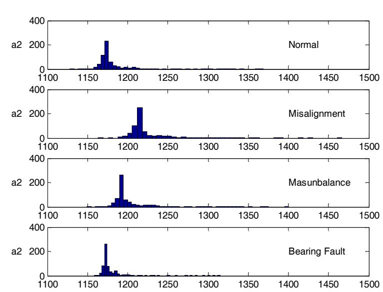
4.1 Wavelet Co-efficient Analysis

Select the level N and type of wavelets, and then determine the coefficients of the thermal image signal by 2D DWT. To do decomposition of signals, we have to decide over many selections, such as the types of mother wavelet, the decomposition levels and type of coefficients e.t.c. In the decomposition of thermal image data from different condition machines, we apply Bio-orthogonal (bior-3.5) wavelets of degree 3.5 and the decomposition level of 3. Due to the dimension of thermal image data, the decomposition level of 3 is selected because there is no data for decomposition after the selected level. Having performed decomposition, four kinds of wavelet coefficients have found from each class of machine conditions data. Among the coefficients (A, HD, DD, VD), approximation coefficients which passed through the low pass filter is considered for feature extraction because the low frequency signals contain most important part of original signal. However, other wavelet coefficients except approximation may be useful to in machine condition diagnosis. The comparison of approximation coefficients of different class thermal image data at same level is shown in figure 6 (a), 6(b) and 6(c). The histogram of approximation coefficients shows the separates condition of machines by either ranges of histograms or amplitude of coefficients.

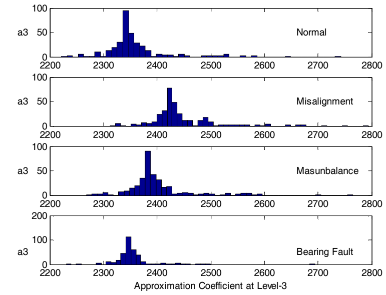
If we closely see, the normal, misalignment and bearing fault can be categorized by ranges. The peak of these conditions of machine lies in different ranges which is the distinguishing feature of machine resonances. In case of bearing fault, the coefficients show the maximum amplitude than other machine conditions. In figure 6, there are only coefficients of one sample presented but we have performed all samples of each machine condition and obtained the similar result.



(a) At level of 1



(b) At level of 2



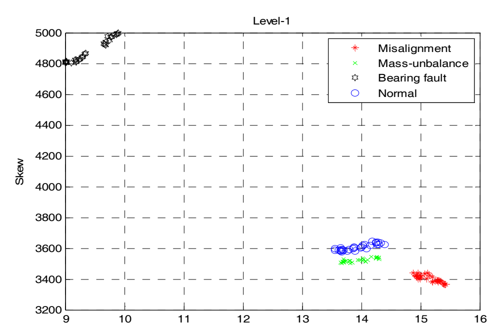
(c) At level of 3

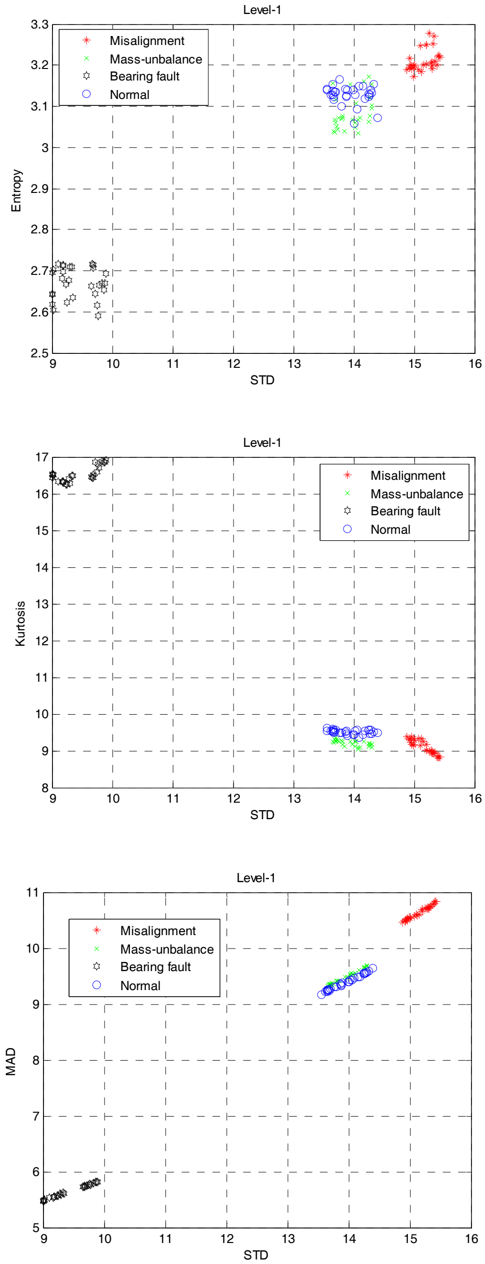
Fig 6. Approximation coefficients at different level and conditions

