

# Fault diagnostics of DC motor using acoustic signals and MSAF-RATIO30-EXPANDED

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**Abstract:** An early fault diagnostic method of Direct Current motors was presented in this article. The proposed method used acoustic signals of a motor. A method of feature extraction called MSAF-RATIO30-EXPANDED (method of selection of amplitudes of frequencies – ratio 30% of maximum of amplitude – expanded) was presented and implemented. An analysis of proposed method was carried out for early fault states of a real DC motor. Four following states of the DC motor were measured and analyzed: the healthy DC motor, DC motor with 3 shorted rotor coils, DC motor with 6 shorted rotor coils, DC motor with a broken coil. Measured states were caused by natural degradation of the DC motor. The obtained results of analysis were good. The presented early fault diagnostic method can be used for protection of DC motors.

**Key words:** acoustic signal, analysis, diagnostic, DC motor, machine

## 1. Introduction

DC motors are easy to control and a speed of a DC motor can be controlled. DC motors are used in propulsion of electric vehicles (for example trams), hoists and elevators. Small DC motors are used in toys and various tools such as: printers, hard disks and CD/DVD ROM drives. Early faults of motors are caused by natural degradation of machines. These early faults may damage a motor. Damaged motors generate economic losses caused by breakdowns in production lines. The damaged motor should be replaced by another one. Methods of fault diagnostics are developed to prevent economic losses. In the literature diagnostic methods have been developed for the detection and localization of faults of a DC motor, induction motor [1, 2] and synchronous motor [3]. A new methodology to assist the preventive maintenance of induction motor was presented in literature [4]. A distributed system for induction motors was also implemented [5]. An on-line condition monitoring system for induction motors was also described [6]. Analyses of vibrations [7-11] and acoustic signals [12-18] were discussed in literature. Analyses of thermal images of faulty states of electrical machines and

equipment were also presented [19-22]. Techniques of material diagnostic were also developed [23]. The most of rotating electrical machines generate acoustic signals. It is a reason to analyze this type of signal for the DC motor. Information about windings of electrical machines can be found in following literature [24]. In this article the author presented a technique of recognition of acoustic signals of the DC motor (Fig. 1). This technique is based on original method of feature extraction called MSAF-RATIO30-EXPANDED (method of selection of amplitudes of frequencies – ratio 30% of maximum of amplitude – expanded).

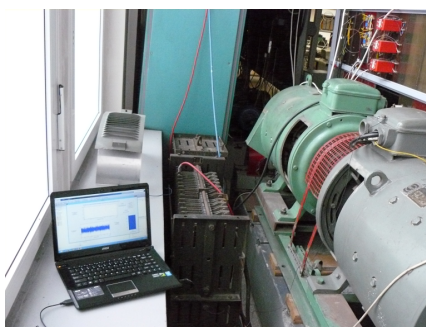


Fig. 1. The analyzed DC motor and computer with microphone

## 2. Technique of fault diagnostics of DC motor

Technique of fault diagnostics of a DC motor is based on processing of an acoustic signal. It is a very difficult task. The proposed technique uses 2 processes: pattern creation and identification.

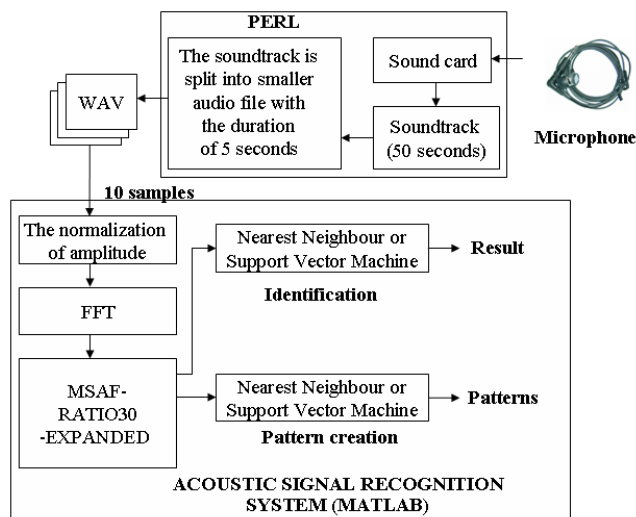


Fig. 2. Block diagram of proposed technique of fault diagnostics of the DC motor

The pattern creation process was used to obtain patterns. The identification process compared a test sample with patterns (processed a training sample). Both processes were implemented for proposed technique (Fig. 2). The implemented technique used a computer with a microphone. The analyzed DC motor was a source of acoustic signals.

