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A. GŁOWACZ*. W. GŁOWACZ*

DIAGNOSTICS OF SYNCHRONOUS MOTOR BASED ON ANALYSIS OF ACOUSTIC SIGNALS WITH APPLICATION OF LPCC AND NEAREST MEAN CLASSIFIER WITH COSINE DISTANCE

DIAGNOSTYKA SILNIKA SYNCHRONICZNEGO OPARTA NA ANALIZIE SYGNAŁÓW AKUSTYCZNYCH Z ZASTOSOWANIEM LPCC I KLASYFIKATORA NEAREST MEAN Z METRYKĄ KOSINUSOWĄ

Paper presents method of diagnostics of imminent failure conditions of synchronous motor. This method is based on a study of acoustic signals generated by synchronous motor. Sound recognition system is based on algorithms for data processing, such as LPCC and Nearest Mean classifier with cosine distance. Software to recognize the sounds of synchronous motor was implemented. Studies were carried out for four imminent failure conditions of synchronous motor. The results confirm that the system can be useful for detecting damage and protect the engines. System can be useful in inspection of metallurgy products.

Keywords: Diagnostics, Recognition, Sound, Nearest Mean, Synchronous motor

Zaprezentowano metodę diagnozowania stanów przedawaryjnych silnika synchronicznego. Metoda ta oparta jest na badaniu sygnałów akustycznych generowanych przez silnik synchroniczny. System rozpoznawania dźwięku oparty jest na algorytmach przetwarzania danych takich jak algorytm LPCC i klasyfikator Nearest Mean z metryką kosinusową. Zaimplementowano oprogramowanie do rozpoznawania dźwięków silnika synchronicznego. Przeprowadzono badania dla czterech stanów przedawaryjnych silnika synchronicznego. Wyniki badań potwierdzają, że system może być przydatny do wykrywania uszkodzeń i zabezpieczania silników. System może być przydatny w kontroli wyrobów hutniczych.

1. Introduction

There is a lot of research on mechanical properties of materials [1-8]. Mechanical properties of materials are very important for the diagnostics. Technical diagnostics concerns with the assessment of technical condition of the machine through the study of properties of work processes. Diagnostics is particularly important for mining, metallurgy and processing industry. There are three factors stimulating the development of diagnostics. The first is the complexity of production systems, where failure of one machine will cause damage of the entire production in large economic losses. The second factor is the large number of machines, which are also in constant movement and without any supervision. For example: the average refinery or steelworks, operated at the same time several thousands small and medium-sized engines. Maintenance and repair of such a vast assembly of machines causes a lot of trouble, if we can not predict the period of repair correctly. The third factor is the high level of reliability required for certain one-time or seasonal use. For example vehicles such as aircraft, where the machine is expected throughout the year for a period of several weeks of work. The main methods of diagnostics of imminent failure conditions of machines are based on the study: magnetic field of machine, ultrasound of machine, electric signals of machine, acoustic signals of machine, visually selected parts of machine, vibroacoustic signals of machine.

In recent years, the methods of sound recognition were developed [9-14]. Hence the idea to use them for machines. Studies concern selected synchronous motor that generates acoustic signals. These studies can be used to application of diagnostics based on acoustic emission in the electrical machines, mechanical machines, hydraulic machines, pneumatic machines. Measurements were made by sound card with microphone OLYMPUS TP-7.

* FACULTY OF ELECTRICAL ENGINEERING, AUTOMATICS, COMPUTER SCIENCE AND ELECTRONICS, AGH UNIVERSITY OF SCIENCE AND TECHNOLOGY, 30-059 KRAKÓW, 23 REYMONTA STR., POLAND

2. Sound recognition process of synchronous motor

Sound recognition process of synchronous motor 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 LPCC algorithm. LPCC algorithm creates feature vectors (75 features). Four averaged feature vectors are created. Steps of identification process are the same as for pattern creation process. Significant change occurs in the classification. In this step, feature vectors are compared with each other (averaged feature vector and new feature vector).

