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DC Motor Fault Analysis with the Use of Acoustic Signals, Coiflet Wavelet Transform, and K-Nearest Neighbor Classifier

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This paper focuses on testing the monitoring system of the Direct Current motor. This system gives the possibility of diagnosing various types of failures by means of analysis of acoustic signals. The applied method is based on a study of acoustic signals generated by the DC motor. A study plan of the DC motor's acoustic signal was proposed. Studies were conducted for a faultless DC motor and Direct Current motor with 3 shorted rotor coils. Coiflet wavelet transform and K-Nnearest neighbor classifier with Euclidean distance were used to identify the incipient fault. This approach keeps the motor operating in acceptable condition for a long time and is also inexpensive.

Keywords: acoustic signal, Coiflet wavelet, fault detection, DC motor.

1. Introduction

In the recent years, wavelet transforms have emerged as methods for many applications. Wavelets are formulated to describe signals in a localized time and frequency format. A linear combination of the shifted and scaled basis functions can be applied to model functions. These functions are defined in a space spanned by the wavelet family.

In approaches based on FFT, windows are used uniformly for spread frequencies. In approaches based on wavelet transforms the short windows are used at high frequencies and the long windows are used at low frequencies. The adaptable window size is useful to supervise nonstationary disturbances. By using a wavelet transform, time and frequency information can be simultaneously obtained (Huang, Hsieh, 2002).

The efficiency of the fault analysis depends on the quality of the features selection. Wavelets can be used as features of the signal. They are used for diagnostics of electrical motors (Abdesh Shafiel Kafiey Khan, Azizzur Rahman, 2010; Jawadekar *et al.*, 2012; Stepien, Makiela, 2013; Stepien, 2014; Stepien *et al.*, 2015).

Many invasive and noninvasive methods of diagnostics were used in the industry. Diagnostics of electrical motors is particularly important for mining, metallurgy, processing, oil and fuel industry. The noninvasive methods were more profitable than the invasive methods because they were based on easily accessible and inexpensive measurements to diagnose the machines' conditions. A particularly well developed part of diagnostics applies to rotating motors. Many methods are used for data collection and processing of diagnostic signals such as: magnetic field, ultrasounds, acoustic, electric, thermals signals (Baranski *et al.*, 2014; Duspara *et al.*, 2014; Glowacz *et al.*, 2014; 2015; Glowacz, 2014; Gornicka, 2014; Gutten *et al.*, 2011; Gutten, Trunkvalter, 2010; Krolczyk *et al.*, 2014a; Li *et al.*, 2015; Nawarecki *et al.*, 2012; Pleban, 2014; Rusinski *et al.*, 2014; Wegiel *et al.*, 2007).

Evolution of materials has influenced largely the development of electrical motors. Recently, mechanical, thermal, electric, and magnetic properties of materials have been analyzed with great interest. Especially the materials like copper, aluminum, steel, and alloys are very essential for the diagnostics of the electrical motor (Krolczyk *et al.*, 2014b; Niklewicz, Smalcerz, 2010; Regulski *et al.*, 2014; Tokarski *et al.*, 2012).

Electric motors have many forms and sizes. In this paper, the study concerns a selected Direct Current motor and selected methods of acoustic signal processing. The monitoring system of the DC motor was presented (Fig. 1).

Fig. 1. Monitoring system of the analyzed DC motor.

2. Process of sound recognition of the DC motor

The process of sound recognition of the DC motor consisted of pattern creation and identification (Fig. 2). During the pattern creation process training samples were processed. During the identification process test samples were processed and compared with the training samples. Steps of these processes were very similar. The identification process had one additional step, i.e., classification.

