COMPARISONS OF THE CONTINUOUS AND DISCRETE WAVELET TRANSFORMS FOR POTENTIAL FAILURE DETECTION IN ELECTRIC MOTORS

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ABSTRACT

This paper, which is focused on bearing damage detection by the accelerated aging processes, presents two different wavelet transform applications to find the potential defect. This potential defect is compared with the faulty case and is used to extract the origin of the bearing damage characteristic that develops during time. Therefore, it exposes the fundamental cause of the bearing damage from the vibration signals for healthy case.

I. INTRODUCTION

The demand for monitoring and fault diagnosis of process dynamics and sensors in industrial systems has increased the efforts to develop new analysis techniques. The main goal of this technological improvement is to obtain more detailed information contained in the measured data than had been previously possible. Standard digital signal processing techniques, such as time series statistics, correlation analysis and fast Fourier transform (FFT) have been used to detect faults in system components [1]. In this sense, machineries that operate in a stationary mode are generally analyzed with standard Fourier transform techniques. When a system is non-stationary or undergoes a transient, the Fourier technique does not provide proper information about the signals. The analysis of non-stationary signals should be performed using time-frequency (short-time Fourier transform, STFT) or time-scale (wavelet transform) techniques [2, 3]. The wavelet transforms can be used for localized analysis of signals continuously as a function of time [4].

The early detection of anomalies in the electrical or mechanical parts of electric motors is very important to the safe and economic operation of an industrial process. In literature several studies have been conducted to identify the cause of failure of induction motors in industrial applications. More than fifty percent of the failures are mechanical in nature, such as bearing, balance and alignment related problems [5, 6].

This paper presents an alternative approach to reveal the fault developing that is based on manufacturing defects. For this purpose, continuous and discrete wavelet analysis methods are applied to vibration signals of 5-HP induction motor subjected to bearing fluting or electrical aging tests. Hence, application methods are compared with each others in terms of the findings appeared in the healthy bearing condition.

II. CONTINUOUS AND DISCRETE WAVELET TRANSFORMS

The use of wavelet transform is particularly appropriate since it gives information about the signal both in frequency and time domains. Let *f(x)* be the signal, the continuous wavelet transform of *f(x)* is then defined as

$$CWT\,(a,b) = \int_{+\infty}^{-\infty} f(x)\psi_{a,b}(x)dx, \tag{1}$$

Where

$$\psi_{a,b}(x) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{x-b}{a}\right) \tag{2}$$

and $a,b \in R,\ a \neq 0$. Also, it provides the admissibility condition as below

$$C_{\psi} = \int_{0}^{+\infty} \frac{|\psi(\omega)|^2}{\omega}\, d\omega \langle \infty \,. \tag{3}$$

And for this reason, it is

$$\int_{-\infty}^{+\infty} \psi(x)dx = 0 \tag{4}$$

Here $\psi(\omega)$ stands for the Fourier transform of $\psi(x)$. The admissibility condition implies that the Fourier transform of $\psi(x)$ vanishes at the zero frequency. Therefore ψ is called as a wave or the mother wavelet and it has two characteristic parameters, namely, dilation (a) and translation (b), which vary continuously. The translation parameter, "b", controls the position of the wavelet in time. A "narrow" wavelet can access high-frequency information, while a more dilated wavelet can access low-frequency information. This means that the parameter "a" varies with different frequency. The parameters "a" and "b" take discrete values, $a = a_0^j$, $b = nb_0 a_0^j$, where $n, j \in Z$, $a_0 > 1$, and $b_0 > 0$. The discrete wavelet transformation (DWT) is defined as [7,8]

$$\text{DWT}[j, k] = \frac{1}{\sqrt{a_0^j}} \sum_n f[n] \psi\left[\frac{k - na_0^j}{a_0^j}\right] \qquad (5)$$