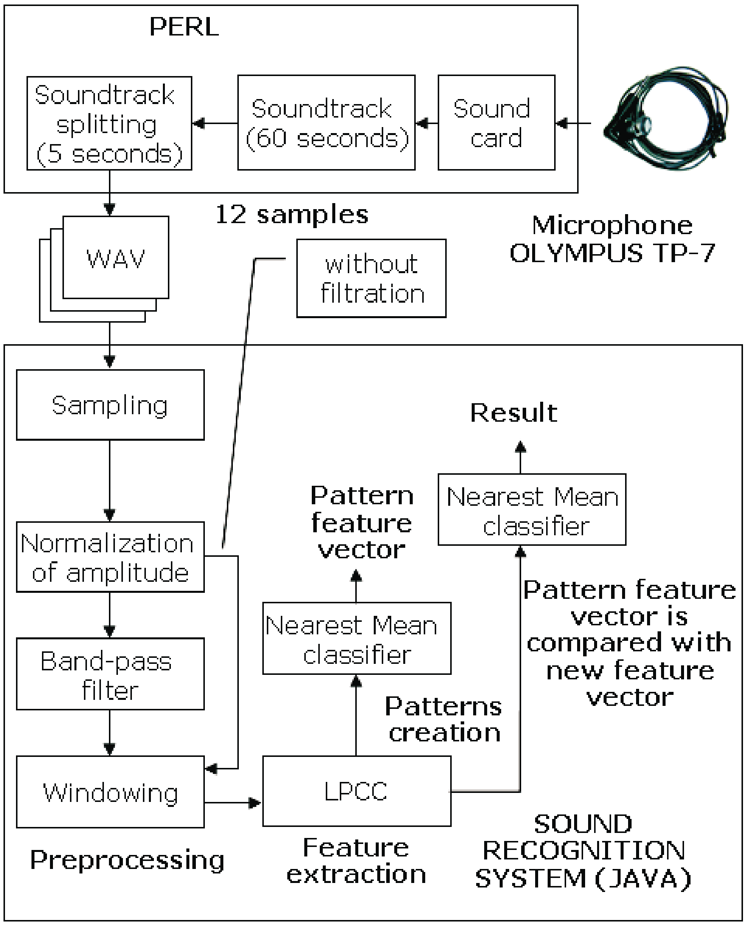

Fig. 1. Sound recognition process with application of LPCC and Nearest Mean classifier

2.1. Recording of acoustic signal

Sound card with analogue-digital converter is able to record sound. Recording of the acoustic signal is the first part of the identification process. Acoustic signal is converted into digital data by the microphone and the sound card. This wave file contains following parameters: sampling frequency is 44100 Hz, number of bits is 16, number of channels is 1.

2.2. Soundtrack division

System divides data. New wave files are obtained. New wave files are used in the identification process. There are following advantages of such solution: precise determination of sound appearing, precise sound identification, application does not have to allocate so much memory in identification process.

2.3. Sampling

Sampling is a technique to convert an analog signal into a digital signal. It periodically samples an input signal and transforms into a sequence of intensity values.

2.4. Quantization

Quantization is a technique to round intensity values to a quantum so that they can be represented by a finite precision. Precision of sample depends on number of bits. Common applied number of bits is 8 or 16. Sound recognition application uses 16 bits because it gives better precision. There is a choice of number of bits depending on input data and calculations speed of the sound recognition process.

2.5. Normalization of amplitude

Normalization is the process of changing of the amplitude of an audio signal. Often sounds aren't recorded at the same level. It is essential to normalize the amplitude of each sample in order to ensure, that feature vectors will be comparable. All samples are normalized in the range [–1.0, 1.0]. The method finds the maximum amplitude in the sample and then scales down the amplitude of the sample by dividing each point by maximum.