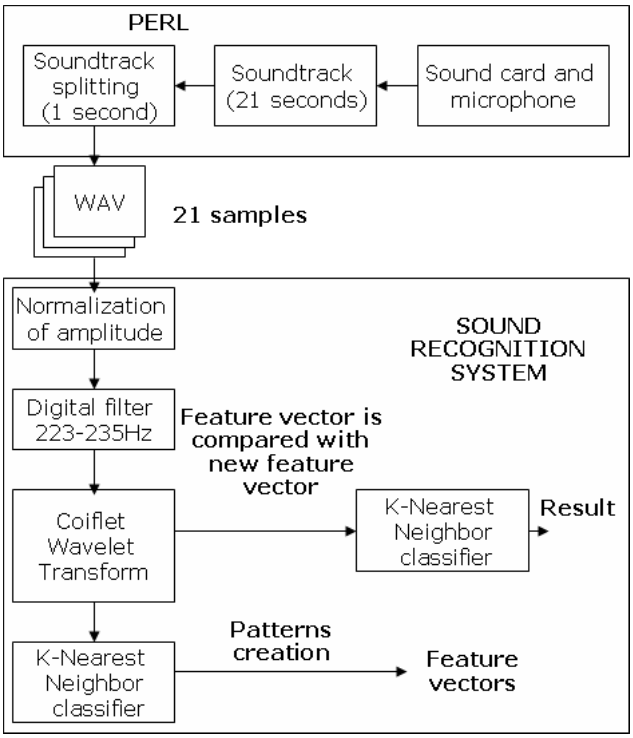

Fig. 2. Process of sound recognition of the DC motor with the use of the Coiflet wavelet transform and K-Nnearest neighbor classifier.

Acoustic signals of the DC motor were recorded at the beginning of both processes. A condenser microphone and sound card (Kulka, 2011) were used to record the acoustic signal. The recorded soundtrack had the following parameters: the sampling rate equal to 44.1 kHz, the 16-bit depth, a single channel. Next the recorded data were split, sampled, normalized, and filtrated 223–235 Hz (Glowacz, 2014). The frequencies 223–235 Hz depended on the rotor speed and type of the motor: $f_c = 4Xr_{\text{speed}}$, $r_{\text{speed}} = 700$ rpm, the DC motor had 4 poles and X was equal 5, $f_c = (4)(5)(700/60) = 233.33$ Hz. This frequency 223.33 Hz was in the range of $\langle 223$ Hz, 235 Hz$\rangle$. The motor with shorted rotor coils had a lower rotor speed, so the frequency had to be lower than 233 Hz.

Next the data were converted through the Coiflet wavelet transform. This algorithm decomposed the signal $\mathbf{s}$ into a number of different sub-series $\mathbf{a}_1$, $\mathbf{d}_1$ (see chapter 2.1 and Fig. 5). It depended on the level of decomposition. In the pattern creation process feature vectors of specific classes were created. Classification was the last step of the processing (K-Nnearest neighbor method).

2.1. Coiflet wavelet transform

A Coiflet wavelet basis function is embedded within the wavelet transform scheme. This wavelet can be derived from a multiresolution analysis such that the scaling function has a certain number of vanishing moments. In the proposed method, the Coiflet wavelet is selected as the wavelet basis function. The discrete Wavelet Transform decomposes the signal by passing it through filters (high-pass and low-pass ones). These filters coefficients of Coiflet wavelet are shown in Table 1. It uses Mallat Algorithm (MathWorks, 2014; Igras, Ziolko, 2013; Ziolko *et al.*, 2010).

Table 1. Decomposition filters of the Coif2 wavelet.

Decomposition Low-pass filter	Decomposition High-pass filter
−0.0007	−0.0164
−0.0018	−0.0415
0.0056	0.0674
0.0237	0.3861
−0.0594	−0.8127
−0.0765	0.4170
0.4170	0.0765
0.8127	−0.0594
0.3861	−0.0237
−0.0674	0.0056
−0.0415	0.0018
0.0164	−0.0007

The Coiflet wavelet was constructed with vanishing moments for the wavelet function $\psi(t)$ and scaling function $\varphi(t)$. The Coiflet wavelet allows a very good approximation of polynomial function at different resolutions (Huang, Hsieh, 2002). The Coiflet wavelet (coif2) was selected for the research (Fig. 3, 4).

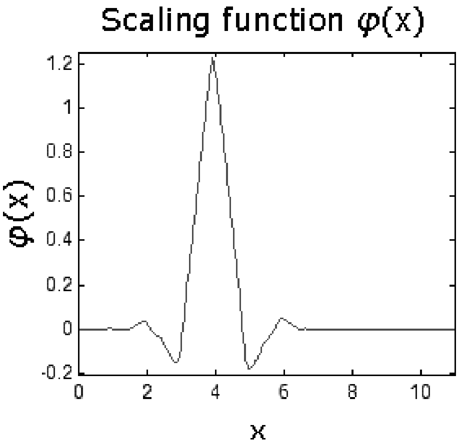

Fig. 3. Scaling function of the Coilflet Wavelet (coif2).