The pattern creation process consisted of following steps: recording of acoustic signals, soundtrack splitting, normalization of amplitude, feature extraction with the use of MSAF-RATIO30-EXPANDED, patterns creation. The identification process consisted of the same steps except the patterns creation. Last step of the identification process is classification of a test sample. In the classification step, two methods can be chosen – Nearest Neighbour and Support Vector Machine (SVM). The recording of acoustic signals was based on the sound card of the computer and condenser microphones such as: OLYMPUS TP-7, ZALMAN ZM-MIC1. These microphones were chosen because of their low costs. The soundtrack was recorded on the computer with following parameters of audio format: WAVE PCM, the number of channels – mono, sampling rate – 44.1 kHz, 16-bit depth. Next soundtrack was split into smaller audio files (5-second samples). Normalization of amplitude was applied in the range of  $[-1, 1]$ . It divided each point by the maximum value of the sample. The next FFT spectrum was calculated for each sample (16384 values, because Hamming window was 32768) [25-28]. The calculated FFT spectra were used by MSAF-RATIO30-EXPANDED. This method was discussed in Section 2.1. At the end of the signal processing, the classification step was performed.

## 2.1. MSAF-RATIO30-EXPANDED

MSAF-RATIO30-EXPANDED is a feature extraction method. The author decided to show a block diagram of the proposed method (Fig. 3).

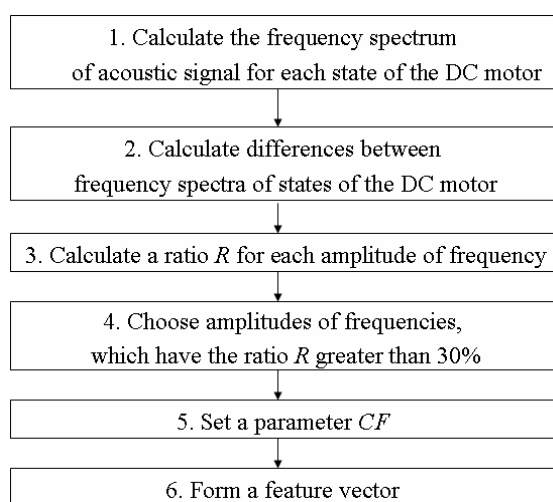


Fig. 3. Block diagram of MSAF-RATIO30-EXPANDED

The steps of the proposed MSAF-RATIO30-EXPANDED method were following:

- 1) Calculate the frequency spectrum of an acoustic signal for each state of the DC motor. The calculated frequency spectrum of an acoustic signal of the healthy DC motor was a vector  $\mathbf{hdc} = [hdc_1, hdc_2, \dots, hdc_{16384}]$ . The calculated frequency spectrum of an acoustic signal of the DC motor with 3 shorted rotor coils was a vector  $\mathbf{sdc} = [sdc_1, sdc_2, \dots, sdc_{16384}]$ . The calculated frequency spectrum of an acoustic signal of the DC motor with 6 shorted rotor coils was a vector  $\mathbf{gdc} = [gdc_1, gdc_2, \dots, gdc_{16384}]$ . The calculated frequency spectrum of an acoustic signal of the DC motor with a broken coil was a vector  $\mathbf{bdc} = [bdc_1, bdc_2, \dots, bdc_{16384}]$ .
- 2) Calculate differences between frequency spectra of states of the DC motor:  $|\mathbf{hdc-sdc}|$ ,  $|\mathbf{hdc-gdc}|$ ,  $|\mathbf{hdc-bdc}|$ ,  $|\mathbf{sdc-gdc}|$ ,  $|\mathbf{sdc-bdc}|$ ,  $|\mathbf{gdc-bdc}|$ .
- 3) Calculate a ratio  $R$  for each amplitude of frequency. The ratio was defined as:

$$R = (100\%)X_y/X_{\max}, \quad (1)$$

where  $X_y$  – amplitude of frequency with index  $y$ ,  $X_{\max}$  – maximum amplitude of frequency in the sample,  $R = 30\%$  for MSAF-RATIO30-EXPANDED,  $X_y$ ,  $X_{\max}$  were based on differences between frequency spectra of training samples.

