Usage of Different Wavelet Families in DC Motor Sounds Feature Analysis

Đorđe Damnjanović, Dejan Ćirić, Miljan Miletić and Dejan Vujičić

***Abstract*—Widespread usage of wavelets in signal analysis places this method in a very high position in many researches, especially when audio signal classification is in focus. Wavelets have become an unavoidable segment in signal processing whose nature leads to more comprehensive results in comparison with standard methods, like Fourier transform. There are many wavelet families that have been developed in quite different forms for different purposes. In this paper, a selected set of wavelets is used in the decomposition of direct current (DC) motor sounds to detail and approximation coefficients for the purposes of finding the most suitable wavelets for audio feature analysis. Selection of wavelets is done according to the obtained results, taking into account all available wavelets in Matlab software package. DC motor sounds are recorded in two different conditions: laboratory condition and factory condition, although only those from the laboratory are presented here.**

***Index Terms*— Wavelet families; Detail coefficients; Approximation coefficients; Audio features; DC motor sounds.**

INTRODUCTION

Considering the applicability of wavelets, they have been used in many of scientific fields including mathematics, signals processing, acoustics, telecommunications, biomedical engineering, etc [1]. Due to their nature and potentials, we can say that the wavelets are quite widespread today. The wavelets are able to overcome some important problems of standard signal processing methods, such as Fourier transform. Consequently, the wavelets are located high on the scale of signal processing algorithms [2].

Almost every programing language has built in the wavelets algorithms for different purposes, like C, C++, Python, Java and many others [3,4]. It is also important to stress that functions related to wavelets are typically compatible in different programming platforms. Recently, the most popular programs for implementing wavelets are Matlab, LabVIEW, SciLab, Octave, etc [3,4].

De-noising using wavelets is widespread nowadays. It can be found in speech, audio signal and image processing. Methods of wavelets decomposition into detail and approximation coefficients lead to applications like feature extraction, classification, focus stabilization in video signals, image compression, motion detection and others [4,5]. The results obtained with wavelets are in most cases better than using other algorithms.

Looking from the historical point of view, wavelets take roots in Fourier's researches, but Alfred Haar first mentioned real term and mathematical representation of wavelets, after which this wavelet was named Haar wavelet family [6]. After that, a number of scientist have researched and "upgraded" the existing algorithm to its new and more advanced forms, which have spread to many areas as mentioned above. Some of the proposed wavelets are named after the scientists who invented them like: Gabor, Morlet, Daubechies, etc. Many of new wavelets are just upgraded version of the old ones. From the perspective of the Matlab software package, there are several wavelets that are the most common in different processing tasks like: Haar, Daubechies, Coiflets, Symlet, biorthogonal, reverse biorthogonal and Meyer [7].

In this paper, focus is on usage of different wavelet families in audio feature extraction of direct current (DC) motor sounds. For this purpose, more than 60 DC motor sounds are investigated, both faulty and non-faulty ones, recorded in the laboratory condition. Analysis is done in accordance with the wavelet nature, and the recorded audio signals are decomposed into detail and approximation coefficients. These coefficients have strong relation to audio features, since they can be treated as wavelet-based features that can be used for future classification [8]. One of the main goals of this research is to create potentials to make a difference between faulty and non-faulty motors using sound that they generate. Impact of using different wavelet families in extraction of wavelet-based features is analyzed here. The analysis is done in Matlab software package, and the most representative examples are presented in this paper.

WAVELETS

It is well known that wavelets are developed during the past century. All started with Haar, as it was mentioned, but a number of different wavelet functions have emerged in the meantime, developed from the existing ones or developed as completely new ones [6,9]. The basic wavelet function is given in (1):

$$\psi_{a,b,}(x) = \frac{1}{\sqrt{a}}\psi(\frac{x-b}{a}), a > 0 \qquad (1)$$

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where a and b are the scaling and translation parameter, respectively [10]. Appropriate selection of parameter's (a and b) values is very important for the correct purpose of the wavelet function [10,11].

The most applications based on wavelets functions basically use the discrete wavelet transformation (DWT), whose algorithm is developed on signal decomposition into detail and approximation coefficients using high-pass and low-pass filters, as it was presented in Fig. 1 [7,8]. where, LP is low-pass filter, HP is high-pass filter, A stands for approximation coefficients, D stands for detailed coefficients and 2↓ is down-sampling.

