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Diagnostics of Direct Current motor with application of acoustic signals, reflection coefficients and K-Nearest Neighbor classifier

***Abstract**. One of the main problems faced by engineers, is to ensure the operation of Direct Current motors. In this paper a pattern recognition method was used to provide the diagnostics of dc motor. This method is based on a study of acoustic signal. Plan of study of acoustic signals for two conditions of Direct Current motor was proposed. Studies were carried out for algorithms of data processing: reflection coefficients and K-Nearest Neighbor classifier with Manhattan distance. Developed method can be performed automatically. This system is a significant step towards the maintenance-free diagnostic systems of Direct Current motors.*

***Streszczenie.** Jednym z podstawowych problemów, z jakim spotykają się inżynierowie, jest zapewnienie funkcjonowania silników elektrycznych. W niniejszej pracy metoda rozpoznawania wzorców została użyta do diagnostyki silnika prądu stałego. Metoda ta oparta jest na badaniu sygnału akustycznego. Zaproponowano plan badania sygnałów akustycznych dla dwóch stanów silnika prądu stałego. Badania zostały przeprowadzone dla algorytmów przetwarzania danych: współczynników odbiciowych i klasyfikatora K-Najbliższego Sąsiada z metryką Manhattan. Opracowana metoda może być wykonywana automatycznie. System ten jest istotnym krokiem w kierunku bezobsługowych systemów diagnostycznych silników prądu stałego.(**Diagnostyka silnika prądu stałego z zastosowaniem sygnałów akustycznych, współczynników odbiciowych i klasyfikatora K-Najbliższego Sąsiada**).*

Keywords: Diagnostics, Recognition, Acoustic signal, Reflection coefficients, Direct Current motor.
Słowa kluczowe: Diagnostyka, Rozpoznawanie, Sygnał akustyczny, Współczynniki odbiciowe, Silnik prądu stałego.

Introduction

During the past twenty years, there has been a large number of researches into the creation of new condition monitoring techniques for Direct Current machines, with new methods being developed and implemented in commercial products for this purpose. The researches and developments of newer and alternative diagnostic techniques are continuous, however, since condition monitoring and fault diagnosis systems should always suit new, specific Direct Current machine applications. These continuous researches and developments are also supported by the fact that no specific techniques may be considered generally the best for all the applications that exist, since an engineer must treat each motor as a unique entity. Therefore, the potential failure modes, mechanical load characteristics and operational conditions have to be carefully taken into consideration. A diagnostic system should be designed for electrical machine [1]. The main methods of diagnostics of imminent failure conditions of machines are based on the study of: magnetic field, ultrasounds, electric signals, acoustic signals, visually selected parts, vibroacoustic signals, infrared signals.

Influence of selected factors on the properties of the steel elements are presented in the literature [2], [3], [4], [5]. Nowadays, there are many methods for testing of electrical and acoustic signals [6], [7], [8], [9], [10], [11], [12], [13], [14]. In this paper, research focuses on acoustic signals of selected Direct Current machine. The results of these studies can be used to improve the diagnostics of electrical machines.

Process of recognition of acoustic signal of Direct Current motor

The process of recognition of acoustic signal of Direct Current motor contains pattern creation process and identification process (Fig. 1). At the beginning of pattern creation process acoustic signals are recorded. Measurements were made by OLYMPUS TP-7 microphone and sound card. Obtained audio file contains following parameters: sampling frequency is 44100 Hz, number of bits is 16, number of channels is 1. Next data are divided. Then signals are sampled and normalized. After that filter 223-235 Hz is used. This filter passes significant amplitudes of harmonics [15]. Afterwards Linear Predictive Coding algorithm is used. Next data are converted into the reflection coefficients. In pattern creation process two feature vectors are created. Steps of identification process are the same as for pattern creation process. Significant change occurs in the classification (Fig. 1). In this step, feature vectors are compared with each other (feature vector and new feature vector).

