# Diagnostics of synchronous motor based on sound recognition with application of Linear Predictive Cepstrum Coefficients and fuzzy classifier

**Adam Głowacz**
AGH University of Science and Technology,
al. Mickiewicza 30, 30-059 Cracow, Poland, e-mail: adglow@agh.edu.pl

**Abstract:** This document provides the concept of investigations of acoustic signals of imminent failure conditions of synchronous motor. Measurements were made by recorder OLYMPUS WS-200S. Sound recognition software has been implemented. Algorithms of signal processing and analysis have been used. The system is based on the LPCC algorithm and fuzzy classifier with triangular membership function. Results confirm the correct operation of the system of sound recognition of synchronous motor.

**Keywords:** Sound recognition, processing, classification, diagnostics, fuzzy classifier

## 1 Introduction

Acoustic signal of electrical machines allows you to specify whether the machine is faulty. Application of processing and analysis of audio signals is an effective and rapid approach. Many methods for signal processing were presented. Widely used methods are based on recognition of electrical signals [1]. In recent years, many of methods to study the acoustic signal were presented [2-11]. Results of investigations confirm the validity of applying these methods to identify imminent failure condition of electrical machine.

Imminent failure condition of synchronous motor is interpreted as a threat to destroy the machine. The aim of paper is to propose a software to investigate acoustic signals of synchronous motor. Measurements were made using a recorder OLYMPUS WS-200S (100-15000 Hz). Sound recognition system contains preliminary data processing, feature extraction and classification algorithm [12,13]. LPCC (Linear Predictive Cepstrum Coefficients) algorithm was used as the method of feature extraction. Fuzzy classifier with triangular membership function was applied. This paper provides usage of algorithms of signal processing and analysis for diagnostics of synchronous motor. Results of sound recognition of synchronous motor were presented.

# 2 Sound recognition process

Sound recognition process contains pattern creation process and identification process (Fig. 2.1). At the beginning of pattern creation process signals are sampled and normalized. Afterwards data are converted through the Hamming window. Next data are converted through the LPCC algorithm. The LPCC algorithm creates feature vectors. Four averaged feature vectors are created. Afterwards these vectors are converted into fuzzy sets. Pattern creation process and identification process are based on the same signal processing algorithms. The difference between them is a sequence of execution. Pattern creation process contains following steps: sampling, quantization, normalization, filtration, windowing, feature extraction, fuzzy sets formation [14].

In the identification process new acoustic signal is recorded. Afterwards it divides wave data. After that signals are sampled and normalized. Next data are converted through the Hamming window. Next data are converted through the LPCC algorithm. The LPCC algorithm creates feature vectors. Fuzzy classifier with triangular membership function was applied. To obtain results of recognition, it compares feature vector of new sample (new fuzzy sets) with averaged feature vectors (fuzzy sets). Identification process contains following steps: recording of acoustic signal, sound track division, sampling, quantization, normalization, filtration, windowing, feature extraction (one feature vector), fuzzy sets formation, classification (fuzzy classifier).

## 2.1 Preprocessing

Recording of acoustic signal is first step in identification process. Acoustic signal is converted into digital data (wave format). Wave data contain following parameters: sampling frequency is 44100 Hz, number of bits is 16, number of channels is 1. Afterwards application divides sound track into sound fragments.