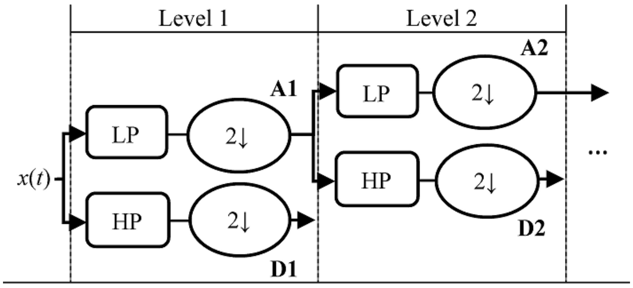

Fig 1. Block diagram of wavelet decomposition.

From the group of wavelet families, Haar (*haar* in Matlab) is the simplest in mathematical form. It is identical to Daubechies 1 (*db1* in Matlab) [6,11]. Equations (2) and (3) give the analytic form of Daubechies 1 or Haar wavelet function:

$$\psi(t) = \begin{cases} 1 & if \quad x \in [0 \quad 0.5] \\ -1 & if \quad x \in [0.5 \quad 1] \\ 0 & if \quad x \notin [0 \quad 1] \end{cases} \tag{2}$$

$$\phi(t) = \begin{cases} 1 & if \quad x \in [0 \quad 1] \\ 0 & if \quad x \notin [0 \quad 1] \end{cases} \tag{3}$$

If the order of Daubechies wavelet is increased, its analytic form becomes more complicated. It is worth mentioning that extension of the Daubechies wavelet family by introducing new functions of higher order leads to a wider usage of this wavelet family in various applications [6,11].

In collaboration with Ingrid Daubechie, Ronald Coifman invented wavelet families named Coiflets (*coif* in Matlab). These wavelets are more symmetric and have more vanishing moments than the Daubechies wavelets. From the application point of view, both (Coiflets and Daubechies wavelets) give good results, especially when feature extraction is in focus [6,11].

Symlets are proposed by I. Daubechie as modification of Daubechies wavelets (properties are nearly the same), and in the most cases they provide similar results as Daubechies wavelets [6,12]. Comparing the shapes of these wavelets (their wave presentation), they can be seen as reflections of each other.

Group of wavelets that are different from orthogonal wavelets (Daubechies, Coiflets, Symlets, Meyer) contains biorthogonal compactly supported spline wavelets [6,11]. These wavelets are grouped in biorthogonal and reverse biorthogonal wavelets (*bior* and *rbio* in matlab, respectively). Main features of these wavelets are symmetry and exact reconstruction, which is possible with finite impulse response filters (FIR filters) [6,11].

Yves Meyer proposed Meyer wavelet (*dmey* in Matlab) as another orthogonal wavelet family. The most common usage of this wavelet is in multi-fault classification, adaptive filtering and fractal random fields [11,13].

METHODS OF ANALYSIS

More than 60 DC motor sounds are recorded in the laboratory environment, while only some representative examples are chosen for presentation here. Approximately half of them are faulty motors, and other half belongs to non-faulty motors. The motors are driven in two directions of rotation. Due to simplicity and having in mind that the results for these two directions are similar, only the results for one direction of rotation (direction 1) are presented in this paper. All sounds are recorded with microphone which is placed in the vicinity of motors, sampled at 16 kHz. Length of the recorded signals is around 2 s.

Investigation process starts with segmentation of each signal, as explained in some of previous papers of the authors [8]. Segmentation is done using the segment size of 50 ms and overlap between segments of 50% (25 ms). In the literature, it can be found that different authors use different size of segments and overlap [12,14]. There is no any formal rule what segment and overlap size to apply, although in a number of studies the segment and overlap size are the same as implemented her [14].

