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Sound recognition of induction motor with the use of discrete Meyer wavelet transform and classifier based on words

***Abstract**. An automatic diagnostics of induction motor was proposed in this paper. This diagnostics is reduced to a pattern recognition problem which relates the extracted data to a type of fault and a systematic technique which utilizes discrete Meyer wavelet transform and classifier based on words. This method is based on a study of acoustic signals generated by induction motor. Plan of study of acoustic signal of induction motor was proposed. Studies were carried out for two conditions of induction motor. Pattern creation process was carried out for 8 samples of sound. Identification process was carried out for 24 samples of sound. Engineers focus efforts on appropriate diagnostics of electrical motors. So it is important to develop diagnostics based on acoustic signals.*

***Streszczenie.** W pracy zaproponowano automatyczną diagnostykę silnika indukcyjnego. Ta diagnostyka sprowadza się do problemu rozpoznawania wzorców, która odnosi się do ekstrakcji danych do danego typu usterki i systematycznej techniki, która wykorzystuje algorytm Dyskretnej transformacji falkowej Meyera i klasyfikatora opartego na słowach. Metoda ta oparta jest na badaniu sygnałów akustycznych generowanych przez silnik indukcyjny. Zaproponowano plan badania sygnału akustycznego silnika indukcyjnego. Przeprowadzono badania dla dwóch stanów silnika indukcyjnego. Proces tworzenia wzorców do rozpoznawania został przeprowadzony dla 8 próbek dźwięku. Proces identyfikacji został przeprowadzony dla 24 próbek dźwięku. Inżynierowie skupiają wysiłki na odpowiedniej diagnostyce silników elektrycznych. Zatem to jest ważne aby rozwijać diagnostykę opartą na sygnałach akustycznych. (**Rozpoznawanie dźwięku silnika indukcyjnego z zastosowaniem dyskretnej transformacji falkowej Meyera i klasyfikatora opartego na słowach**).*

Keywords: Diagnostics, Recognition, Acoustic signal, Meyer wavelet, Induction motor
Słowa kluczowe: Diagnostyka, Rozpoznawanie, Sygnał akustyczny, Falka Meyera, Silnik indukcyjny

Introduction

A fault in an electrical machinery and apparatus should be quickly detected and localized for safety operation and for prevention of sequential faults. 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 [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 of machine. Engineers should also take into account the properties of the material of machine [2-5]. Depending on the material properties some methods may be better than others.

Process of sound recognition of induction motor

The process of sound recognition of induction motor contains pattern creation and identification process (Fig. 1).

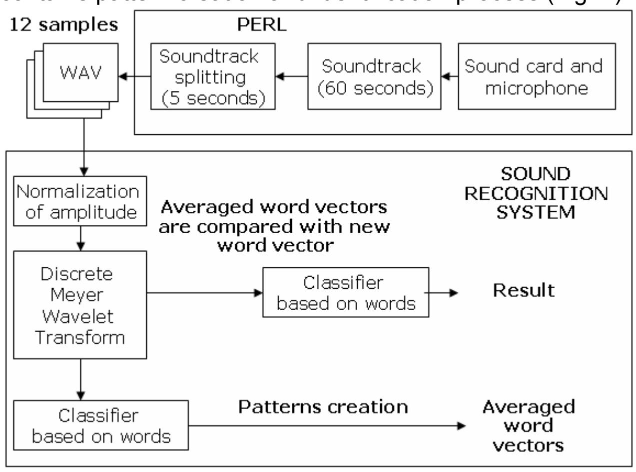

Fig.1. Process of sound recognition of induction motor with the use of discrete Meyer wavelet transform and classifier based on words

At the beginning of pattern creation process acoustic signals are recorded. Acoustic signals were recorded by OLYMPUS TP-7 microphone and sound card. Created 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 discrete Meyer wavelet transform. In pattern creation process two averaged word vectors are created. 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).

Discrete Meyer Wavelet Transform

Discrete Meyer wavelet transform was implemented in sound recognition system [6], [7]. Figures 2 and 3 show scaling and wavelet function of discrete Meyer wavelet. The wavelet transform of an original signal is calculated by passing it through a series of filters: low-pass filter and high-pass filter. We obtain detail coefficients from the high-pass filter ($\mathbf{d}_1$, $\mathbf{d}_2$, $\mathbf{d}_3$,…, $\mathbf{d}_n$) and approximation coefficients from the low-pass ($\mathbf{a}_1$, $\mathbf{a}_2$, $\mathbf{a}_3$,…, $\mathbf{a}_n$), where n is the level of decomposition.

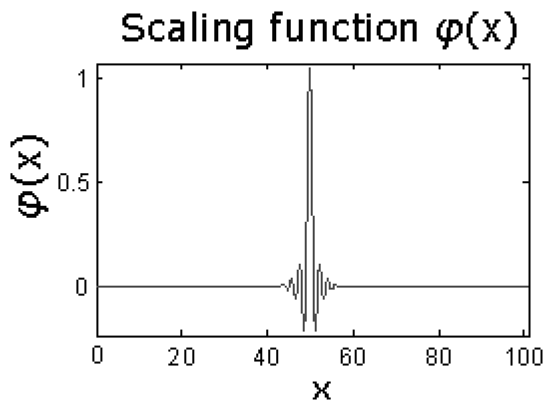

Fig.2. Scaling function of discrete Meyer Wavelet (dmey)