- 4) Select amplitudes of frequencies, which have the ratio  $R$  greater than  $(30\%)X_{\max}$ . Sometimes the calculated differences  $|\mathbf{hdc-sdc}|$ ,  $|\mathbf{hdc-gdc}|$ ,  $|\mathbf{hdc-bdc}|$ ,  $|\mathbf{sdc-gdc}|$ ,  $|\mathbf{sdc-bdc}|$ ,  $|\mathbf{gdc-bdc}|$  may have maximum values at different frequencies. In this case, selection of proper frequencies may be difficult. Let's discuss the example MSAF-RATIO30-EXPANDED when following frequencies are selected 80, 120, 160, 200, 240, 280 Hz for  $|\mathbf{hdc-sdc}|$ ; 80, 130, 170, 210, 250, 290 Hz for  $|\mathbf{hdc-gdc}|$ ; 80, 160, 180, 190, 210 Hz for  $|\mathbf{hdc-bdc}|$ ; 80, 160, 240, 320 Hz for  $|\mathbf{sdc-gdc}|$ ; 80, 110, 160, 220, 310 Hz for  $|\mathbf{sdc-bdc}|$ ; 160, 210, 230, 340 Hz for  $|\mathbf{gdc-bdc}|$ . It can be noticed that frequencies 80 Hz and 160 Hz are the best (5 common frequencies). For this reason, the parameter  $CF$  was introduced. This parameter expanded a normal MSAF-RATIO30 method.
- 5) Set the parameter  $CF$ . This parameter was defined as:

$$CF = (\text{the number of required common frequencies})/(\text{the number of differences}). \quad (2)$$

The parameter  $CF$  was responsible for common frequencies. In the example above the parameter  $CF$  was equal to 0.83, then 5 of 6 frequencies were required  $((5/6) > 0.83)$  to make decision about selection of common frequencies. Then frequencies 80 Hz and 160 Hz were selected. 1 of 6 frequencies was required  $((1/6) > 0.16)$  for the parameter  $CF$  equaled to 0.16. The higher value of the parameter  $CF$  the better for analysis.

- 6) Form a feature vector.

Differences of frequency spectra of acoustic signals of the DC motor  $|\mathbf{hdc-sdc}|$ ,  $|\mathbf{hdc-gdc}|$ ,  $|\mathbf{hdc-bdc}|$ ,  $|\mathbf{sdc-gdc}|$ ,  $|\mathbf{sdc-bdc}|$ ,  $|\mathbf{gdc-bdc}|$  were presented in Figs. 4-9.

The author used 3 training sets to select the best frequencies for analysis. Each of them had 4 training samples. There were 18 differences of frequencies spectra (6 for each training set). Common frequencies of 4 acoustic signals of the DC motor were selected depending on the parameter  $CF$  and training sets (Table 1).

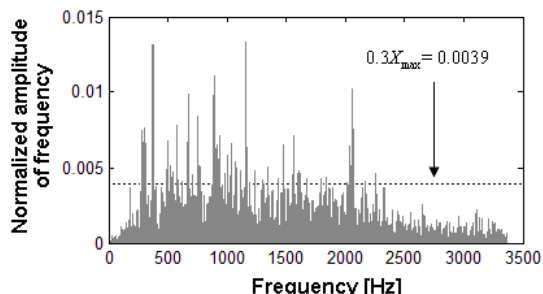


Fig. 4. The difference between frequency spectra of acoustic signal of healthy DC motor and acoustic signal of the DC motor with 3 shorted rotor coils (*|hdc-sdc|*) – rotor speed of 500 rpm