Next step is wavelet-based feature extractions. It involves wavelet decomposition process described in Fig. 1. Here, each segment is decomposed with the wavelets into detail and approximation coefficients (high and low frequency components) at each level of decomposition. In this research, the decomposition level varies from 1 up to 8. So, in that manner, the obtained detail coefficients are observed at 8 different levels. Besides the level of decomposition, different wavelet families are applied in this research in order to analyze their effects on the extracted wavelet-based audio features, that is, the detail coefficients. Haar and Meyer wavelets have only one its kind in Matlab, while other wavelets (Daubechies, Coiflets, Symlet, biorthogonal and reverse biorthogonal) have many different types that can be chosen. For instance, Daubechies has more than 45 types in Matlab [7]. In this research, all of the mentioned wavelet families are used, however not all the types, but only the chosen ones.

From the obtained detail coefficients at each level and for every segment, absolute value is first calculated, and then the mean value is applied. Standard deviation (std) of the absolute value of detail coefficients is also calculated and used in this research. However, since the results obtained with standard deviation and mean value generally show similar trends, and the results obtained using the mean value are more consistent and stable, focus is only on those results here.

Besides the analysis carried out in the domain of wavelet-based features, the recorded signals for non-faulty and faulty motors are compared also in the time and frequency. All processing is done in Matlab software package with standard commands for wavelet analysis: *wavedec* for wavelet decomposition, *appcoef* and *detcoef* for obtaining the approximation and detail coefficients, *abs* and *mean* for calculating absolute and mean values, respectively [7,8].

Special attention is paid to differences between non-faulty and faulty motors in all used domains - time and frequency domain, but also in the domain of wavelet-based features (detail coefficients and values calculated from them).

Results

Several different cases of correlation between the results in time/frequency domain and wavelet-based features domain are identified in this research. Two of them, considered to be the most common ones, are presented here. The first case is related to scenario where there are visible differences between non-faulty and faulty motors in both spectra and detail coefficients. The second scenario is opposite to the first one, and consists of samples where differences between non-faulty and faulty motors are negligible in all considered domains. In other words, there are no significant differences between them in time signals, spectra or detail coefficients.

A. Prominent differences between non-faulty and faulty motors

The first domains that are observed are time and frequency domains. Characteristic examples of time domain signals and spectra for one non-faulty and one faulty motor are shown in Fig. 2. In this and other figures given in the rest of the paper, the style of lines is the same: blue solid line for non-faulty motors, and red dashed line for faulty motors.

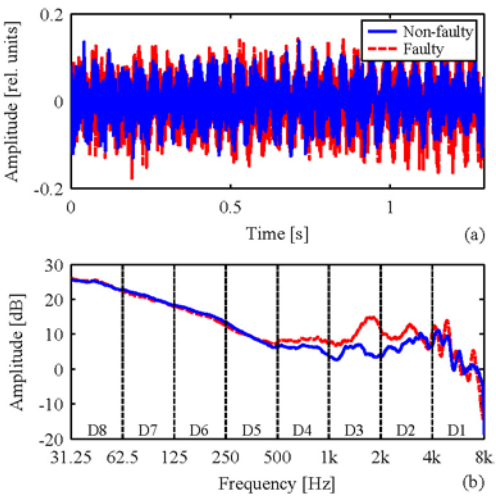

Fig. 2. Characteristic example of prominent differences between signals (sounds) of non-faulty (blue) and faulty (red) DC motors: a) time domain, b) frequency domain

Comparing these two domains, time domain is the one where it is the most difficult to notice difference between the motors. The amplitude of the motor sound typically shows some fluctuations in time. Since most of energy is located at low frequency, the slower fluctuations that corresponds to these low frequency components are more prominent in the time domain signal.

On the other hand, frequency domain analysis can provide visible differences between compared motors (non-faulty and faulty ones), see, for example Fig. 2(b). In this particular example, more prominent differences exist at mid and high frequencies (above 500 Hz).

In order to understand in an easier way, the ratio standing behind the correlation between differences in the considered domains, especially in the frequency and wavelet-based features domains, the decomposition process using the wavelets is explained here from another perspective. All signals are sampled at 16 kHz, so the maximum frequency in signals is 8 kHz. At the first level of decomposition, signal passes through a high pass and low pass filter. Signals at the filters' output are down sampled by 2, generating the detail and approximation coefficients (the procedure is illustrated in Fig. 1). In the frequency domain, this decomposition corresponds to dividing the frequency range by 2 in two subranges. Thus, the detail coefficients at decomposition level 1 correspond to frequency range from 4 kHz to 8 kHz. In this manner, the detail coefficients at decomposition level 2 correspond to the frequency range from 2 kHz to 4 kHz, etc [15].

