A R C H I V E S O F M E T A L L U R G Y A N D M A T E R I A L S
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DIAGNOSTICS OF INDUCTION MOTOR BASED ON ANALYSIS OF ACOUSTIC SIGNALS WITH THE APPLICATION OF EIGENVECTOR METHOD AND K-NEAREST NEIGHBOR CLASSIFIER

DIAGNOSTYKA SILNIKA INDUKCYJNEGO OPARTA NA ANALIZIE SYGNAŁÓW AKUSTYCZNYCH Z ZASTOSOWANIEM METODY WEKTORA WŁASNEGO I KLASYFIKATORA K-NAJBLIŻSZEGO SĄSIADA

In this paper numerical experiments are proposed to investigate differences between the acoustic signals of induction motors. Four conditions of induction motor were considered. Investigations were carried out with application of eigenvector method and K-Nearest Neighbor classifier with Minkowski distance. Pattern creation process was conducted for 20 samples of sound. Identification process used 96 samples of sound. The obtained results confirm the correctness of the solutions methodology.

Keywords: Diagnostics, Recognition, Acoustic signal, Induction motor

W tym artykule eksperymenty numeryczne są proponowane w celu zbadania różnic między sygnałami akustycznymi silników indukcyjnych. Rozważano cztery stany silnika indukcyjnego. Badania zostały przeprowadzone z zastosowaniem metody wektora własnego i klasyfikatora K-Najbliższego Sąsiada z metryką Minkowskiego. Proces tworzenia wzorców do rozpoznawania został przeprowadzony dla 20 próbek dźwięku. Proces identyfikacji wykorzystywał 96 próbek dźwięku. Uzyskane efekty potwierdzają poprawność rozwiązań metodycznych.

1. Introduction

Electrical machines have been used for many different industrial applications since several decades ago. These applications range from pumps, electric vehicle propulsion systems, and computer-cooling fans to electric pumps used in power plants. The electrical energy that is consumed in induction motors accounts for around 60% of the electrical energy that is consumed by industry. Requirement of the present-day for the reliability of induction motors is now more important than ever before and it grows constantly. Advances are continually being made in this area as a result of the demand from the power generation and transportation industries. Because of the new technologies in engineering and materials science, electrical machines are becoming both faster and lighter, as well as being required to run for longer periods of time. All of these factors mean that the detection, location, and analysis of faults play a vital role in the good operation of the electrical motors and are essential for major concerns such as the safety, reliability, efficiency, and performance of applications involving electrical motors. Despite continual improvement in design and manufacturing has become a priority task among contemporary manufacturers of electrical motors, faults still can and do occur [1].

Effect of selected factors on the properties of the steel elements are presented in the literature [2], [3], [4], [5], [6], [7], [8], [9], [10]. The main methods of diagnostics of imminent failure conditions of electrical motors are based on the study of: magnetic field of machine, ultrasounds of machine, electric signals of machine, acoustic signals of machine, visually selected parts of machine, vibroacoustic signals of machine.

Methods of diagnostics are based on a study of electrical and acoustic signals [11], [12], [13], [14]. In this paper the research focuses on acoustic signals of selected induction motor. The results of these studies can be used to improve the reliability of electrical machines.

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2. Process of sound recognition of induction motor

The process of sound recognition of induction motor contains pattern creation process and identification process. 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. After that signals are sampled, normalized. Afterwards data are converted through the eigenvector method. This algorithm creates features (130 features). In pattern creation process 20 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. The nearest neighbor is found (the nearest feature vector).

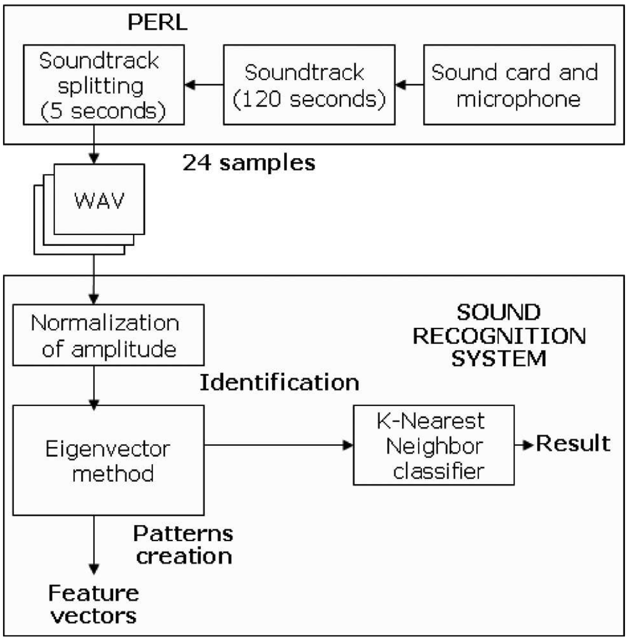

Fig. 1. Process of sound recognition of induction motor with the use of eigenvector method and K-Nearest Neighbor Classifier