4.2 Feature Extraction

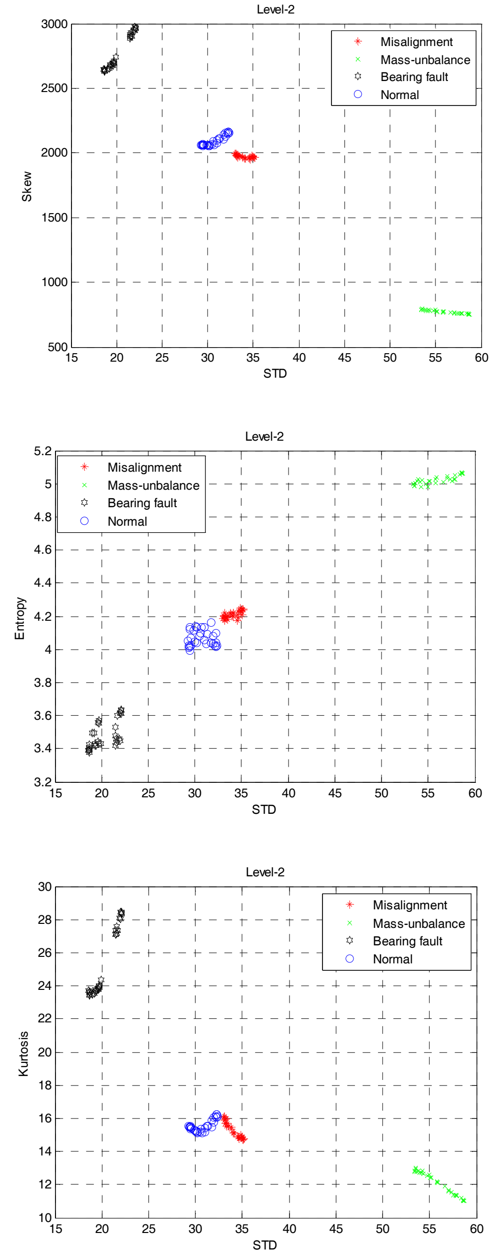
In this work, we work with the 2D signals means of thermal image data. After decomposition by DWT, the 2D coefficients have been found. So feature should be calculated according to 2D statistical features calculation. There are six features have been extracted from four different machine conditions where each condition has thirty samples. The standard deviation, Mean, Entropy, Skew, Kurtosis, Mean absolute deviation are statistical measurement of any kinds of data been used here as feature. The all features from thermal image is shown in figure 7 where wavelet decomposition coefficient of all machine's conditions from level 1 to 3 are presented. All features are plotted against standard deviation to find significant distinguish features of machine condition. First let's come to the coefficient of level 1 in figure 7(a) where machine's conditions are clearly separated for skew versus standard deviation and remaining features are either scattered or overlapped each other.

At level of 2, all features are apparently well separated that indicates , in this study, all machine conditions can be understand easily using coefficients of level 2 in figure 7(b). Entropy and Mean absolute deviation versus standard deviation cannot provide the decision about the machine conditions at the coefficients of level 3 because they coincide each other figure 7(c).