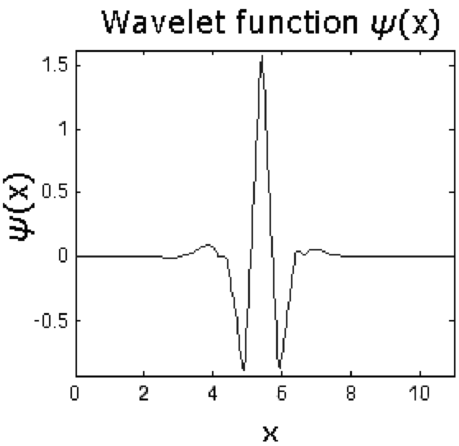

Fig. 4. Wavelet function of the Coilflet Wavelet (coif2).

An original signal (normalized and filtrated) is calculated by a low-pass and high-pass filters. Detailed coefficients are obtained from the high-pass filter (**d1**, **d2**,..., **dp**) and approximation coefficients are obtained from the low-pass one (**a1**, **a2**,..., **ap**), where p is the level of decomposition (Figs. 5, 6).

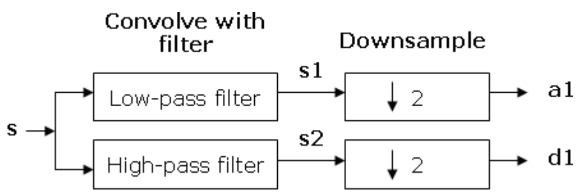

Fig. 5. One-Dimensional Discrete Wavelet Transform.

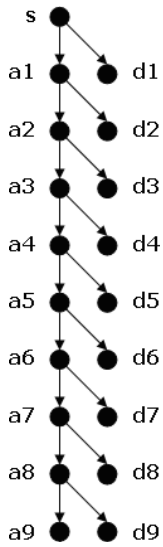

Fig. 6. Coefficients of the 9-th level of wavelet decomposition.

The low-pass and high-pass filters have the length equal to 2n. If N = length (**s**), the signals **s1** and **s2** are of the length $N+2n-1$, and then the vectors **a1** and **d1** are of the length $(N+2n-1)/2$. After that the approximation coefficient **a1** is split into two signals using the same method, replacing **s** by **a1** and producing **a2** and **d2**, and so on (MathWorks, 2014).

The feature vectors consist of the absolute values of the coordinates of the vectors **d1**,..., **dp**. On the basis of the analysis, the author noticed that the absolute values should be used because the negative values cause errors in the classification step. The K-NN classifier is based on a distance function (formula 1). The feature vectors of the detailed coefficient |**d9**| of the acoustic signal of the DC motor are showed (Figs. 7, 8).

The obtained feature vectors are of a high dimensionality. These vectors have 97 features:

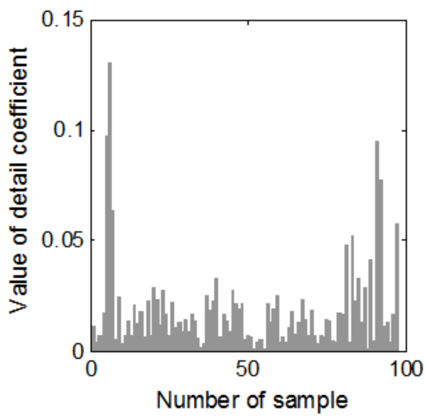

Fig. 7. Absolute value of the detailed coefficient d9 of the acoustic signal of a faultless DC motor (coif2 wavelet).

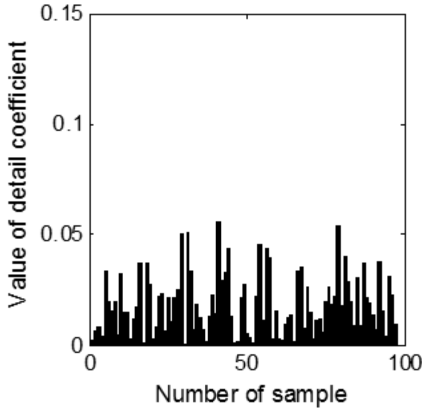

Fig. 8. Absolute value of the detailed coefficient d9 of the acoustic signal of a DC motor with shorted rotor coils (coif2 wavelet).

df9=[$|f_1|$,$|f_2|$, ..., $|f_{97}|$] is the acoustic signal of the faultless DC motor, **ds9**=[$|s_1|$,$|s_2|$, ..., $|s_{97}|$] is the acoustic signal of the DC motor with 3 shorted rotor coils. A suitable classifier is needed to classify such vectors. The best candidates are the K-Nnearest neighbor, Nearest Neighbor, Nearest Mean, and their modifications such as a classifier based on words or modified classifier based on words. These classifiers are very good to classify high dimensionality feature vectors.