2.6. Windowing

Hamming window is used to avoid distortion of the overlapped window functions. It is defined as:

$$w(n) = 0.53836 - 0.46164 \cdot \cos(\frac{2\pi n}{m-1} \tag{1}$$

where: $w(n)$ is the new sample amplitude, n is the index in the window, m is the total length of the window.

2.7. Feature extraction

LPCC (Linear Predictive Cepstral Coefficients) is used as a feature extraction algorithm. LPCC is based on LPC (Linear Predictive Coding). LPC 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 [15, 16]. 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:

$$H(z) = \frac{1}{1 - \sum_{k=1}^{p} a_k z^{-k}} \tag{2}$$

where p is the order of the filter, a_k is prediction coefficient.
Prediction a sound sample is based on a sum of weighted past samples:

$$s'(n) = \sum_{k=1}^{p} a_k \cdot s(n-k) \tag{3}$$

where $s'(n)$ is the predicted value based on the previous values of the sound signal $s(n)$.

LP analysis requires estimating the LP parameters for a segment of sound. Formula (3) provides the closest approximation to the sound samples. This means that $s'(n)$ is closest to $s(n)$ for all values of n in the segment. The spectral shape of $s(n)$ is assumed to be stationary across the frame, or a short segment of sound. The error between the actual sample and the predicted one can be expressed as:

$$e(n) = s(n) - s'(n) \tag{4}$$

The summed squared error E over a finite window of length N is defined as:

$$E = \frac{1}{N-p} \sum_{n=p}^{N-1} e^2(n) \tag{5}$$

The minimum value of E occurs when the derivative is zero with respect to each of the parameters a_k. By setting the partial derivatives of E, a set of p equations are obtained. The matrix form of these equations is:

$$\begin{bmatrix} r(0) & r(1) & \cdots & r(p-1) \\ r(1) & r(0) & \cdots & r(p-2) \\ \vdots & \vdots & \ddots & \vdots \\ r(p-1) & r(p-2) & \cdots & r(0) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_r \end{bmatrix} = \begin{bmatrix} r(1) \\ r(2) \\ \vdots \\ r(p) \end{bmatrix} \tag{6}$$

where $r(i)$ is the autocorrelation of lag i computed as:

$$r(i) = \frac{1}{N-p} \sum_{m=p}^{N-1} e^2(n) \tag{7}$$

where N is the length of the sound segment $s(n)$.
The Levinson-Durbin algorithm solves the n-th order system of linear equations.

$$R \cdot a = r \tag{8}$$

For the particular case where R is a Hermitian, positive definite, toeplitz matrix and r is identical to the first column of R shifted by one element.
The autocorrelation coefficients $r(k)$ are used to compute the LP filter coefficients a_i, $i = 1,\ldots p$ and k=1,... p. These coefficients are used in calculations. The Levinson-Durbin algorithm is used to estimate the linear prediction coefficients from a given sound waveform. This method is efficient, as it needs only the order of M^2 multiplications to compute the linear prediction coefficients.
To obtain Linear Prediction Cepstral Coefficients it is necessary to use equation (9):

$$c(n) = \begin{cases} a_n + \sum_{k=1}^{n-1} \frac{k}{n} c(k) a_{n-k} & 1 \leqslant n \leqslant p \\ \sum_{k=n-p}^{n-1} \frac{k}{n} c(k) a_{n-k} & n \leqslant p \end{cases} \tag{9}$$

where $c_0 = r(0)$, p – order of the filter, n – number of cepstral coefficients.

75 coefficients were calculated for each sample (Fig. 2-5).