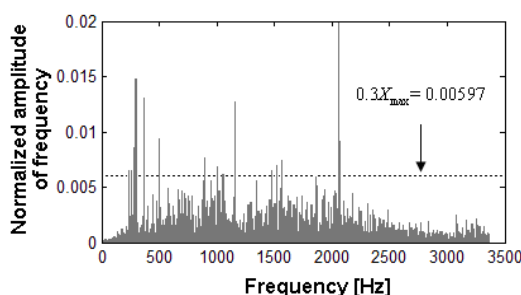


Fig. 5. The difference between frequency spectra of acoustic signal of healthy DC motor and acoustic signal of the DC motor with 6 shorted rotor coils (*|hdc-gdc|*) – rotor speed of 500 rpm

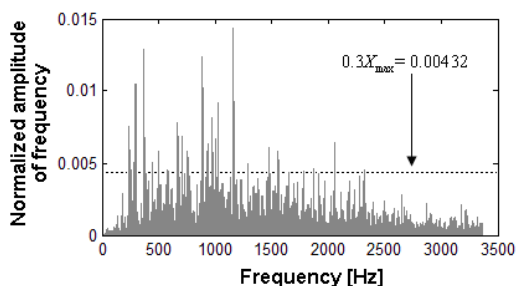


Fig. 6. The difference between frequency spectra of acoustic signal of healthy DC motor and acoustic signal of the DC motor with broken coil (*|hdc-bdc|*) – rotor speed of 500 rpm

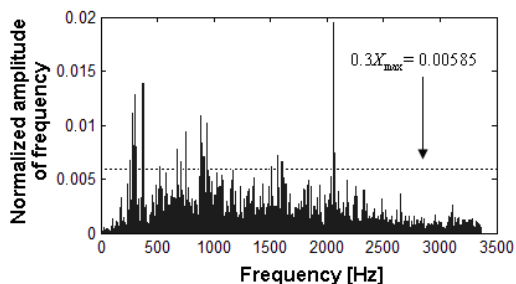


Fig. 7. The difference between frequency spectra of acoustic signal of DC motor with 3 shorted rotor coils and acoustic signal of the DC motor with 6 shorted rotor coils (*|sdc-gdc|*) – rotor speed of 500 rpm

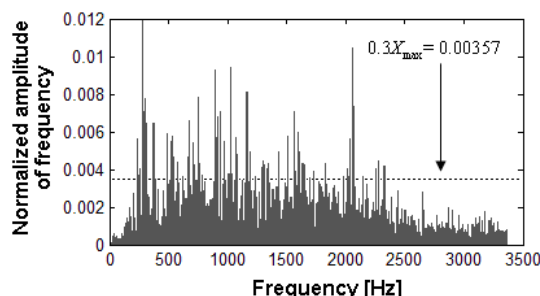


Fig. 8. The difference between frequency spectra of acoustic signal of DC motor with 3 shorted rotor coils and acoustic signal of the DC motor with broken coil ( $|sdc-bdc|$ ) – rotor speed of 500 rpm

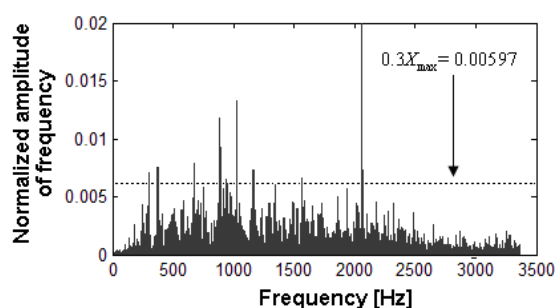


Fig. 9. The difference between frequency spectra of acoustic signal of DC motor with 6 shorted rotor coils and acoustic signal of the DC motor with broken coil ( $|gdc-bdc|$ ) – rotor speed of 500 rpm

Table 1. Common frequencies of 4 acoustic signals of the DC motor depending on the parameter  $CF$  and training sets

$CF = 0.98$ (6 common frequencies)	Frequency [Hz]
Common frequencies	–
$CF = 0.83$ (5 common frequencies)	Frequency [Hz]
Common frequencies	293, 371, 880, 895, 1049

