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DIAGNOSTICS OF DC MACHINE BASED ON ANALYSIS OF ACOUSTIC SIGNALS WITH APPLICATION OF MFCC AND CLASSIFIER BASED ON WORDS

DIAGNOSTYKA MASZYNY PRĄDU STAŁEGO OPARTA NA ANALIZIE SYGNAŁÓW AKUSTYCZNYCH Z ZASTOSOWANIEM MFCC I KLASYFIKATORA OPARTEGO NA SŁOWACH

Technical diagnostics is concerned with the assessment of technical conditions of the machine through the study of properties of machine processes. Diagnostics is particularly important for factories and ironworks. In paper is presented method of diagnostics of imminent failure conditions of DC machine. This method is based on a study of acoustic signals generated by DC machine. System of sound recognition uses algorithms for data processing, such as Mel Frequency Cepstral Coefficient and classifier based on words. Software to recognize the sounds of DC machine was implemented on PC computer. Studies were carried out for sounds of faultless machine and machine with shorted coils. The results confirm that the system can be useful for diagnostics of dc and ac machines used in metallurgy.

Keywords: diagnostics, acoustic signal, DC machine, classifier

Techniczna diagnostyka zajmuje się oceną stanu technicznego maszyny poprzez badania własności procesów zachodzących w maszynie. Diagnostyka jest szczególnie ważna dla fabryk i hut. W artykule jest przedstawiona metoda diagnostyki stanów przedawaryjnych maszyny prądu stałego. Metoda ta oparta jest na badaniu sygnałów akustycznych generowanych przez maszynę prądu stałego. System rozpoznawania dźwięku wykorzystuje algorytmy przetwarzania danych, takich jak algorytm MFCC i klasyfikator oparty na słowach. Zaimplementowano oprogramowanie do rozpoznawania dźwięków maszyny prądu stałego na komputerze PC. Przeprowadzono badania sygnałów akustycznych maszyny bez uszkodzeń i maszyny ze zwartymi uzwojeniami. Wyniki badań potwierdzają, że system może być przydatny w diagnostyce maszyn prądu stałego i przemiennego używanych w hutnictwie.

1. Introduction

A fault in an electrical machinery and apparatus should be quickly detected and localized for safety operation and for prevention of sequential faults. Effect of various factors on the properties of the steel elements are mentioned in the literature [1], [2], [3], [4], [5], [6], [7], [8], [9]. Automatic fault diagnosis, which is based on on-line or off-line data processing of sensed voltage and current information from the equipment is useful. Furthermore it is possible to extract essential information which characterizes a type of fault by numerical signal processing from sensed data. This fault diagnosis is finally reduced to a pattern recognition problem which relates the extracted data to a type of fault. Various techniques have been proposed for the diagnosis [10]. Technical diagnostics is concerned with the assessment of technical condition of the machine through the study of properties of work processes. Diagnostics of DC machines is particularly important for factories and ironworks. In the literature, popular diagnostic methods uses electrical and acoustic signals [11], [12], [13], [14]. In this paper, researches include the issue of recognition of acoustic signals of selected DC machine. The results of these studies can be used to improve the diagnostics of electrical machines, mechanical machines, hydraulic machines, pneumatic machines.

2. Sound recognition process of DC machine

Recordings were made by digital voice recorder OLYMPUS WS 200S. Recorded audio file contains fol-

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lowing parameters: sampling frequency – 44100 Hz, number of bits – 16, number of channels – 1.

Sound recognition process of DC machine contains pattern creation process and identification process (Fig. 1). Soundtrack is recorded and split. At the beginning of pattern creation process signals are sampled, normalized and filtrated. Afterwards data are converted through the Hamming window (window size 256). Next data are converted through the MFCC algorithm. MFCC algorithm creates feature vectors (one feature). Two averaged feature vectors are created. Next these vectors are converted into two averaged word vectors (patterns). Steps of identification process are the same as for pattern creation process. Significant change occurs in the classification. In this step, word vectors are compared with each other (averaged word vector and new word vector).