Of course there are more schemes of feature extraction of the DC motor, for example the PCA (Principal component analysis), FFT + digital filtration, LPC (Linear predictive coding), LPCC (Linear Predictive Cepstral Coefficients), LSF (Line Spectral Frequencies). In this paper the author considered only the Discrete Wavelet Transform.

2.2. K-Nnearest neighbor Classifier

The classification methods such as K-Nnearest neighbor, Fuzzy Logic and Neural networks are discussed in the literature (Augustyniak *et al.*, 2014; Czopek, 2012; Dudek-Dyduch *et al.*, 2009; Dzwonkowski, Swedrowski, 2012; Hachaj, Ogiela, 2013; Jaworek, Tadeusiewicz, 2014; Jun, Kochan, 2014; Krolczyk, 2014; Mazurkiewicz, 2014; Pribil *et al.*, 2014; Roj, 2013; Valis *et al.*, 2015; Valis, Pietrucha-Urbanik, 2014; Zhang, Xia, 2014). K-Nnearest neighbor Classifier is described in the literature (Glowacz *et al.*, 2012). It is worthy of attention that this classifier is very good to classify high dimensional feature vectors. In this paper the Euclidean distance is applied for recognition of acoustic signals of the DC motor. The Euclidean distance d_e is the measure of the distance between two feature vectors. For example, $\mathbf{p} = [p_1, p_2, \ldots, p_n]$ and $\mathbf{c} = [c_1, c_2, \ldots, c_n]$ are feature vectors with the same length n. Then the Euclidean distance is expressed as:

$$d_e(\mathbf{p}, \mathbf{c}) = \sqrt{\sum_{i=1}^{n} (p_i - c_i)^2}. \tag{1}$$

The test sample is identified by the majority decision rule – it is compared with the number of the training samples. Next, the class that has the largest number of k nearest neighbors is selected as a recognized class.

3. Results of sound recognition of the DC motor

In order to perform measurements and analysis a test bench was set up. The test bench consisted of a DC motor, microphone, computer with a sound card and software for recognition of acoustic signals. The analyzed DC motor had the following operational parameters: $P_{\text{Motor}} = 13$ kW, $U_{NRV} = 75$ V, $I_{NRC} = 200$ A, $U_{ENV} = 220$ V, $I_{ENC} = 4$ A, $n_{RS} = 700$ rpm, where: P_{Motor} is the motor power, U_{NRV} is the nominal rotor voltage, I_{NRC} is the nominal rotor current, U_{ENV} is the excitation nominal voltage of the DC generator, I_{ENC} is the excitation nominal current of the DC generator, n_{RS} is the rotor speed. Each group of three loop rotor coils of the DC motor is shortened with the use of resistance $R_{bz} = 7.7$ mΩ.

An external resistance generated by the load torque was connected with the DC motor. It was used to avoid a damage of rotor windings of the DC motor during the short circuit. The acoustic signals of the faultless DC motor and DC motor with 3 shorted rotor coils (Fig. 9) were used in the investigations. To show the ef-

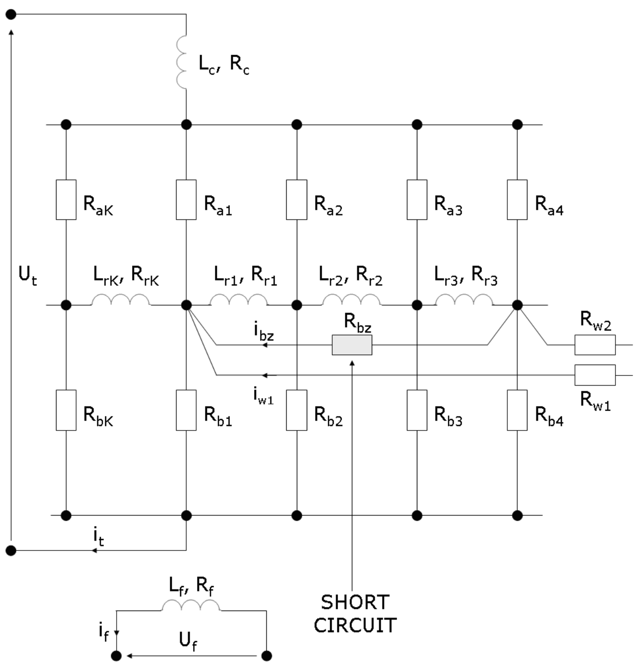

Fig. 9. Scheme of rotor winding of the DC motor with shortened rotor coils.

fectiveness of the proposed method, efficiency of sound recognition was introduced.

$$EoSR = \frac{NoPITS}{NoATS}100\% , \tag{2}$$

where $EoSR$ is the efficiency of sound recognition, $NoPITS$ is the number of properly identified test samples, $NoATS$ is the number of all test samples.