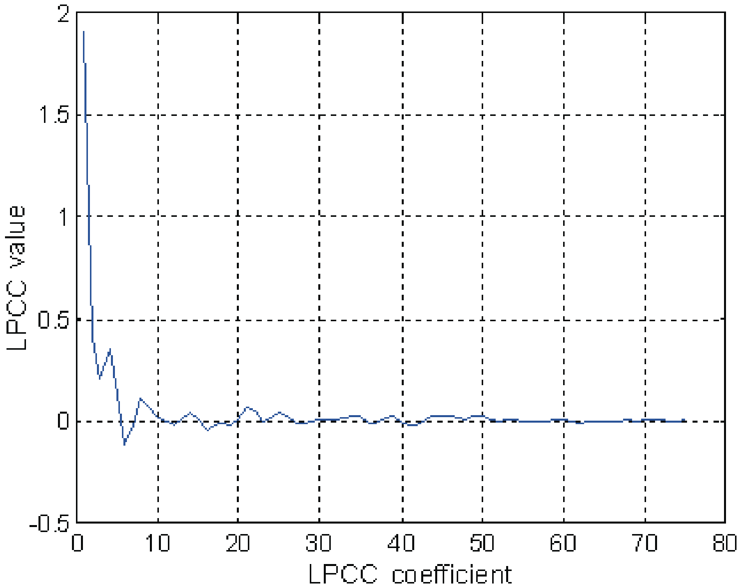

Fig. 2. LPCC values for sound of faultless synchronous motor after normalization

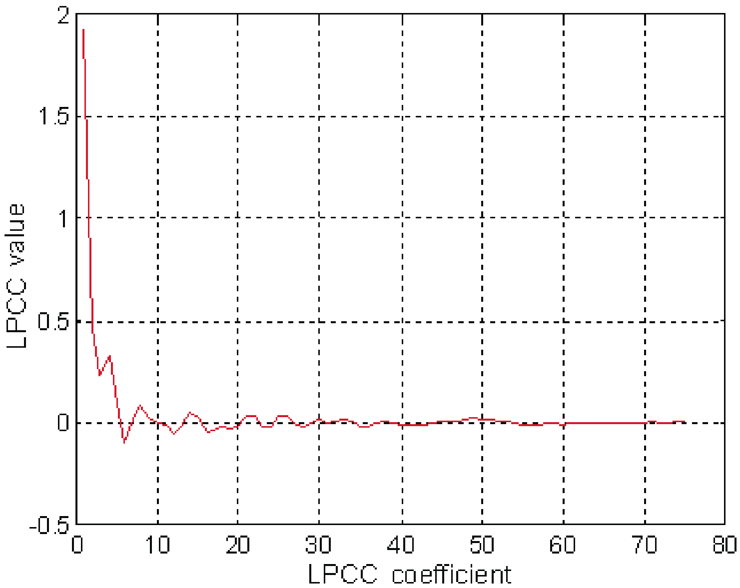

Fig. 3. LPCC values for sound of synchronous motor with shorted stator coils after normalization

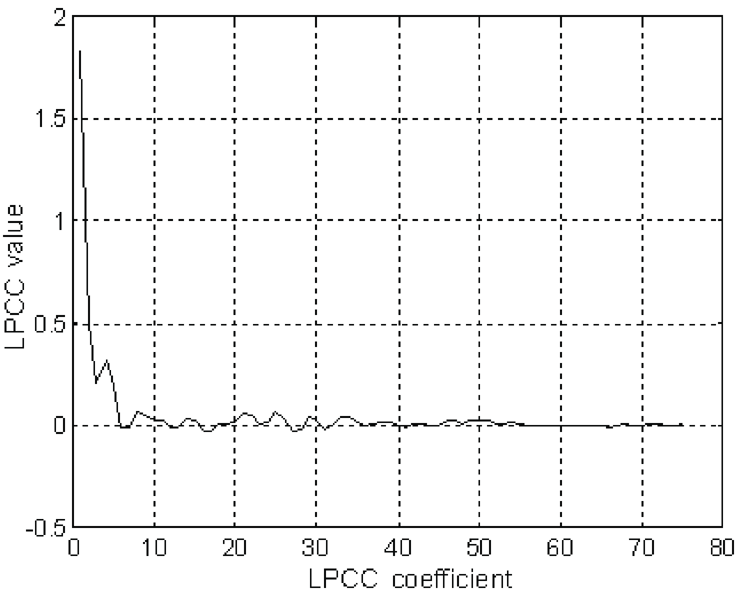

Fig. 4. LPCC values for sound of synchronous motor with one broken coil after normalization