Amplitudes of frequencies 293, 371, 880, 895, 1049 Hz ( $hdcv = [hdc_{219}, hdc_{277}, hdc_{657}, hdc_{665}, hdc_{783}]$ ,  $sdcv = [sdc_{219}, sdc_{277}, sdc_{657}, sdc_{665}, sdc_{783}]$ ,  $gdcv = [gdc_{219}, gdc_{277}, gdc_{657}, gdc_{665}, gdc_{783}]$ ,  $bdcv = [bdc_{219}, bdc_{277}, bdc_{657}, bdc_{665}, bdc_{783}]$ ) formed feature vectors for  $CF = 0.83$ . The calculated feature vectors  $hdcv$ ,  $sdcv$ ,  $gdcv$ ,  $bdcv$  were processed by the Nearest Neighbour classifier and Support Vector Machine.

## 2.2. Nearest Neighbour classifier

The classification was the last step of recognition of an acoustic signal of the DC motor. The problem of classification was already discussed in literature [29–45]. Neural networks were described in many scientific articles [37–42]. However the author decided to use the Nearest Neighbour classifier [2, 36, 43, 44] and Support Vector Machine [45], because they had high efficiency of recognition of similar problems. The Nearest Neighbour classifier was

very good to classify a high dimensional feature vector. The author used the Manhattan distance for the Nearest Neighbour classifier. Of course other distance functions such as: Jacquard, Euclidean [36] and Minkowski distances were also proper for recognition of an acoustic signal of the DC motor. The author decided to use the Manhattan distance, because the results of recognition for other mentioned distance functions were similar. The Manhattan distance  $M$  was expressed as:

$$M(\mathbf{hdcv}, \mathbf{sdcv}) = \sum_{i=1}^5 |(\mathbf{hdcv}_i - \mathbf{sdcv}_i)|, \quad (3)$$

where feature vectors  $\mathbf{hdcv} = [\mathbf{hdc}_{219}, \mathbf{hdc}_{277}, \mathbf{hdc}_{657}, \mathbf{hdc}_{665}, \mathbf{hdc}_{783}]$  and  $\mathbf{sdcv} = [\mathbf{sdc}_{219}, \mathbf{sdc}_{277}, \mathbf{sdc}_{657}, \mathbf{sdc}_{665}, \mathbf{sdc}_{783}]$ . The calculations were performed for 4 feature vectors  $\mathbf{hdcv}$ ,  $\mathbf{sdcv}$ ,  $\mathbf{gdcv}$ ,  $\mathbf{bdcv}$ .

### 2.3. Support Vector Machine

A support vector machine (SVM) was a very well-known method of classification. It constructed a hyperplane. SVM classified feature vectors by finding the best hyperplane that separated all vectors between the classes. The mentioned hyperplane had the largest distance between training vectors (support vectors) of any class. The decision function was:

$$svm = \sum_i w_i f(sv_i, x) + q, \quad (4)$$

where  $w_i$  were the weights,  $f$  was a kernel function,  $sv_i$  were the support vectors,  $x$  was a feature vector,  $q$  was the bias.

The advantages of SVM was: it used support vectors in the decision function (memory efficient), SVM used different Kernel functions for the decision function, classifier has high efficiency in high dimensional spaces. More about SVM was available in the literature [45].

## 3. Analysis of acoustic signals of the DC motor

The author used 4 acoustic signals of the DC motor: a healthy DC motor, a DC motor with 3 shorted rotor coils, a DC motor with 6 shorted rotor coils, a DC motor with broken coil. The DC motor had a rotor speed of 500 rpm. Motor power was  $P = 13$  kW (Fig. 1). Parameters of the DC motor were depended on states:

- healthy DC motor:  $U_{av} = 42.8$  V,  $I_{ac} = 56.7$  A,  $U_{ev} = 159.3$  V,  $I_{ec} = 2.5$  A,
- DC motor with 3 shorted rotor coils:  $U_{av} = 42.6$  V,  $I_{ac} = 58$  A,  $U_{ev} = 160.9$  V,  $I_{ec} = 2.5$  A,  $I_{csc} = 49$  A (Fig. 10),
- DC motor with 6 shorted rotor coils:  $U_{av} = 42$  V,  $I_{ac} = 57.5$  A,  $U_{ev} = 162$  V,  $I_{ec} = 2.5$  A,  $I_{csc} = 106$  A (Fig. 11),
- DC motor with broken coil:  $U_{av} = 42.7$  V,  $I_{ac} = 58.25$  A,  $U_{ev} = 163.4$  V,  $I_{csc} = 2.5$  A (Fig. 12),

where  $I_{ec}$  is the excitation current of the DC motor,  $I_{ac}$  is the armature current of the DC motor,  $I_{sc}$  is the current of the short-circuit,  $U_{ev}$  is the excitation voltage of the DC motor,  $U_{av}$  is the armature voltage of the DC motor.

Three and six loops of rotor coils were shorted out by resistance  $R_{scDC} = 0.5 \Omega$ . The author used 12 training samples (3 training sets) and 80 test samples for the analysis of acoustic signals of the DC motor. Each sample had duration of 5 seconds (220500 values, window was 32768, so the author calculated FFT from 5 windows). Training and test samples were processed. Next amplitudes of frequencies 293, 371, 880, 895, 1049 Hz were obtained and classified. Efficiency of recognition of an acoustic signal was calculated by the following formula:

$$E_F = \frac{N_p}{N_a} 100\% , \quad (5)$$

where:  $E_F$  is the efficiency of recognition of acoustic signal.  $N_p$  is the number of properly recognized test samples,  $N_a$  is the number of all test samples.

The results of recognition of acoustic signals with the use of MSAF-RATIO30-EXPANDED, Nearest Neighbour were presented in Table 2. The value of  $E_F$  was from 85% to 100%.

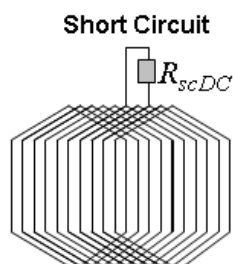


Fig. 10. Rotor windings of the DC motor with 3 shorted coils

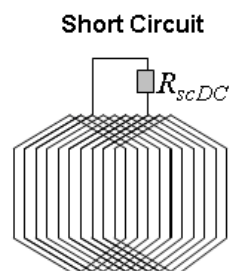


Fig. 11. Rotor windings of the DC motor with 6 shorted coils

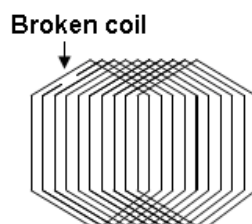


Fig. 12. Rotor windings of the DC motor with broken coil



Table 2. Results of recognition of acoustic signals of the DC motor using MSAF-RATIO30-EXPANDED and Nearest Neighbour classifier

State of DC motor	$E_F$ [%]
Healthy DC motor	100
Motor with 3 shorted rotor coils	90
Motor with 6 shorted rotor coils	100
Motor with broken coil	85

The results of recognition of acoustic signals with the use of MSAF-RATIO30-EXPANDED, SVM were presented in Table 3. The value of  $E_F$  was from 80% to 95%.

Table 3. Results of recognition of acoustic signals of the DC motor using MSAF-RATIO30-EXPANDED and SVM

State of the DC motor	$E_F$ [%]
Healthy DC motor	95
Motor with 3 shorted rotor coils	90
Motor with 6 shorted rotor coils	80
Motor with broken coil	80

#### 4. Conclusions

In this paper the author proposed the early fault diagnostic method of the DC motor. The proposed method used acoustic signals of the DC motor. A method of feature extraction called MSAF-RATIO30-EXPANDED was presented and analyzed. The analysis was conducted out for the healthy DC motor and DC motor with early faults (a rotor speed of 500 rpm). Efficiency of recognition of acoustic signals of the DC motor was better for the Nearest Neighbour classifier than SVM. It was from 85% to 100%. The proposed early fault diagnostic method was not expensive (price of computer – 300\$). The presented early fault diagnostic method can be used for protection of DC motors. It can found application for monitoring electrical motors in mining and fuel industry. The further analyses should be performed for different types, sizes and parameters of DC motors. The next researches will be carried out for other diagnostic signals such as: thermal radiation, vibration, currents and voltages.

#### Acknowledgements

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