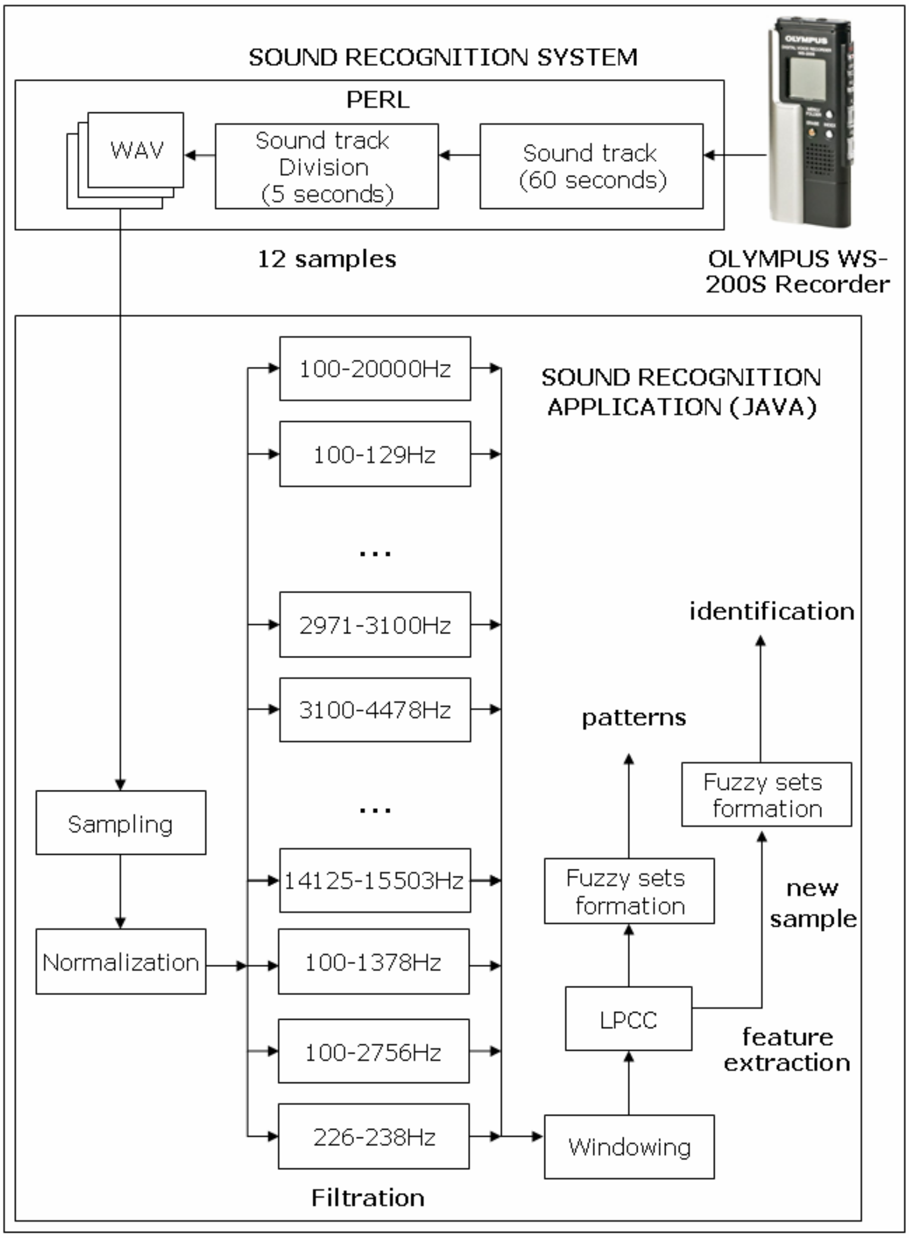


**Figure 2.1** Pattern creation process and identification process

There are following advantages of such solution: precise determination of sound appearing, precise sound identification, application does not have to allocate as much memory in identification process. Next application reads data. Sound recognition application uses sampling frequency 44100 Hz and 16 bits. It gives better precision. There is a choice of number of bits depending on quantity of input data and calculations speed. The compromise is important to obtain good results in short time. Normalization is the process of changing of the amplitude of an audio signal. It changes 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 this maximum [6]. Filtration is used to modify the frequency domain of the input sample. After that the Hamming window is used to avoid distortion of the overlapped window functions.

## 2.2 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 [15-18]. It determines a set of coefficients approximating the amplitude versus frequency function. These coefficients $a_k$ create feature vectors which are used in calculations. Transmittance is given by the following formula:

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

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

$$s'(n) = -\sum_{k=1}^{p} a_k \cdot s(n-k) \tag{2}$$

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

Linear predictive analysis requires estimating the linear predictive parameters for a segment of sound. Formula (2) 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:

$$e(n) = s(n) - s'(n) \tag{3}$$

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

$$E = \frac{1}{N-p} \sum_{n=p}^{N-1} e^2(n) \tag{4}$$

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:

$$a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_p \end{bmatrix}, R = \begin{bmatrix} r(0) & r(1) & \cdots & r(p-1) \\ r(1) & r(0) & \cdots & r(p-2) \\ \vdots & \vdots & \ddots & \vdots \\ r(p-1) & r(p-2) & \cdots & r(0) \end{bmatrix}, r = \begin{bmatrix} r(1) \\ r(2) \\ \vdots \\ r(p) \end{bmatrix} \tag{5}$$

$$r(k) = \frac{1}{N-p} \sum_{m=p}^{N-1} s(m) \cdot s(m+k) \tag{6}$$

where $N$ is the length of the sound segment $s(n)$.