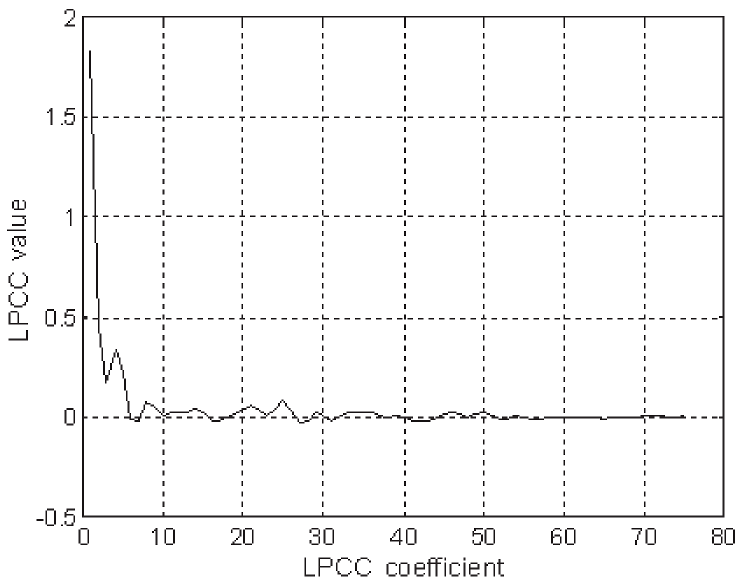

Fig. 5. LPCC values for sound of synchronous motor with three broken coils after normalization

2.8. Nearest mean classifier

In the literature there are many methods of classification [17,18]. Nearest Mean classifier is based on training set and identification set. Training set contains averaged feature vectors. Identification set contains new feature vectors. Next the least distance is calculated between feature vectors (feature vector of new sample and averaged feature vector of specific category). Cosine distance is the measure of distance between two points (vectors). For vectors **x** and **y** with the same length n it is defined as:

$$d_{\cos}(\mathbf{x}, \mathbf{y}) = 1 - \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}} \tag{10}$$

8 where **x** and **y** are feature vectors with the same lengths, $\mathbf{x}=[x_1, x_2, \ldots, x_n]$, $\mathbf{y}=[y_1, y_2, \ldots, y_n]$.

3. Results of sound recognition

Synchronous machine worked as synchronous motor. Short circuit and broken coils were located in the stator circuit (Fig. 6). Synchronous motor had following operation parameters:

– sound of faultless synchronous motor, U_{RS} = 100 V, I_R = 30.9 A, n_N = 1500 rpm, $I_w \approx 0$ A,

– sound of synchronous motor with shorted stator coils, U_{RS} = 100 V, I_R = 31.2 A, n_N = 1500 rpm, $I_w \approx 0$ A, R_z=2.5 Ω,

– sound of synchronous motor with one broken coil, U_{RS} = 100 V, I_R = 24 A, n_N = 1500 rpm, $I_w \approx 0.3$ A,

– sound of synchronous motor with three broken coils, U_{RS} = 100 V, I_R = 36 A, n_N = 1500 rpm, $I_w \approx 0.245$ A,

Investigations were carried out for sound of faultless synchronous motor, sound of synchronous motor with shorted stator coils (U3-X3), sound of synchronous motor with one broken coil (X1-X4), sound of synchronous motor with three broken coils (X1-X4, Y1-Y4, Z1-Z4).