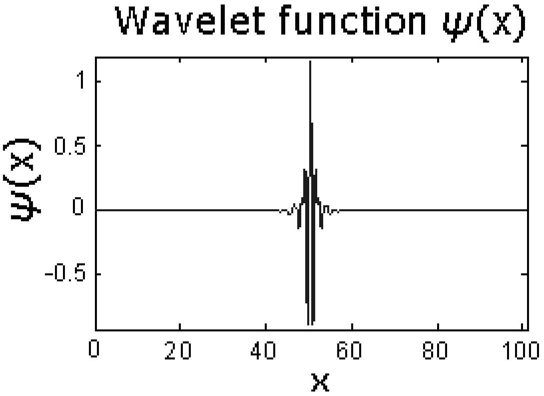

Fig.3. Wavelet function of discrete Meyer Wavelet (dmey)

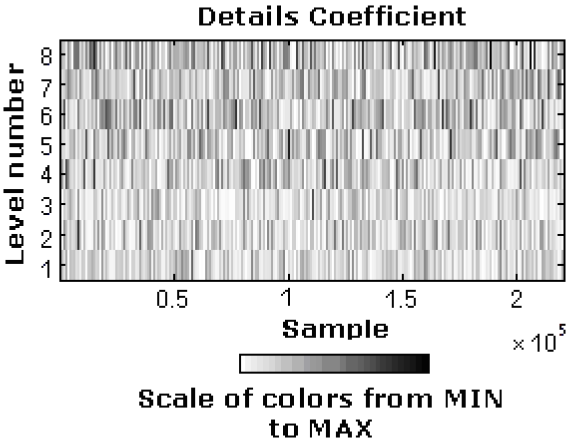

Fig.4. Detail coefficients of sound of faultless induction motor (dmey wavelet)

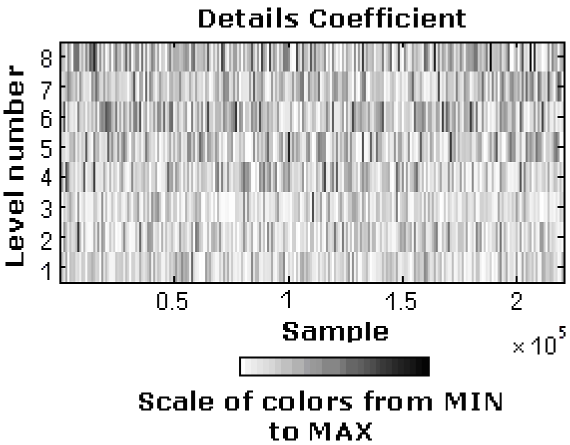

Fig.5. Detail coefficients of sound of induction motor with one faulty rotor bar (dmey wavelet)

Vectors $\mathbf{d_1}, \ldots, \mathbf{d_n}$ are important (Fig. 4, 5). Absolute values of the coordinates of the vectors $\mathbf{d_1}, \ldots, \mathbf{d_n}$ are used in next calculations.

Classifier based on words

In the literature there are many methods of classification [8-15]. Classifier based on words uses word 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 is obtained during pattern creation process. Training set contains averaged feature vectors $\mathbf{m_1}, \mathbf{m_2}, \ldots, \mathbf{m_j}$ (1),

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

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),

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

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 $\mathbf{f}$,

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

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 applied:

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

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 applied:

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

where $\mathbf{f}$ is word vector, U_j are numbers 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. Researches will be conducted for different parameter k.

Results of sound recognition

Researches were carried out for two induction motors with power P_N = 500W. Moreover, power supply was 220V, n_N = 1400 rpm. Categories of sound include: sound of faultless induction motor, sound of induction motor with one faulty rotor bar. Failure of induction motor was prepared by an engineer. One rotor bar was cut. It is possible that such failure occurs during normal operation of induction motor. Then experiments were carried out. Failure was detected on the basis of diagnostic system. Pattern creation process was carried out for 8 five-second samples. New samples were used in the identification process. 48 five-second samples were used in identification process.

Efficiency of sound recognition was expressed by formula:

$$E = \frac{N_1}{N} \cdot 100\% \quad (5)$$

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

Results of diagnostic system was verified by Matlab. The benefit of this diagnostic method is that we can detect failure with the help of diagnostic system based on acoustic and electrical signals. These results in a much better way to determine failure of induction motors. The best recognition results were obtained for d8 (961 features). Efficiency of sound recognition of faultless induction motor was 75-83,33%. Efficiency of sound recognition of induction motor with one faulty rotor bar was 100% (Fig. 6).

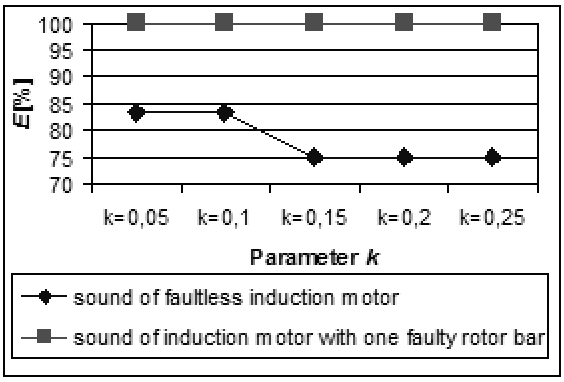

Fig.6. Sound recognition efficiency of induction motor depending on parameter *k*

Figure 6 shows sound recognition efficiency depending on parameter *k*. The best results were obtained for parameter *k*=0.05 and *k*=0.1.

Conclusions

This paper proposed an automatic fault diagnostics for induction motor. This diagnostics is reduced to a pattern recognition problem which relates the extracted data to a type of fault and a systematic technique which utilizes discrete Meyer wavelet transform and classifier based on words. Sound recognition efficiency of induction motor was 75-100%. Engineers focus efforts on appropriate diagnostics of electrical motors. So it is important to develop diagnostics based on acoustic signals.

Acknowledgments

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