The Levinson-Durbin algorithm solves the nth order system of linear equations:

$$a=-R\text{-}1r \tag{7}$$

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 $M2$ multiplications to compute the linear prediction coefficients.

### 2.3 Linear Predictive Cepstrum Coefficients

LPCC is based on LPC. Linear predictive coefficients $ak$ are obtained after applying the method of the LPC. Subsequently, the formula (8), transforms them into linear predictive cepstrum coefficients $cn$. The form may be used to compare the signals effectively [19]. 75 coefficients were calculated for each sample (Fig. 2.2).

$$c_n = \begin{cases} a_n + \sum_{k=1}^{n-1} \frac{k}{n} c_k a_{n-k} & 1 \le n \le p \\ \sum_{k=n-p}^{n-1} \frac{k}{n} c_k a_{n-k} & n > p \end{cases} \tag{8}$$

Where $c0=r(0)$, $p$ – order of the filter, $n$ – number of cepstral coefficients.

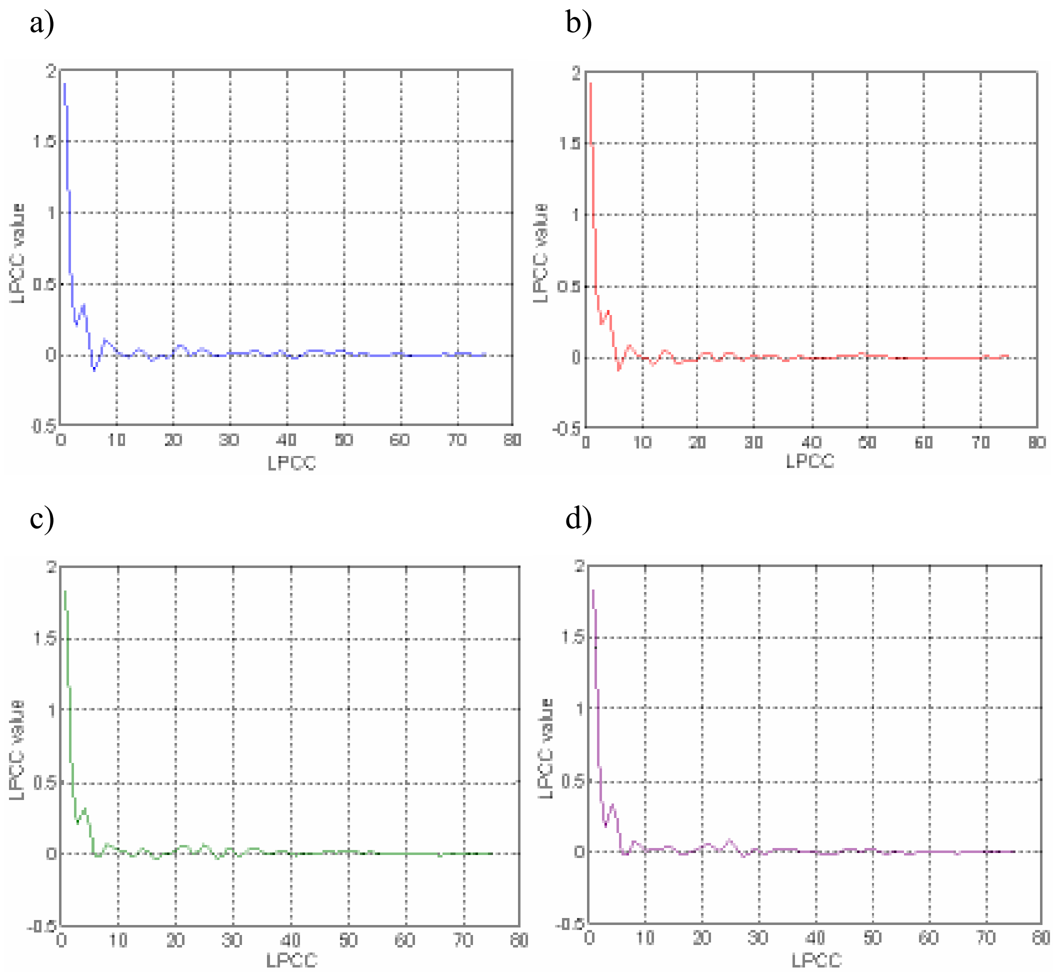


**Figure 2.2** LPCC values for five seconds of samples of sound of synchronous motor after normalization (analyzed frequencies 100-22050 Hz). a) faultless synchronous motor, b) synchronous motor with shorted stator coils, c) synchronous motor with one broken coil, d) synchronous motor with three broken coils