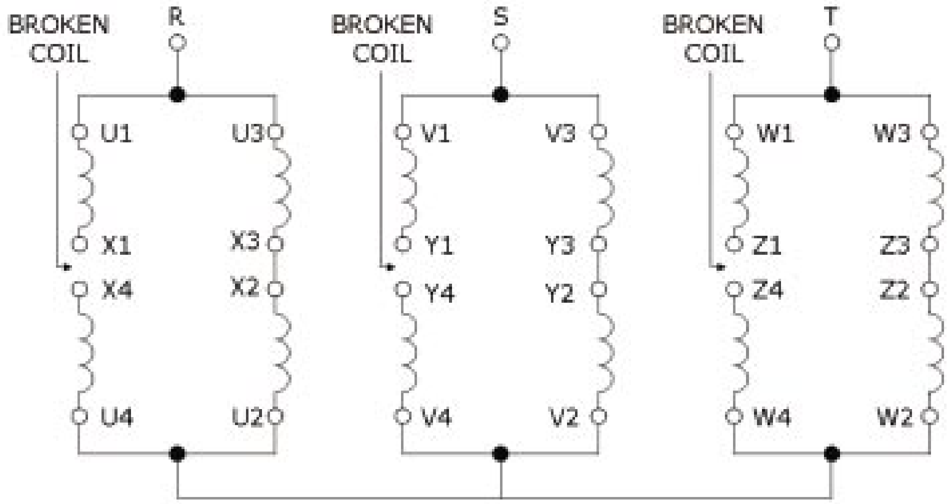

Fig. 6. Scheme of stator winding for synchronous motor with three broken coils in stator circuit (X1-X4, Y1-Y4, Z1-Z4)

Pattern creation process was carried out for ninety five-second samples for each category. New samples were used in the identification process. The system should determine the state of synchronous motor correctly.

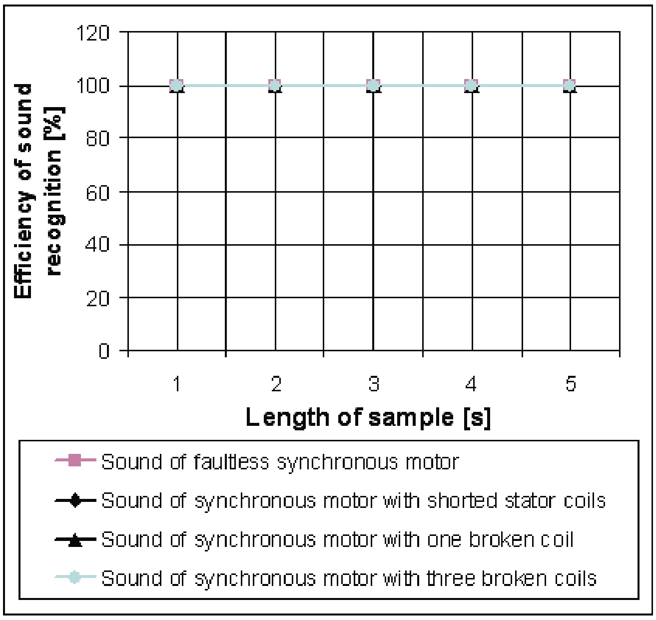

Fig. 7. Efficiency of sound recognition of synchronous motor depending on length of sample

Efficiency of sound recognition is defined as:

$$E = \frac{N_1}{N} \qquad (11)$$

where: E – sound recognition efficiency, N_1 – number of correctly identified samples, N – number of all samples. Efficiency of sound recognition of synchronous motor depending on length of sample is presented in Fig. 7.

4. Conclusions

Sound recognition system was implemented for synchronous motor. Results of sound recognition were very good for LPCC and Nearest Mean classifier. Sound recognition efficiency of synchronous motor was 100% (1-5 second sample).

Time of performance of identification process of five-second sample was 0.562 s for Intel Pentium M 730 processor (normalization of amplitude, LPCC, NM classifier with cosine distance). Time of performance of identification process of one-second sample was 0.203 s. Sound recognition system can be useful for detecting damage and protect the engines. The system can be useful in inspection of metallurgy products. In the future, the sound recognition system of synchronous motor can be applied with other effective data processing algorithms.

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