The next step in signal processing is the segmentation and calculation of wavelet-based features (the detail coefficients and their mean and std values from the segments). Fig. 3 presents the detail coefficients of the signals from Fig. 2 generated using Daubechies 2 wavelet after applying the absolute values to the detail coefficients and mean values of those absolute values from the segments.

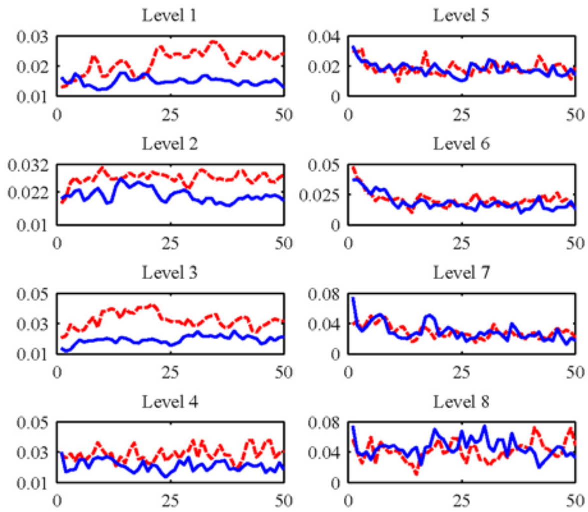

Fig. 3. Detail coefficients obtained after applying Daubechies 2 wavelet to segmented signals (with taking coefficient absolute value and mean value) for non-faulty (blue) and faulty motor (red), and using the decomposition levels from 1 to 8.

Now, the differences between non-faulty and faulty motors can be compared observing both frequency domain, see Fig 2(b), and features domain, see Fig. 3. In both domains, the differences are prominent at the decomposition levels from 1 to 4, that is, in the spectra, in the frequency range from 500 Hz to 8 kHz. In order to clarify the relation between the frequency ranges and the decomposition levels, the vertical lines are shown in Fig. 2(b) splitting the frequency range. Daubechies 2 wavelet provides good results in this case, and the differences between the motors are prominent. Other wavelet families need to be considered in this regard, too.

It is already mentioned that the Daubechies wavelet family consists of more than 45 types. Several of them are applied in this research (Daubechies 4, 5, 6, 8, 15), and all of them give similar results as Daubechies 2. In Fig. 4, the wavelet-based features for the decomposition levels 1 and 3 calculated using the wavelet families Symlet, Coiflets, Meyer, biorthogonal and reverse biorthogonal are presented.

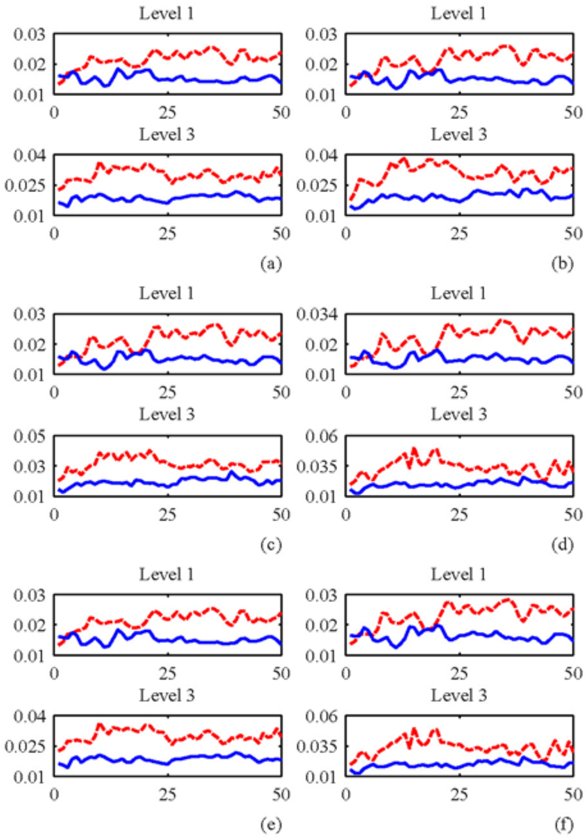

Fig. 4. Detail coefficients of segmented signals (with taking coefficient absolute value and mean value) obtained for non-faulty (blue) and faulty motor (red), and using the decomposition levels from 1 and 3, after applying wavelet: a) Haar, b) Symlet 4, c) Coiflet 3, d) Meyer, e) biorthogonal 1.1 and f) reverse biorthogonal 6.8; the case where differences between motors are prominent.