## 2.4 Classification

Classical logic is based on binary logic with two values of truth. These two values are true and false. Fuzzy logic is a multivalued logic with truth represented by a value on the closed interval [0, 1], where 0 is equated with the classical false value and 1 is equated with the classical true value. Additional values between 0 and 1 are added. The border between them is "fuzzy" [20-24]. Fuzzy classifier uses fuzzy sets or fuzzy logic in the course of its training or operation.

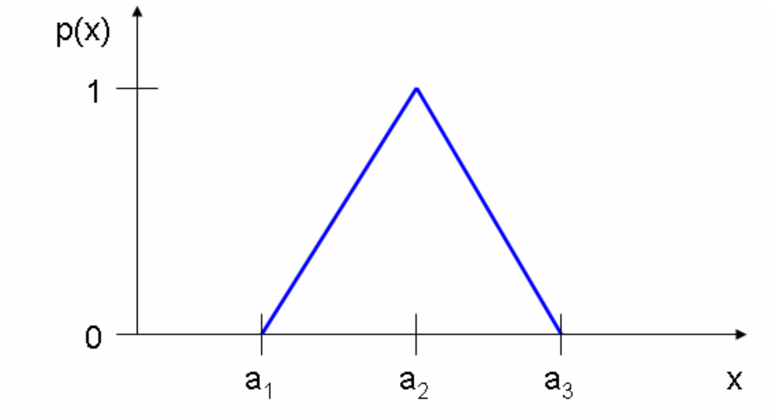


**Figure 2.3** Triangular membership function

At the beginning of the process of classification, feature vectors are transformed into fuzzy sets. There were 260 triangular membership functions (Fig. 2.3). Fuzzy classifier compares fuzzy sets (new fuzzy sets of investigated sample, fuzzy sets of specific category). Membership functions use amplitude of the sample to determine values (fuzzy sets formation). Triangular membership function is defined as:

$$p(x) = \begin{cases} 0 & x < a_1 \\ \dfrac{x - a_1}{a_2 - a_1} & a_1 \le x < a_2 \\ \dfrac{a_3 - x}{a_3 - a_2} & a_2 \le x < a_3 \\ 0 & x \ge a_3 \end{cases} \tag{9}$$

Investigations were carried out for triangular membership functions. Triangle basis was a parameter that was adjusted accordingly. In the process of identification, fuzzy sets were compared with each other. A larger number of valid fuzzy sets determined the appropriate category.

## 3 Sound recognition results

Investigations were carried out for sound of faultless synchronous motor, sound of synchronous motor with shorted stator coils, sound of synchronous motor with one broken coil, sound of synchronous motor with three broken coils. Ten five-second samples were used in pattern creation process for each category. New unknown samples were used in the identification process. The system should determine the state of synchronous motor correctly. The pattern creation process was carried out for five-second samples.