However, S. Mallat introduced an efficient algorithm to perform the DWT known as the multi-resolution analysis (MRA) [8]. The MRA is similar to a two-channel sub-band coder in high-pass (H) and low-pass (L) filters, from which the original signal can be reconstructed [8]. The low frequency sub-band is referred to as 'approximation Ca_i' and the high-frequency sub-band by 'detail Cd_i'. Thus, the signal may be reconstructed as $S = Ca_n + Cd_1 + Cd_2 + \ldots + Cd_N$ at the N^{th} stage. Finally, in this study, signal reconstruction for three stages is given as

$$S = C\,a_3 + Cd_1 + Cd_2 + Cd_3.$$

III. ELECTRICAL DISCHARGE MACHINING AND DATA ACQUISITION

In order to simulate the electrical discharge from the shaft to the bearing, a special test setup was designed [9]. A schematic presentation of this Electrical Discharge Machining (EDM) for the bearing elements is shown in Figure 1. At each aging cycle, the motor was run at no load for 30 minutes, with an externally applied shaft current of 27 Amperes at 30 Volts AC.

The EDM aging was followed by thermal aging in order to accelerate the aging process. After each cycle of accelerated aging, the test motor was put on a motor performance test platform. From the experimental setup, high frequency data with a sampling frequency of 12 kHz was acquired for the motor currents and voltages, rotor speed, torque and six vibration measurements There are eight measurement sets so that one healthy and seven aged cases.

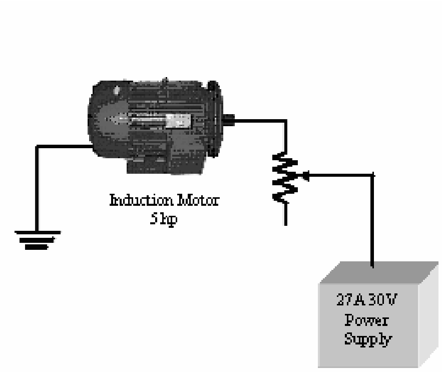


Figure1. Schematic of the electrical motor bearing EDM setup.

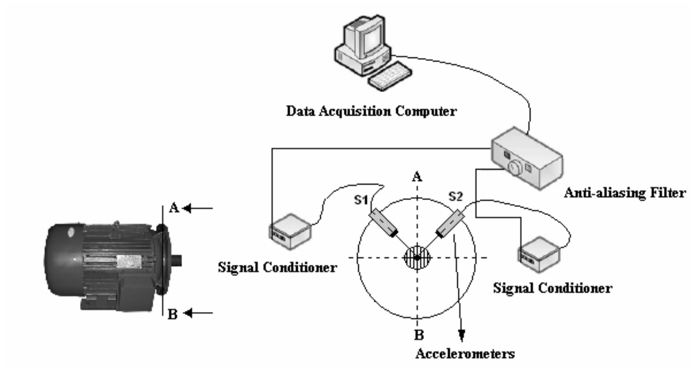
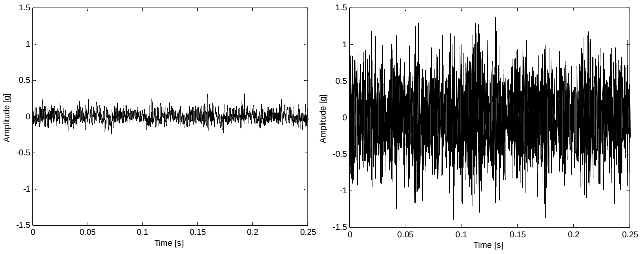


Figure 2. Motor load testing and data acquisition system: Experimental set-up configuration; and Cross-section (A-B) at short end to show sensors S_1 and S_2.

Figure 2 shows the experimental setup for processing the measured electrical and vibration data and then transferring them to a host personal computer. There are six accelerometers used in this set-up for independent vibration measurements. As shown in Figure.2, sensors S1 and S2 are placed in plane A-B.