In this analysis the efficiency of sound recognition has been evaluated for 14 one-second training samples (7 samples of the acoustic signal of a faultless DC motor, 7 samples of the acoustic signal of a DC motor with 3 shorted rotor coils) and 42 test samples (21 samples of the acoustic signal of the faultless DC motor, 21 samples of the acoustic signal of the DC motor with 3 shorted rotor coils). The results of the recognition of the acoustic signal of the DC motor with the use of the Coiflet wavelet transform and K-nearest neighbor classifier are presented in Table 1.

Table 2. Results of the recognition of the acoustic signal of the DC motor with the use of the Coiflet wavelet transform and K-nearest neighbor classifier.

State of DC motor	$EoSR$ [%]			
Parameter k	$k = 1$	$k = 3$	$k = 5$	$k = 7$
Faultless DC motor	95.23	85.71	80.95	85.71
Motor with 3 shorted rotor coils	90.47	95.23	100	90.47

The evaluated efficiency of the sound recognition of the faultless DC motor was 80.95–95.23%. The efficiency of the sound recognition of the DC motor with 3 shorted rotor coils was 90.47–100%. Figure 10 shows the experimental results of the efficiency of the sound recognition depending on the parameter k(see the k-Nearest Neighbor classifier).

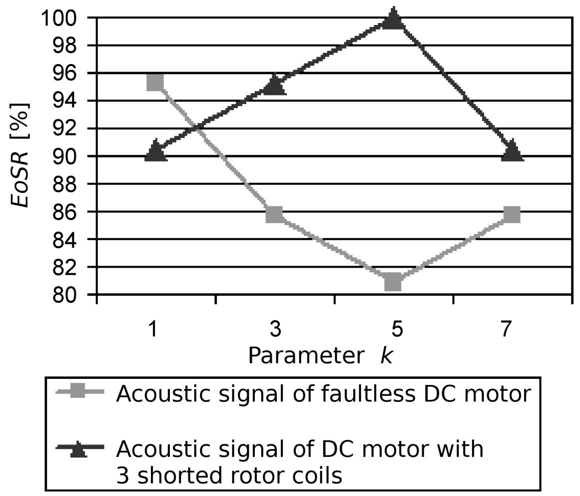

Fig. 10. Efficiency of the sound recognition of the DC motor depending on the parameter k.

4. Discussion

The first problem is number of states used in the recognition process. What will happen for other states of the DC motor? It was shown that by using the proposed method good results for 2 states can be reached. In the literature the author conducted an analysis for more states of the DC motor and the results were good (Glowacz *et al.*, 2015). It can be noticed that the proposed method based on acoustic signals is not as good as the method based on current signals. Acoustic signals of the DC motor have disturbances. On the other hand, the proposed method of recognition of acoustic signals is non-invasive and inexpensive. A computer with a microphone cost about 300$.

The second problem is the number of machines used in a recognition process. What will happen for other types of the DC motor? The author analyzed acoustic signals from one DC motor. Analysis of many motors is not an easy task, as access to many various DC motors can be problematic. Cooperation with motor operators, engineers, and industry is required. A construction scheme and prepared faults of each analyzed motor are required. Different parameters of DC motors such as: current, voltage, power, rotor speed have many variants. There is also a problem with spare parts when shorted rotor coils damage the machine permanently.

The third problem is the influence of environment conditions on the efficiency of recognition of acoustic signals. What will happen for 10 DC motors operating in one hall? The author conducted his analysis in laboratory conditions. If there are 10 DC motors operating in one hall the results will depend on the training samples in the database. In this case the database should contain training samples with disturbances caused by other DC motors. The second solution of this problem is separation of the DC motors by a partition wall.

5. Conclusions

In this paper, an early fault detection method of the DC motor has been proposed. This method was based on processing of acoustic signals of a faultless DC motor and a DC motor with 3 shorted rotor coils. The proposed method used the Coiflet wavelet transform and K-Nnearest neighbor classifier with the Euclidean distance. The conducted studies showed that the efficiency of sound recognition of the DC motor was 80.95–100%. The major contributions of this paper are the method of recognition and analysis of the proposed method for acoustic signals of the DC motor. The proposed approach can keep a DC motor operating in acceptable conditions for a long time and it is also inexpensive.

The further research of the acoustic signals of the DC motor will include other faults of the DC motor and methods of their recognition. There is also an idea to combine the methods based on acoustic, electric, and thermal signals.

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