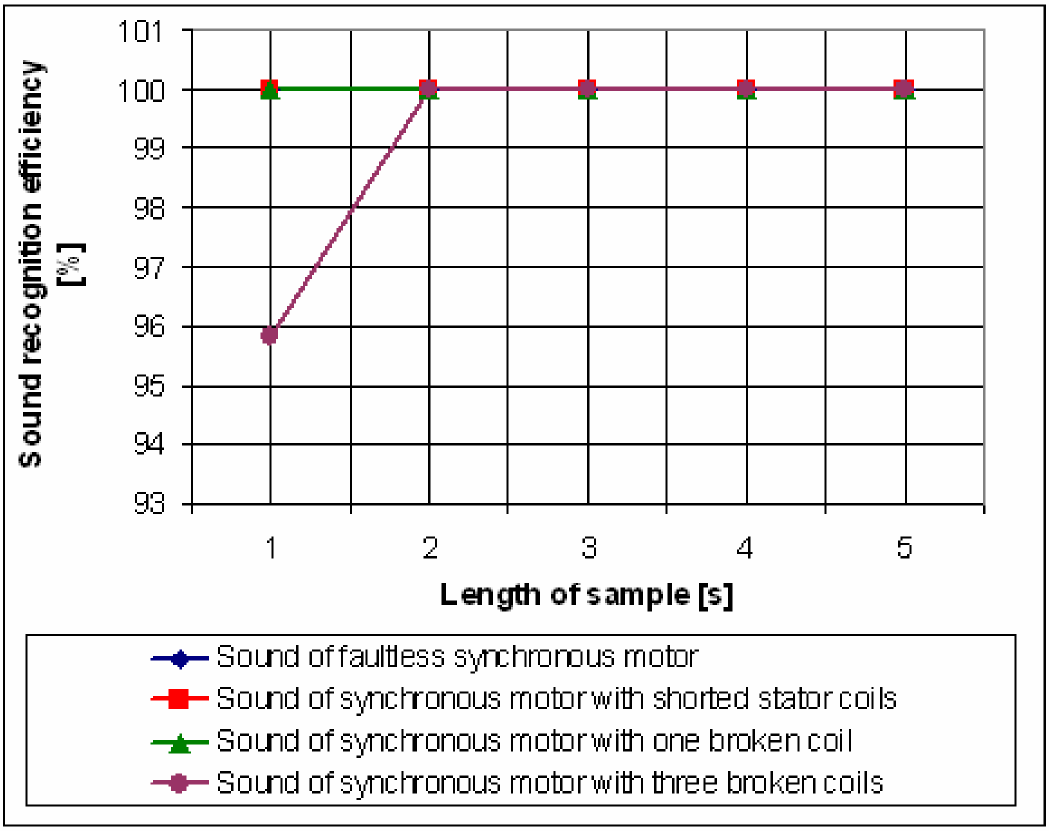


**Figure 3.1** Sound recognition efficiency of synchronous motor depending on the length of the sample. There were used amplitude normalization, low-pass filter which passes frequencies 100-1378 Hz and fuzzy classifier with triangular membership function

Identification process was carried out for one-second, two-second, three-second, four-second, five-second samples. The sound recognition efficiency depending on length of sample is presented in Fig. 3.1. Sound recognition efficiency is defined as:

$$E = \frac{N_1}{N} \tag{10}$$

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

The best recognition result was obtained for five-second, four-second, three-second, two-second samples. Sound recognition efficiency of faultless synchronous motor was 100%. Sound recognition efficiency of synchronous motor with shorted stator coils was 100%. Sound recognition efficiency of synchronous motor with one broken coil was 100%. Sound recognition efficiency of synchronous motor with three broken coils was 100%.

## 4 Conclusion

Sound recognition system was implemented. It identifies category including the most correct fuzzy sets. The algorithms of signal processing and fuzzy classifier were used in the identification process. Analysis shows the sensitivity of methods which are based on fuzzy classifier in dependence on input data. Investigations show that fuzzy classifier with triangular membership function works for different input data. The best results were obtained for five-second, four-second, three-second, two-second samples. It also used band-pass filter which passes frequencies 100-1378 Hz. Sound recognition efficiency of synchronous machine was 100% for each category. Time of the identification process of five-second sample was 2.015 s for Intel Pentium M 730 processor (normalization, 100-1378 Hz, LPCC, fuzzy classifier). Time of the identification process of one-second sample was 1.297 s.