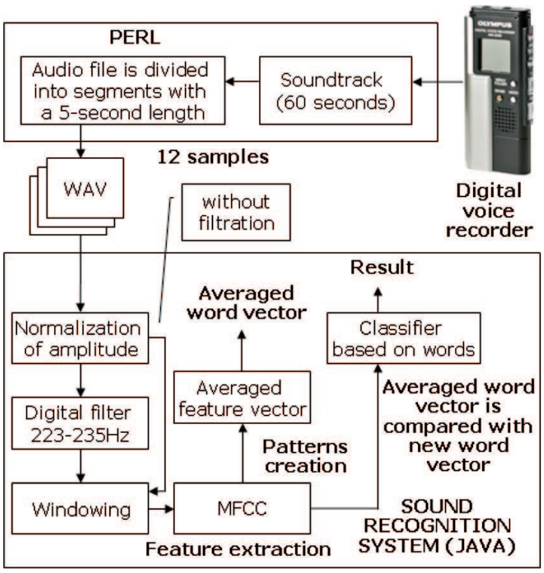

Fig. 1. Sound recognition process with application of MFCC and classifier based on words

2.1. MFCC Algorithm

The quest for better sound parameterization led to various sound features, which were reported to provide advantage in specific conditions and applications. MFCC (Mel Frequency Cepstral Coefficient) algorithm performs feature extraction. MFCC are commonly used as features in speech recognition systems, such as the systems which can automatically recognize numbers spoken into a telephone. They are also common in speaker recognition, which is the task of recognizing people from their voices. MFCC are also increasingly finding uses in music information retrieval applications such as genre classification, audio similarity measures [15], [16]. Figure 2 shows block diagram of MFCC algorithm.

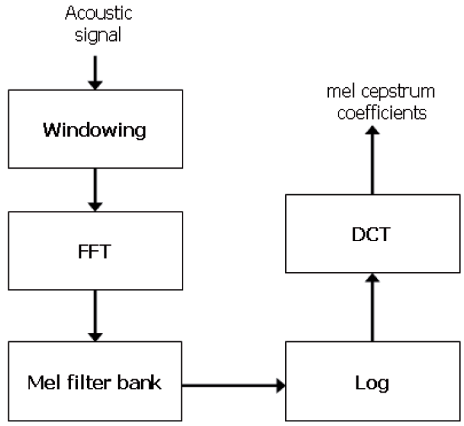

Fig. 2. Block diagram of MFCC algorithm

Currently, there are different methods of MFCC, such as MFCC FB-20, MFCC FB-40, MFCC FB-24 HTK. MFCC FB-40 was used for sound recognition system of DC machine (Fig. 3). The MFCC FB-40 features were described in the Slaney's Auditory Toolbox [16]. Slaney implemented a filter bank of 40 equal area filters, which cover the frequency range [133 Hz, 6854 Hz]. The centre frequencies of the first 13 of them are linearly spaced in the range [200 Hz, 1000 Hz] with a step of 66.67 Hz and the ones of the next 27 are logarithmically spaced in the range [1071 Hz, 6400 Hz] with a step $lStep$=1.0711703. Here f_c =6400 Hz is the centre frequency of the last of the logarithmically spaced filters, and S =27 is the number of logarithmically spaced filters. Number of MFCCs is Y = 1 for algorithm used in sound recognition system of DC machine.

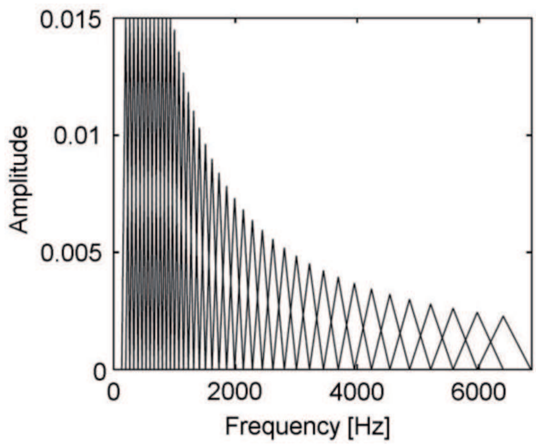

Fig. 3. Mel filter bank for MFCC-FB40

MFCC values for two different sounds DC machine are shown in figure 4. These coefficients have created feature vector of the category of sound.