All the results presented in Fig. 4 are very similar with those ones obtained using the Daubechies 2 wavelet at the decomposition levels 1 and 3. This means that the shapes of the wavelet-based features obtained using different wavelets are not completely the same, but there are significant differences between non-faulty and faulty motors. For all other levels, the situation is almost the same. For some wavelets, the differences between the motors are somewhat larger, while for some other they are somewhat smaller.

Another comparison of effects of using different wavelets is given in Fig. 5, where detail coefficients at the decomposition level 2 are presented for several wavelets. Daubechies 2 is chosen as the reference one to be compared with the others. The results (wavelet-based features) for the Symlet 15 wavelet are rather similar to the ones for the Daubechies 2, since these two algorithms are rather similar to each other in the mathematical representation [6]. The results for other two wavelets are more interesting to analyze. Biorthogonal 3.9 leads to smaller differences between coefficients for the non-faulty and faulty motor in the first half of the segments (in the first part of the wavelet-based feature). The differences get larger in the second part of the feature. In the case of reverse biorthogonal 6.8 wavelet, the differences are even greater than those obtained with Daubechies 2 and Symlet 15 wavelets.

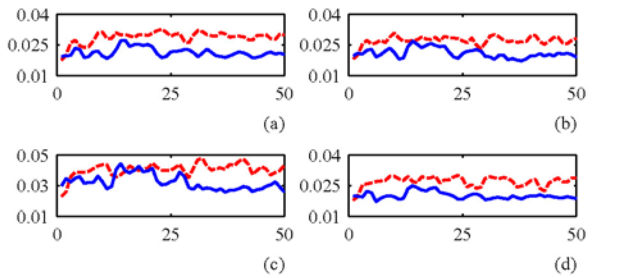

Fig. 5. Detail coefficients of segmented signals (with taking coefficient absolute value and mean value) for non-faulty (blue) and faulty motor (red) and using the decomposition level 2, after applying wavelet: a) Daubechies 2, b) Symlet 15, c) biorthogonal 3.9, d) reverse biorthogonal 6.8; the case where differences between motors are prominent.

Generally speaking, all wavelet families whose results are presented here provide useful results in the feature separation (distinction between non-faulty and faulty motors). The literature proposes usage of some wavelets more than others [12,16]. In similar manner, here several promising wavelet families are identified for a particular task of making a difference between non-faulty and faulty DC motors.

B. Negligible differences between non-faulty and faulty motors

In the second analyzed case, the differences between non-faulty and faulty motors are either small or do not exist at all. A few facts can be attributed to this phenomenon. One is that faulty motor do not have serious faults in their construction and work. If it is so, its sound can be very close to the non-faulty motors. Another option is that a motor is characterized as faulty by mistake.

An illustrative example of a pair of non-faulty and faulty motor from this case (scenario) is given in Fig. 6, where time and frequency domain of motor sounds are presented. In both domains, the differences between these motors are negligible.

When these signals are segmented and decomposed into detail and approximation coefficients, the obtained results using the Daubechies 2 wavelets are presented in Fig. 7. In this case, there are some minor differences at the levels 1 and

2. However, they are much smaller than those given in Fig. 3. At the other decomposition levels (from 3 to 8), the trends for the wavelet-based features are very similar for non-faulty and faulty motors. This means that wavelet-based features for the non-faulty motor coincide very well with the features for the faulty motor. There are certain differences in the feature values in particular segments, but they are not large enough and consistent to make a distinction between these motors.