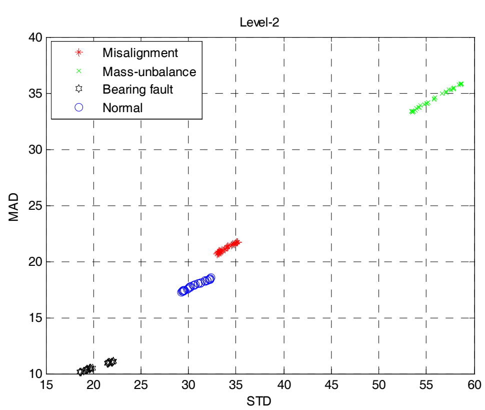


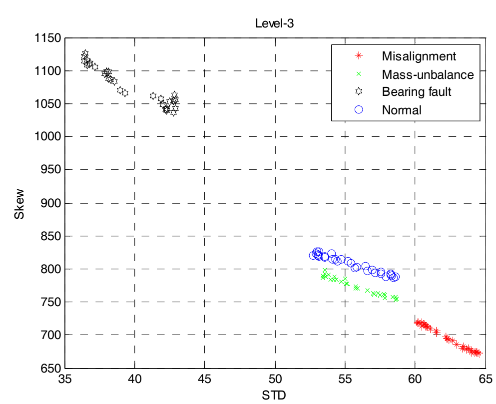


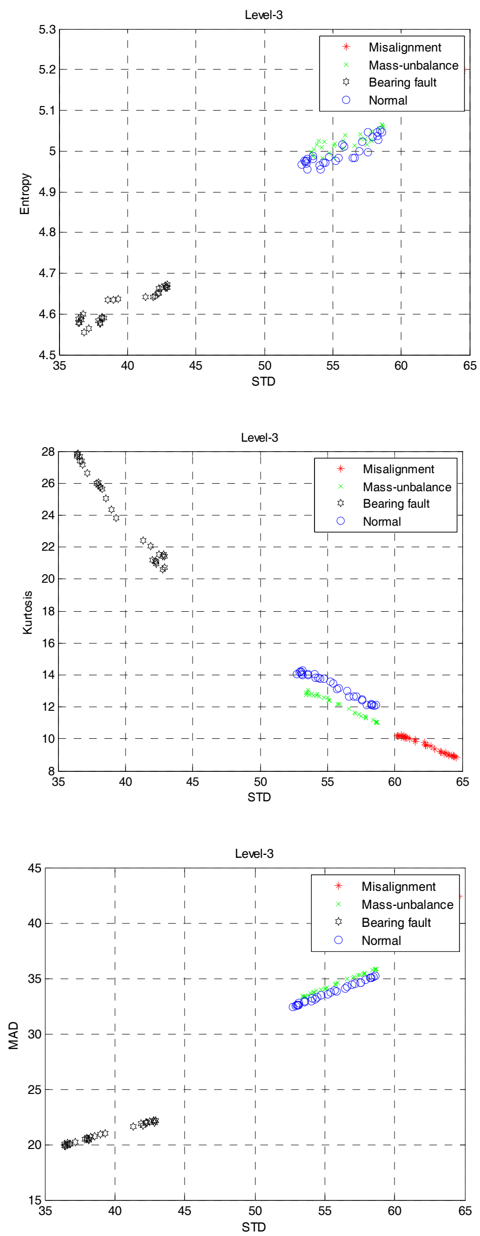
(a) Features at level of 1



(b) Features at level of 2







(c) Features at level of 3

Fig 7. Features at different levels

5. CONCLUSIONS

In this study, infrared thermograph has been applied to evaluate the four machine conditions: normal, misalignment, mass unbalance and bearing fault. The goal in image analysis is to extract information useful for application based problem. In this work, bio-orthogonal wavelet algorithm has been successfully implemented to obtain real machine's condition. More clearly get information; we have calculated statistical features that help to make decision to about machine's conditions. Here, coefficients of level 2 shows the best result among the others levels of coefficients. Indeed, the current study demonstrates how to extract useful condition indicators from raw thermal image signature by using wavelet decomposition. In this analysis we also try to show the behavior of image at operating condition of machine by statistical feature.

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