IV. APPLICATION TO VIBRATION SIGNALS

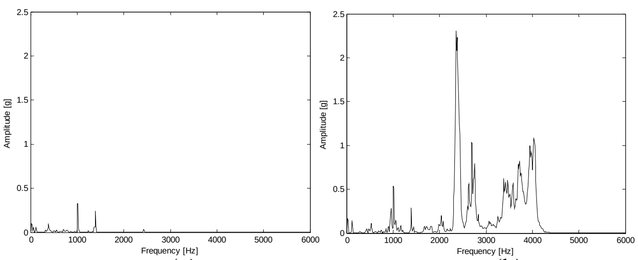
Most effective sensor information for mechanical vibration that represents bearing damage come from sensors S1 and S2 as shown in Figure 2. These accelerometer type vibration sensors are almost identical sensors for each other. Therefore, only sensor-S1 is considered for the analysis. Time series plots of vibration signals for the healthy and aged motor cases which come from the sensor S1 are as shown in Figure. 3. It is clearly notable that vibration amplitude is increasing while aging progresses and this gives a correspondence of increasing standard deviation.



(a) (b)

Figure 3. Vibration signal time series for a) healthy and b) aged motor.

To extract the changing of the frequency components of the signal with the aging, the Fourier transformation is performed and the power spectral densities of these signals are plotted as shown in Figure. 4.



(a) (b)

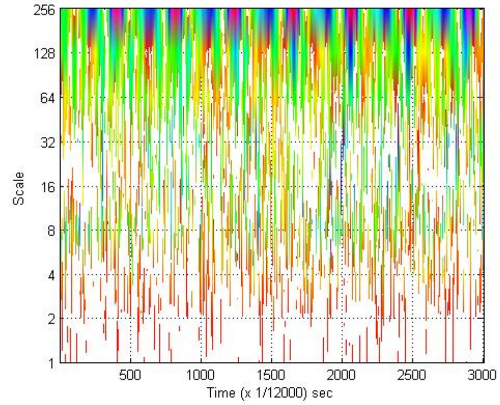
Figure 4. Power spectral densities of vibration signals for a) healthy and b) aged motor.

Comparing these figures it is shown that high frequency components occur between 2-4 kHz, which denotes the bearing damage.

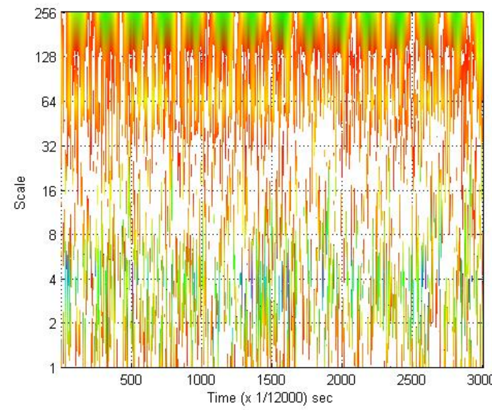
APPLICATION OF CONTINUOUS WAVELET TRANSFORM

Continuous wavelet transform (CWT) is applied to the vibration signals to see how scale or frequency changes with time. These signals were decomposed into 256 scales using mother wavelet type of symlet. The CWT coefficients are shown in time-scale plane for healthy and aged motor in Figure. 5-a and 5-b. Comparing these figures it can be observed that bearing damage effect shows itself at low scales. Hence, while it can be observed that the rare variations are at the low scale values, high scale values shown as Figure. 5-a, and 5-b indicate some periodical variations at low frequencies.

If the first scale variation is taken outside to plot it individually as shown in Figure. 6-a, it gives the high frequency components represented by very small amplitudes. Fig. 6-b is also due to the first scale of the CWT for aged case. This is also related to big amplitudes of the bearing damage.



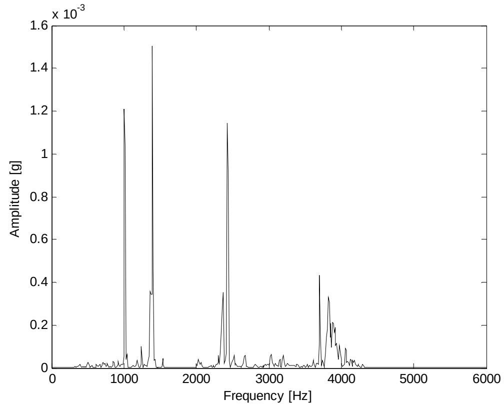
(a)