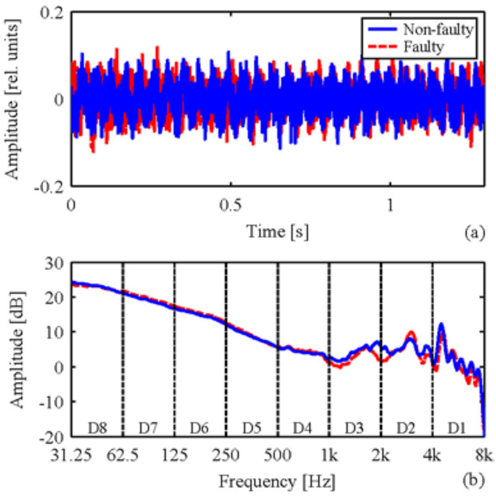

Fig. 6. Signals (sounds) of non-faulty (blue) and faulty (red) DC motors and negligible differences between them: a) time domain, b) frequency domain.

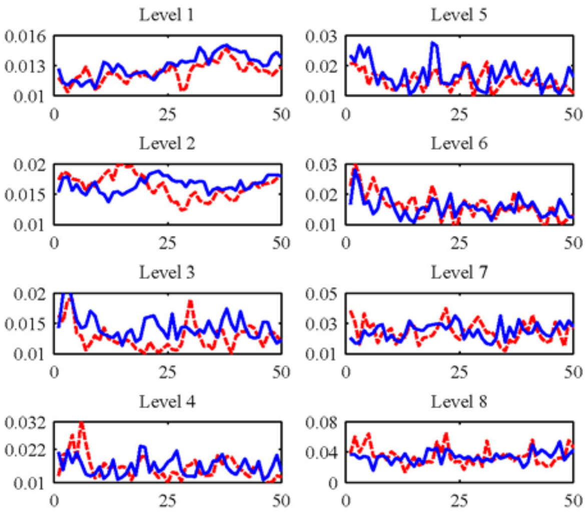

Fig. 7. Detail coefficients after applying Daubechies 2 wavelet to segmented signals (with taking coefficient absolute value and mean value) for non-faulty (blue) and faulty motor (red), and using the decomposition levels from 1 to 8; the case where differences between motors are negligible.

The analysis continues using different wavelet families for signal decomposition and features extraction. In Fig. 8, some characteristic results for wavelet-based features from this case are shown at the decomposition levels 2 and 3. Here, the same wavelets are used as in Fig. 4. The results are similar for all these wavelet families, where differences between non-faulty and faulty motors are generally small again. For some wavelets, they are slightly larger, such as Meyer and reverse biorthogonal 6.8 at the decomposition level 3, while for the other wavelets the differences are slightly smaller.

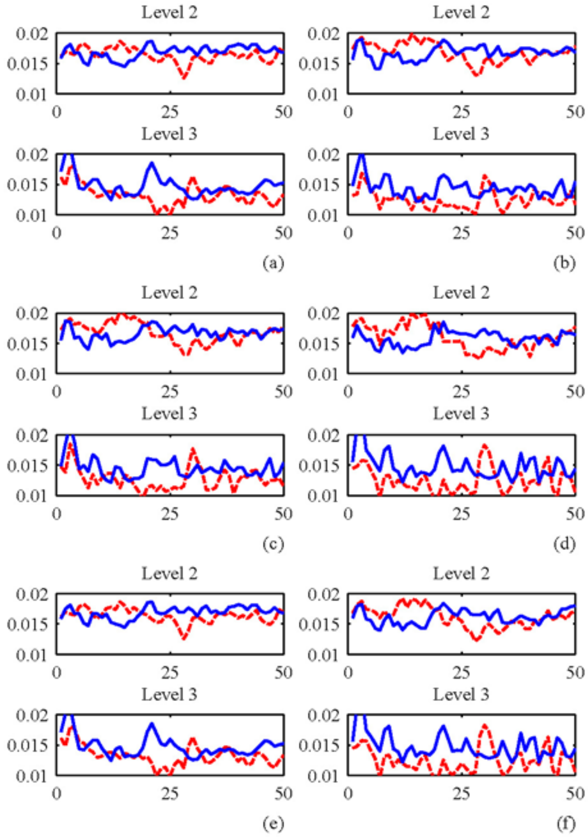

Fig. 8. Detail coefficients of segmented signals (with taking coefficient absolute value and mean value) for non-faulty (blue) and faulty motor (red), and using the decomposition levels 2 and 3, after applying wavelet: a) Haar, b) Symlet 4, c) Coiflet 3, d) Meyer, e) biorthogonal 1.1 and f) reverse biorthogonal 6.8; the case where differences between motors are negligible.