2.1. Eigenvector method

The eigenvector method estimates the spectrum from a signal or a correlation matrix using a weighted version of the MUSIC algorithm derived from Schmidt's eigenspace analysis method. The algorithm performs eigenspace analysis of the signal's correlation matrix in order to estimate the signal's frequency content. The eigenvalues and eigenvectors of the signal's correlation matrix can be estimated using SVD (Singular value decomposition). This algorithm is particularly suitable for signals that are the sum of sinusoids with additive white Gaussian noise. The eigenvector method produces a spectrum estimate given by:

$$P_{ev}(f) = \frac{1}{\left(\sum\limits_{k=p+1}^{N} \left|\mathbf{v}_{\mathbf{k}}^{H}\mathbf{e}(\mathbf{f})\right|^{2}\right)/\lambda_k} \tag{1}$$

where N is the dimension of the eigenvectors and $\mathbf{v_k}$ is the k−th eigenvector of the correlation matrix of the input signal. The integer p is the dimension of the signal subspace, so the eigenvectors $\mathbf{v_k}$ used in the sum correspond to the smallest eigenvalues λ_k of the correlation matrix. The eigenvectors used span the noise subspace. The vector $\mathbf{e(f)}$ consists of complex exponentials, so the inner product

$$\mathbf{v}_{\mathbf{k}}^{H}\mathbf{e}(\mathbf{f}) \tag{2}$$

amounts to a Fourier transform. This is used for computation of the spectrum. The FFT is computed for each $\mathbf{v_k}$ and then the squared magnitudes are summed and scaled [15].

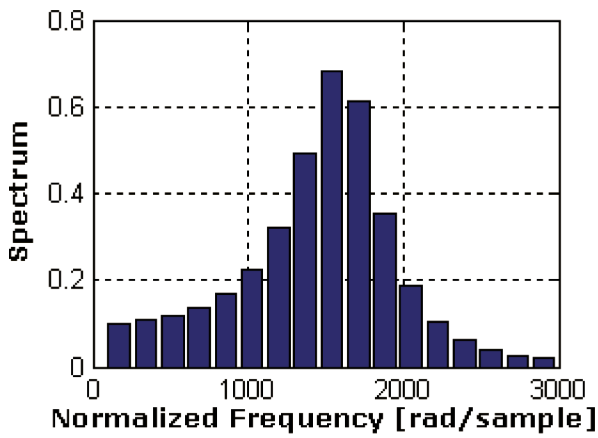

Fig. 2. Spectrum estimate of sound of faultless induction motor (17 features)

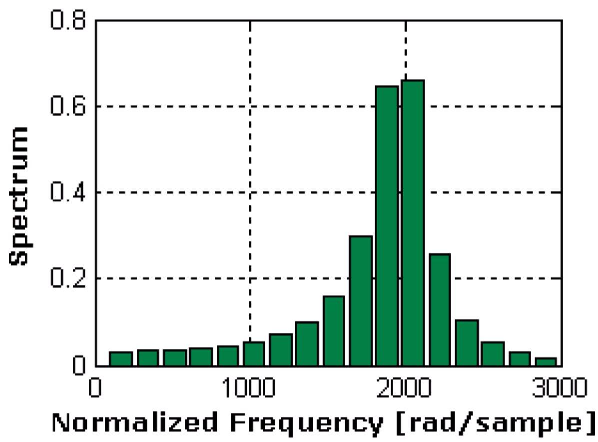

Fig. 3. Spectrum estimate of sound of induction motor with one faulty rotor bar of squirrel-cage (17 features)

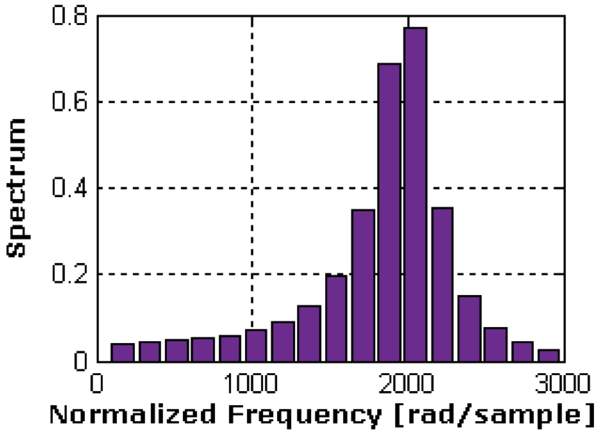

Fig. 4. Spectrum estimate of sound of induction motor with two faulty rotor bars of squirrel-cage (17 features)