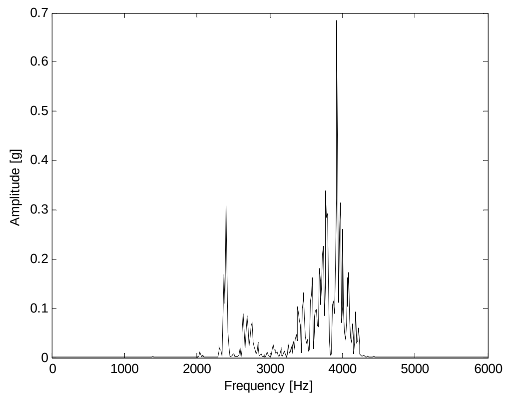
(b)

Figure 5. Absolute values of continuos wavelet transform coefficients for scales 1, 2, 4, 8, 16, 32, 64, 128, 256 of vibration signals for a) healthy and b) aged motor.

Very small amplitudes located at high frequency region of the overall spectrum can be extracted to indicate as shown in Figure. 6-a at low scale values. When compared with the results of Figure.4-a, one advantage of the CWT over the STFT can be easily determined. Also, Figure.6-b shows the extra amplitudes which are caused by the bearing damage between the 2-4 kHz. The effect of the bearing damage denoted between 2-4 kHz are observed by the big amplitudes which are several hundred times greater than amplitudes of the healthy case at same frequency interval, that is 2-4 kHz. Therefore, this study indicates an advantage of CWT over the STFT in terms of getting more sensitive fault detection and hence, this possibility can be represented as an important contribution for this study.



(a)



(b)

Figure 6. Power spectral densities of scale 1 of vibration signals for a) healthy and b) aged motor.

APPLICATION OF DISCRETE WAVELET TRANSFORM

The vibration signal that comes from sensor S1 is decomposed into three frequency sub-band levels as shown in Table 1, corresponding to the sampling frequency of the vibration signals.

Table 1. Three frequency subbands to be analyzed vibration signal.

Subband Levels	**Approximations**	**Details**
1	a1: 0-3000 Hz	d1: 3000-6000 Hz
2	a2: 0-1500 Hz	d2: 1500-3000 Hz
3	a3: 0-750 Hz	d3: 750-1500 Hz

Considering results of the Table 1, reconstructed signal can be reperesented by s=d1+d2+d3+a3, and signal decompositions in the form of the subbands are shown by Figure 7 and 8 for the healty and aged motor cases.

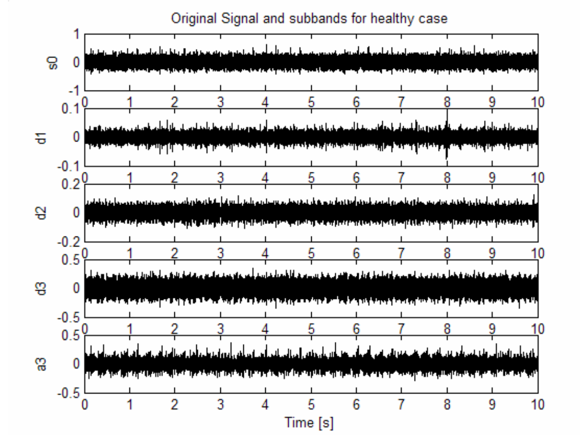


Figure 7. Vibration measurement of the healthy motor case and its sub bands.

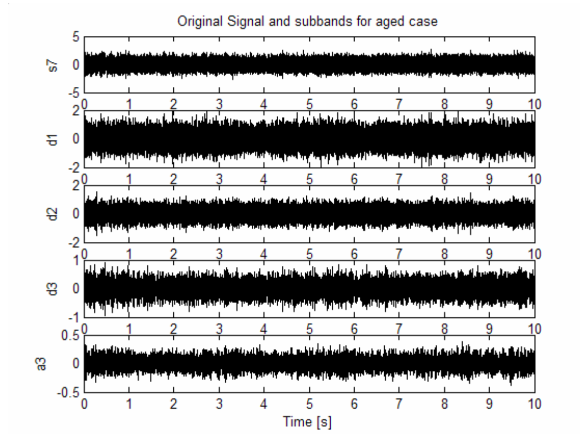


Figure 8. Vibration measurement of the aged motor and its sub-bands.