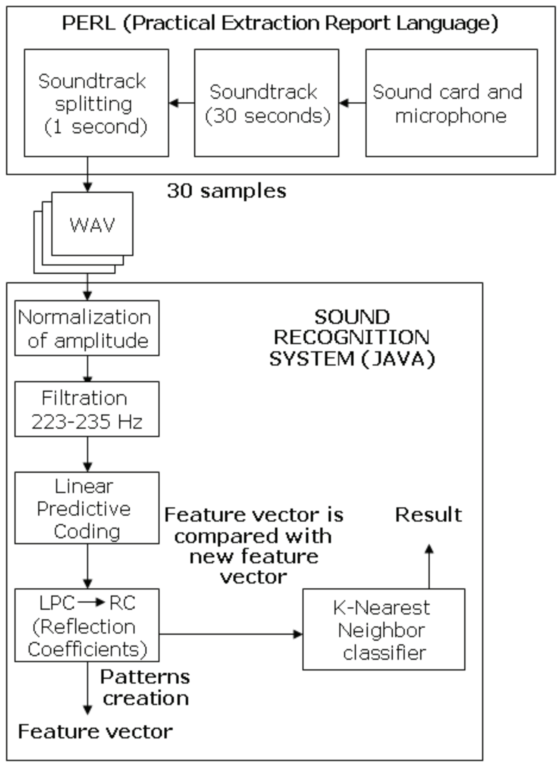

Fig.1. Process of recognition of acoustic signal of Direct Current motor with the use of reflection coefficients and K-Nearest Neighbor classifier

Linear Predictive Coding

LPC (Linear Predictive Coding) analyzes the sound signal by estimating the formants, removing their effects from the sound signal, and estimating the intensity and frequency of the remaining buzz [16], [17]. It determines a set of coefficients approximating the amplitude versus frequency function. These coefficients create feature vectors which are used in calculations. The model of shaping filter is defined as:

$$H(z) = \frac{1}{1 - \sum_{k=1}^{p} a_k z^{-k}} \tag{1}$$

where p is the order of the filter, a_k is prediction coefficient.

Reflection coefficients

The LPC to RC block converts linear prediction coefficients (LPCs) to reflection coefficients (RCs). This block uses backward Levinson recursion to convert linear prediction coefficients (LPCs) to reflection coefficients (RCs). For a given N-th order LPC vector LPC_N=[1, a_{N1}, a_{N2},..., a_{NN}], the block calculates the N-th reflection coefficient value using the formula $\gamma_N = -a_{NN}$. The block then finds the lower order LPC vectors, LPC_{N-1}, $LPC_{N-2,\dots}$, LPC_1, using the following recursion [18].

for $p = N$, $N - 1$,..., 2,

$\gamma_p = a_{pp}$

$F = 1 - \gamma_p^2$

$a_{p-1,m} = (a_{p,m} / F) - (\gamma_p\, a_{p,p-m} / F)$, $1 \le m < p$

end

Finally, $\gamma_1 = -a_{11}$, the reflection coefficient vector is [γ_1, γ_2, ..., γ_N]. In the literature, 10-20 LPC coefficients are considered [14]. It is assumed that the number of coefficients is 10. LPC coefficients are converted into reflection coefficients. The number of coefficients is the same. These coefficients are used in next calculations (Fig. 2, 3).

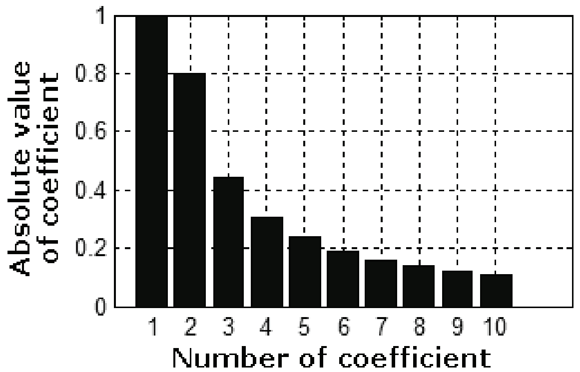

Fig. 2. Absolute value of reflection coefficients of faultless Direct Current motor

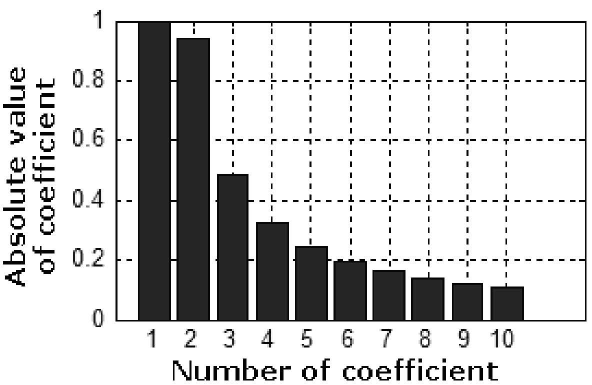

Fig. 3. Absolute value of reflection coefficients of Direct Current motor with shorted rotor coils

***K*-Nearest Neighbor classifier**

In the literature there are many methods of classification [19], [20], [21], [22], [23], [24]. *K*-Nearest Neighbor Classifier is based on training set and identification set. *K*-Nearest Neighbor Classifier uses feature vectors to identify the type of acoustic signal. Pattern is a vector of features $\mathbf{x}$=[x_1, x_2,..., x_n]. Classes of patterns are denoted as w_1, w_2,..., w_M, where M is the index number of the class. Training set contains feature vectors $\mathbf{x_1}$, $\mathbf{x_2}$,..., $\mathbf{x_j}$.