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## References

1. Głowacz Z., Zdrojewski A., *Analiza spektralna sygnałów silnika komutatorowego prądu stałego zasilanego ze źródła napięcia stałego*, Przegląd Elektrotechniczny; 82 (2006) nr 11, 76–79.
2. Mitrovic D., Zeppelzauer M., Eidenberger H., *Analysis of the Data Quality of Audio Features of Environmental Sounds*, Journal of Universal Knowledge Management, vol. 1, no. 1 (2006), 4-17.
3. Yoshii K., Goto M., Okuno H.G., *Drum Sound Recognition for Polyphonic Audio Signals by Adaptation and Matching of Spectrogram Templates With Harmonic Structure Suppression*, IEEE Transactions on Audio, Speech, and Language Processing, Vol. 15, No. 1, January 2007, 333-345.
4. Dubois D., Guastavino C., *Cognitive evaluation of sound quality: Bridging the gap between acoustic measurements and meanings*. Proceedings of 19th International Congress on Acoustics - ICA07, September 2-8 2007, Madrid, Spain.
5. Lee K., *Effective Approaches to Extract Features and Classify Echoes in Long Ultrasound Signals from Metal Shafts*, Ph. D. dissertation, Brisbane, Australia, 2006.
6. The MARF Development Group, *Modular Audio Recognition Framework v.0.3.0-devel-20050606 and its Applications*, Application note, Montreal, Quebec, Canada, 2005.
7. Kinnunen T., Karpov E., Fränti P., *Real-Time Speaker Identification and Verification*, IEEE Transactions on Audio, Speech, and Language Processing, Vol. 14, No. 1, Jan 2006, 277- 288.
8. Lovekin J.M., Yantorno R.E., Krishnamachari K.R., Benincasa D.B., and Wenndt S.J., *Developing usable speech criteria for speaker identification*, IEEE, International Conference on Acousitcs and Signal Processing, May 2001, 424–427.
9. Rak R.J., Majkowski A., *Praktyczne aspekty analizy widmowej Fouriera*, Przegląd Elektrotechniczny, 2004, R. 80, nr 4, s. 391-396.
10. Rak R.J., Majkowski A., *Czasowo-częstotliwościowa analiza sygnałów*, Przegląd Elektrotechniczny, 2004, R. 80, nr 5, s. 515-520.

11. Tadeusiewicz R., *Speech recognition versus understanding of the nature of speech deformation in pathological speech analysis* (Abstract), Archives of Acoustics, vol. 28, No. 3, 2003, pp. 260.
12. Wiśniewski A., *Wprowadzenie do programowania zorientowanego obiektowo w C++*, Wydaw. Akademii Podlaskiej, 2004, Siedlce.
13. Horstmann C.S., Cornell G., *Core Java 2: Volume 1 Fundamentals*, Prentice Hall, 2004.
14. Pasko M., Walczak J., Teoria Sygnałów, Wydawnictwo Politechniki Śląskiej, 2007.
15. Corneliu M., Costinescu B., *Implementing the Levinson-Durbin Algorithm on the StarCore™ SC140/SC1400 Cores*, Application Note Freescale Semiconductor AN2197, 1/2005.
16. ITU-T Recommendation G.729 - Coding of speech at 8 kbit/s using conjugate-structure algebraic-code-excited linear prediction (CS-ACELP), 01/2007.
17. ITU-T Recommendation G.723.1 - Dual rate speech coder for multimedia communications transmitting at 5.3 and 6.3 kbit/s, 05/2006.
18. Zhu X., Wyse L., *Sound Texture Modelling and Time-Frequency LPC*, Proc. 7th International Conference on Digital Audio Effects, Naples, Italy, 2004, pp. 345–349.
19. Antoniol G., Rollo F., Venturi G., Linear Predictinve Coding and Cepstrum Coefficients for Mining Time Variant Information from Software Repositories, Second International Workshop on Minig Software Repositories , St. Louis, USA, May, 17 2005, 74-78.
20. Szabat K., Orłowska-Kowalska T., *Adjustment of classical and fuzzy logic speed controllers for electrical drives with elastic joint*, Proceedings of XVI International Conference on Electrical Machines (ICEM 2004), Cracow, 2004.
21. Kosanovic B.R., Chaparro L.F., Sclabassi R.J., *Signal Analysis In Fuzzy Information Space, Fuzzy Sets and Systems*, vol. 77, 1996, pp. 49-62.
22. Kowal M., Korbicz J., *Robust fault detection using neuro-fuzzy models*, Przegląd Elektrotechniczny, 2006, No 1, pp. 32-36.
23. Cyran K., *Combining Rough Sets and Neural Network Approaches in Pattern Recognition*, Studia Informatica, vol. 2(6), 2005, 7-20.
24. Nazarko J., Jakuszewicz I., *Prognozowanie przestrzennego obciążenia mocą z zastosowaniem zbiorów rozmytych*, Prace Naukowe Instytutu Energoelektryki Politechniki Wrocławskiej, Konferencje, 2000, nr 91/34, s. 347-352.