Also, spectral variations of the vibration signals are shown for the healthy and aged cases. These variations can be seen by Figure 9.

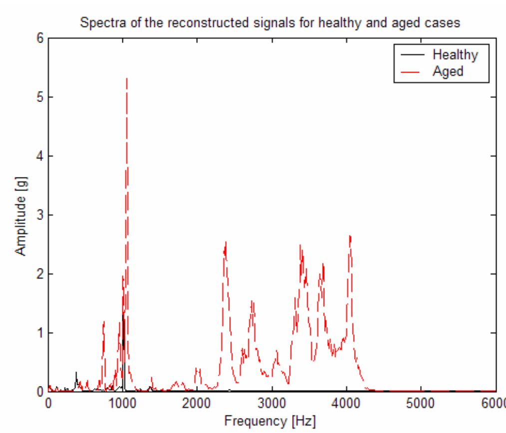


Figure 9. Spectral Variations for the healthy and aged cases of the motor bearing.

As seen in the Figure 9, additional frequency components are observed in the frequency range 2-4 kHz. This frequency band is a feature indicating the bearing damage. However, for healthy case of the related spectral variation, this frequency band is at the zero-level, namely there is no frequency component in the range 2-4 kHz. But, this is not possible in terms of the physical meaning, so any manufactured system is not perfect. To find the origin of this result, the spectral variation for first detail sub-band of the vibration signal in the healthy case is examined. Very small amplitude variations, in the frequency range 2-4 kHz, which is the main cause of the bearing damage, are easily detected. This detection is interpreted as a potential defect of the bearing damage.

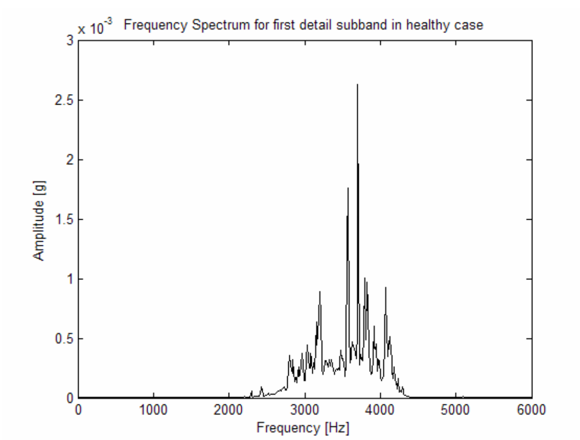


Figure 10. Spectral Variation of the first detail sub band of the vibration signal for the healthy bearing case.

As seen from the Figure 10, the existence of the bearing damage characterization is extracted as a hidden information from the third detail sub band of the vibration signal for healthy case.

V. CONCLUSIONS

This research reflects two different aspects of bearing damage characterization. The fist one is that the bearing damage property is characterized between 2-4 kHz in the frequency domain. As a second one, its existence depends on the manufacturing defect and it is observed as a primitive cause of the aging case. Hence, this pre-existing condition is interpreted as the main cause of the development of bearing damage under the aging process. This result is very important in tracking and detecting the bearing damage property during the operation of the motor. Thus, this method can be implemented as a real-time condition monitoring system in future.

In terms of the wavelet transform applications, both of the continuous and discrete wavelet transform show the similar bearing damage characterization, which is indicated in the frequency interval of 2-4 kHz, through the vibration signals in the healthy case. This characterization can be interpreted as a common feature. However, it can be said that the CWT reflects the potential case, which covers the overall frequency range of the vibration signal for healthy case, while the DWT discriminates the frequency band of 2-4 kHz regarding to bearing damage from the original vibration signal of the healthy case. In this manner, as seen in Figure 6-a and Figure 10, the CWT detects the existence of the defects which will be appeared during the time by means of the degradation and the DWT also isolate this frequency band related to the bearing damage. As a result of this research, in the hybrid usage of the CWT and DWT, this new approach provides a new possibility as a fault detection and isolation method.

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