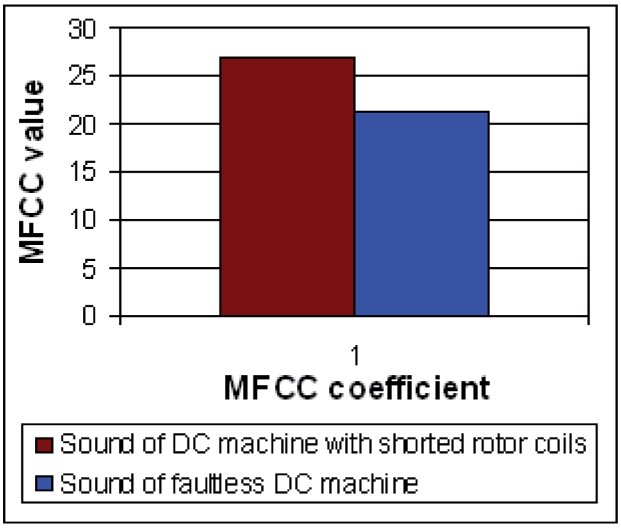

Fig. 4. Averaged feature vectors of two sounds of DC machine

2.2. Classifier based on words

In the literature there are many methods of classification [17], [18], [19], [20], [21], [22]. Classifier based on words contains: pattern creation and identification. At the beginning of creation of patterns, feature vector denoted as $\mathbf{x}=[x_1,x_2,\ldots,x_n]$ is used. This vector was calculated on the basis of selected sample of sound in training set. Classes of patterns are denoted as w_1, $w_2,\ldots$, w_M, where M is the number of classes. Patterns are obtained during pattern creation process. Patterns are averaged feature vectors $\mathbf{m_1}, \mathbf{m_2},\ldots$, $\mathbf{m_j}$:

$$\mathbf{m_j} = \frac{1}{P_j}\sum_{i=1}^{P_j}\mathbf{x_i} \tag{1}$$

where $\mathbf{x_i} \in w_j$, P_j is the number of patterns from class w_j.

Averaged feature vector $\mathbf{m_j}$ is converted into averaged word vector $\mathbf{v_j}$. Averaged word vector is denoted as: $\mathbf{v_j} =[v_1,v_2,\ldots,v_n]$, where $v_1,v_2,\ldots,v_n$ are coordinates (words). Averaged word vector corresponds to the category of recognition.

Each coordinate m_i of averaged feature vector $\mathbf{m_j}$ is converted into coordinate of averaged word vector $\mathbf{v_j}$ (coordinate is a word which represents a range of values),

$$\begin{cases} m_i \in [k,2k) \Rightarrow m_i \rightarrow v_{i1} \\ m_i \in [2k,3k) \Rightarrow m_i \rightarrow v_{i2} \\ \ldots \\ m_i \in [gk,gk+k) \Rightarrow m_i \rightarrow v_{ig} \end{cases} \tag{2}$$

where k is rational number, g is the number of words, v_{ig} denotes word, m_i is coordinate of averaged feature vector.

Classifier based on words uses various ranges containing the coordinates of averaged feature vectors. Classifier uses a limited number of words $v_{i1}, v_{i2},\ldots,v_{ig}$. Subsequently the parameter k should be chosen so as to obtain high accuracy.

New word vector is denoted as $\mathbf{f}=[f_1,f_2,\ldots,f_n]$, where $f_1,f_2,\ldots,f_n$ are coordinates (words). In identification process a new sample is converted into new feature vector $\mathbf{y}$. Next feature vector $\mathbf{y}$ is converted into word vector $\mathbf{f}$,

$$\begin{cases} y_i \in [k,2k) \Rightarrow y_i \rightarrow v_{i1} \\ y_i \in [2k,3k) \Rightarrow y_i \rightarrow v_{i2} \\ \ldots \\ y_i \in [gk,gk+k) \Rightarrow y_i \rightarrow v_{ig} \end{cases} \tag{3}$$

where k is rational number, g is the number of words, v_{ig} denotes word, y_i is coordinate of new feature vector.

Subsequently sample is assigned to the class whose averaged word vector is the closest to the new word vector $\mathbf{f}$. Classifier uses lexicographical comparison. Two strings are compared with each other (coordinate of averaged word vector and coordinate of new word vector). This can be presented as follows:

$$f_1 \overset{?}{=} v_1$$

$$f_2 \overset{?}{=} v_2$$

$$\ldots$$

$$f_n \overset{?}{=} v_n$$

The result of each comparison is either *true* or *false*. Following formula is presented:

$$U_j = \frac{U_1}{U_2}\cdot 100\% \tag{4}$$

Where U_1 is the number of correctly compared words, U_2 is the number of all comparisons, U_j is a number representing the percentage of well-recognized words.

Finally the following formula is obtained:

$$\max\left(U_j\right) \Rightarrow \mathbf{f} \rightarrow w_j \qquad j = 1,2,\ldots,M, \tag{5}$$

where $\mathbf{f}$ is word vector, U_j is the number representing the percentage of well-recognized words.

Number of words will be 260, because it is sufficient for recognition. The biggest influence on sound recognition results using the classifier based on words will have the data contained in the feature vector and parameter k. Research will be conducted for different parameter k.

2.3. Results of sound recognition

DC machine 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. Each group of three loop rotor coils was shorted through resistance $R_{bz} = 7.7$ mΩ.

The DC machine connected with external resistance produced the load torque. The additional resistance were used in short-circuit to avoid damage of rotor winding. Researches were conducted for acoustic signals of faultless DC machine and DC machine with shorted rotor coils (Fig. 5).

Nine five-second samples were used in pattern creation process for each type of signal. New samples were used in the identification process. 9 five-second samples, 11 four-second samples, 15 three-second samples, 23 two-second samples, 46 one-second samples were used for each category.