Identification set contains new feature vectors $\mathbf{y_1}$, $\mathbf{y_2}$,..., $\mathbf{y_j}$. Next the least distance is calculated between feature vectors (feature vector of new sample and feature vector of specific category). Manhattan distance is the measure of distance between two points (vectors). For vectors $\mathbf{y}$ and $\mathbf{x}$ with the same length n it is expressed as follows:

$$d(\mathbf{y},\mathbf{x}) = \sum_{i=1}^{n} (|\, y_i - x_i \,|) \tag{2}$$

where $\mathbf{y}$ and $\mathbf{x}$ are feature vectors, $\mathbf{y}$=[y_1, y_2,..., y_n], $\mathbf{x}$=[x_1, x_2,..., x_n].

It should be noted that the *K*-Nearest Neighbor classifier compares the number of k nearest neighbors (feature vectors) and selects the class that has the most of them ($k=2n-1$, $n=1, 2, \dots, +\infty$). The research will be conducted for the parameters $k=1$, $k=3$, $k=5$.

Investigations of acoustic signals of Direct Current motor

Direct Current motor had following operation parameters: P_N = 13 kW, U_N = 75 V, I_N = 200 A, U_{fN} = 220 V, I_{fN} = 4 A, n_N = 700 rpm. It was assumed that each group of three loop rotor coils is shorted through resistance R_{bz} = 7.7 mΩ. Direct Current motor connected with external resistance produced the load torque. The additional resistance was used in short-circuit to avoid damage of rotor winding. Investigations were conducted for acoustic signal of faultless Direct Current motor and acoustic signal of Direct Current motor with shorted rotor coils.

Pattern creation process was conducted for 10 one-second samples. 60 new one-second samples were used in identification process. Efficiency of acoustic signal recognition was defined as:

$$E = \frac{N_1}{N} \cdot 100\% \tag{3}$$

where: E – efficiency of acoustic signal recognition, N_1 – number of correctly identified samples, N – number of all samples.

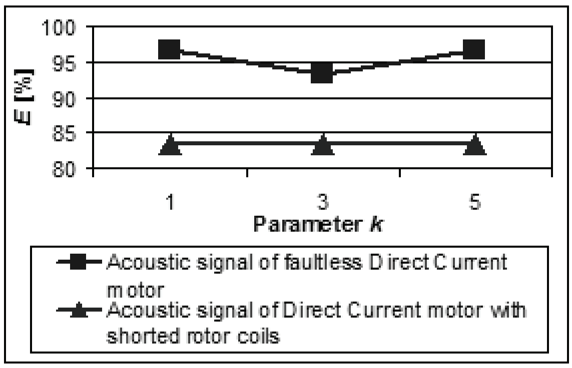

Fig. 4. Efficiency of acoustic signal recognition of Direct Current motor depending on k parameter

Studies have been conducted in a room without any interferences, and other failures. Figure 4 shows efficiency of acoustic signal recognition of Direct Current motor depending on *k* parameter. The best results were obtained for *k*=1 and *k*=5. The efficiency of acoustic signal recognition of faultless Direct Current motor was contained in the range of 93.3-96.7%. The efficiency of acoustic signal recognition of Direct Current motor with shorted rotor coils was 83.3%.

Conclusions

This paper proposes an automatic fault diagnostics for Direct Current motor. This diagnostics is based on patterns recognition of acoustic signals. Techniques of feature extraction and classification were used. Reflection coefficients were used to extract features. *K*-Nearest Neighbor classifier was applied to classify feature vectors. The researches and obtained results prove the effectiveness of the proposed method of diagnosis of a Direct Current motor. Efficiency of acoustic signal recognition of Direct Current motor was contained in the range of 83.3-96.7%. The experimental implementation of the diagnostic method provides new and efficient means of monitoring of electrical equipment.

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