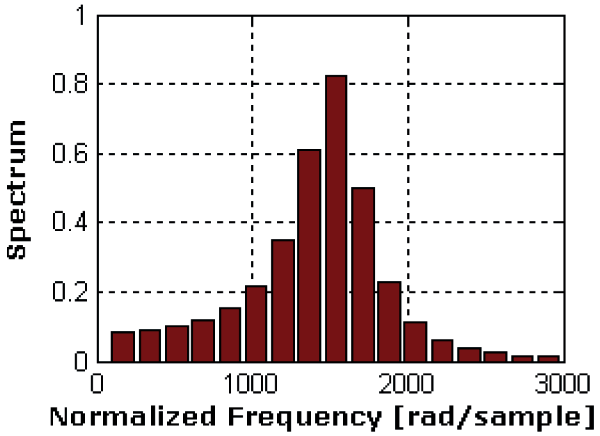

Fig. 5. Spectrum estimate of sound of induction motor with faulty ring of squirrel-cage (17 features)

Spectrum estimate is used in next calculations (Fig. 2, 3, 4, 5).

2.2. K-Nearest Neighbor Classifier

In the literature there are many methods of classification [16], [17], [18], [19], [20], [21]. 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 $\mathbf{x}=[x_1, x_2, \ldots, x_n]$. Classes of patterns are denoted as $w_1, w_2, \ldots, w_M$, where M is the index number of the class. Training set contains feature vectors $\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_j}$.

Identification set contains new feature vectors $\mathbf{y_1}, \mathbf{y_2}, \ldots, \mathbf{y_j}$. Next the least distance is calculated between feature vectors (feature vector of new sample and feature vector of specific category). Minkowski 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:

$$d(\mathbf{y}, \mathbf{x}) = \left(\sum_{i=1}^{n} (|y_i - x_i|)^r \right)^{\frac{1}{r}} \tag{3}$$

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.

3. Results of sound recognition

Researches were conducted for four induction motors with power $P_N = 500$W. Categories of sound include: sound of faultless induction motor, sound of induction motor with one faulty rotor bar, sound of induction motor with two faulty rotor bars. Moreover, power supply was 220V, $n_N = 1400$rpm. Pattern creation process was conducted for 20 five-second samples. New samples were used in the identification process. Identification process used 96 samples of sound. Minkowski distance was calculated for $r = 3$.

Efficiency of sound recognition is defined as follows:

$$E = \frac{N_1}{N} \cdot 100\% \tag{4}$$

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

TABLE 1

Results of sound recognition for $k = 1$

Kind of sound	Efficiency of sound recognition for filter 50-22050 Hz	Efficiency of sound recognition for filter 258-387 Hz
Sound of faultless induction motor	100%	91.66%
Sound of induction motor with one faulty rotor bar	83.33%	83.33%
Sound of induction motor with two faulty rotor bars	75%	75%
Sound of induction motor with faulty ring of squirrel-cage	100%	83.33%

Calculations were conducted for 130 features. Efficiency of sound recognition was shown (Tab. 1).

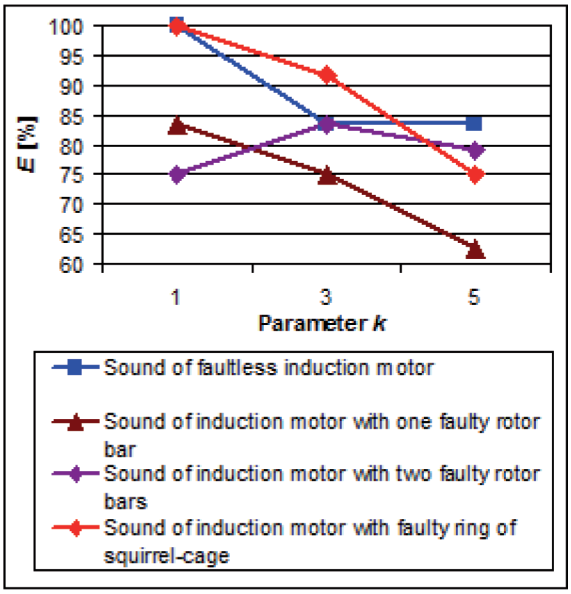

Fig. 6. Sound recognition efficiency of induction motor depending on parameter k

Figure 6 presents sound recognition efficiency depending on parameter k. The best results were obtained for parameter k =1.

4. Conclusions

This paper proposes an original approach for detection, localization of faults appearing in induction motor. The used method in this work deals with the analysis of acoustic signals of induction motor. Sound recognition system was designed and implemented. Algorithms of data processing were applied for diagnostics of induction motor. Results of sound recognition were good for Eigenvector method and K-Nearest Neighbor classifier with Minkowski distance. Sound recognition efficiency of induction motor was 62.5-100%. The best recognition results were obtained for k =1 without filtration.

The obtained results confirm the correctness of the solutions methodology. This approach can be useful for detecting failures of the engines.

Acknowledgements

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