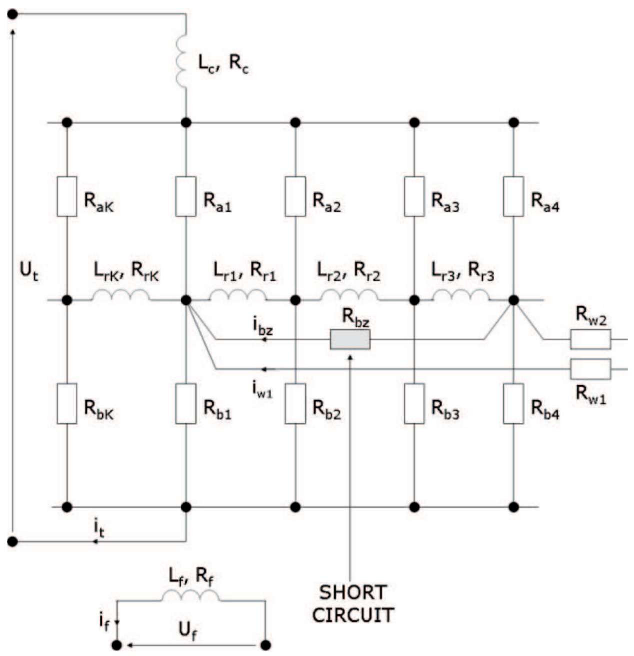

Fig. 5. Scheme of rotor winding of DC machine with shorted rotor coils

Efficiency of sound recognition is defined as:

$$E = \frac{N_1}{N} \cdot 100\% \tag{6}$$

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

The best recognition results were obtained using the normalization of the amplitude and the digital filter which passed frequencies from 223 Hz to 235 Hz. Parameter k was 6.0 (Fig. 6).

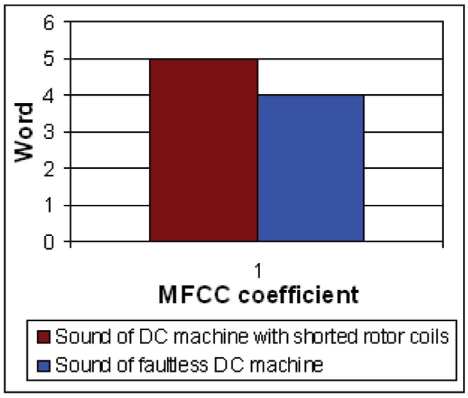

Fig. 6. Words obtained from averaged feature vectors for k =6.0

Efficiency of sound recognition of faultless DC machine was 71.73-100%. Efficiency of sound recognition of DC machine with shorted rotor coils was 67.39-100%. Efficiency of sound recognition of DC machine depending on length of sample is presented in Fig. 7.

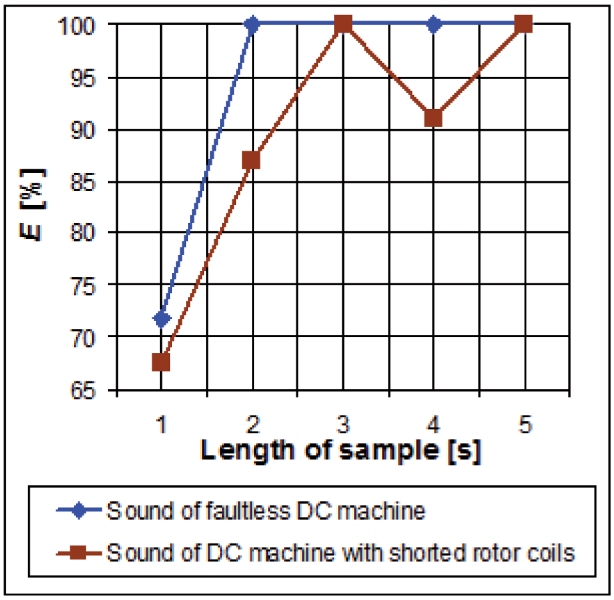

Fig. 7. Efficiency of sound recognition of DC machine depending on length of sample

3. Conclusions

Results of sound recognition were very good for MFCC and classifier based on words. Sound recognition efficiencies of DC machine were 67.39-100% for 1-5 second samples and 90.9-100% for 3-5 second samples. Time of performance of identification process of five-second sample was 7.5 s for Intel Pentium M 730 processor (normalization of amplitude, digital filter 223-235 Hz, MFCC, classifier based on words). Time of performance of identification process of one-second sample was 2.4 s. The system can be useful in diagnostics of dc and ac machines in metallurgy. In the future, the sound recognition system can be applied with other effective data processing algorithms.

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