The level 4 in the decomposition process with Daubechies 2 wavelet (Fig. 7) shows somehow interesting behavior. In the beginning of the wavelet-based feature, there is a peak for the faulty motor leading to a certain difference between motors in this part of the feature. This is why, and similar as done in Fig. 5, the results for different wavelets (Daubechies 2, Symlet 15, biorthogonal 3.9 and reverse biorthogonal 6.8) and only decomposition level 4 are presented in Fig. 9. The mention peak is present in all given features. It is also noticed that the features of the non-faulty motor obtained using Symlet 15 and biorthogonal 3.9 wavelets has somewhat larger fluctuations than in other two cases.

For this case (scenario) of negligible differences between motors, it is important to emphasize that wavelet-based features (the detail coefficients) behave in similar manner as the spectra of corresponding signals meaning that the differences between non-faulty and faulty motors are either not present or they are rather small. Another observation is that there are no significant differences among the wavelets whose results are presented here.

To quantify the differences between the wavelet-based features for non-faulty and faulty motors, a quantity named feature difference is calculated in two ways. This quantity is obtained as the mean of differences between the features from all segments normalized by the mean feature value. This mean of differences is calculated taking into account either signed differences between features (difference A) or absolute value of the differences (difference B). The results for the analyzed cases (prominent and negligible differences between non-faulty and faulty motors) are presented in Fig. 10. Both differences A and B are larger at the decomposition levels from 1 to 4 in Fig. 10(a). Larger values of difference A show consistent trend of having larger feature values for one of the motors in most of the segments. This is not the case with the difference B showing larger values wherever there are larger differences in feature values for most of segments independently of the sign of these differences.

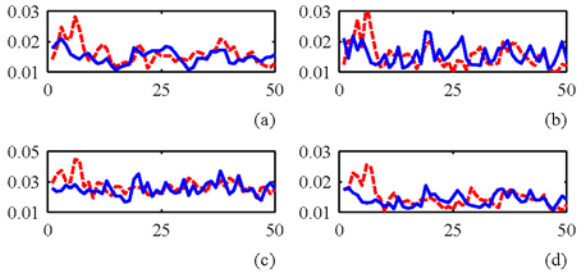

Fig. 9. Detail coefficients of segmented signals (with taking coefficient absolute value and mean value) for non-faulty (blue) and faulty motor (red) and using the decomposition level 4, after applying wavelet: a) Daubechies 2, b) Symlet 15, c) biorthogonal 3.9, d) reverse biorthogonal 6.8; the case where differences between motors are negligible.

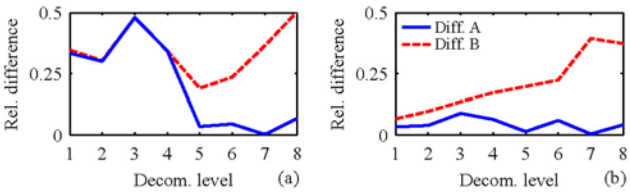

Fig. 10. Differences A and B between wavelet-based features for non-faulty and faulty motors at different decomposition levels for (a) prominent and (b) negligible differences between these motors

Conclusion

Wavelets usage in different fields of research becomes more spread every day. The exemplary applications include feature extraction and classification. This is enabled by its ability to decompose a signal into detail and approximation coefficients that could be used as features.

Two typical cases of correlation between the results for the DC motor sounds in frequency and feature domain are investigated in this research, the one where there are obvious differences between non-faulty and faulty motors and another one where differences are either very small or they are not present at all. More than 60 motors are included in the analysis using various wavelet families: Haar, Daubechies, Coiflets, Symlet, biorthogonal, reverse biorthogonal and Meyer. The decomposition is done from the level 1 to the level 8, and all processing is done in Matlab software package. Besides in the feature domain, the signals also are observed in the time and frequency domain. Special attention is paid to the relation between the results in different domains.

The presented results show that wavelets can be used for obtaining the audio features from DC motor sounds. The features are calculated applying the segmentation first, then wavelet decomposition, and some basic operations such as absolute and mean value on the generated detail coefficients.

Regarding the wavelets applied for the purpose of feature extraction, the effects of changing the wavelet function on the extracted features are not that large if the function belongs to the set used in this research.

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