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Analysis of the possibility of using an audio signal to detect the state of the machine based on the sound it generates

Abstract. *As part of the experiments, research was carried out to detect the condition of the electric machine. In the first place, a laboratory stand was designed to test acoustic signals. This process included, m.in, the selection of an electric machine, load system, measuring devices, recording device, and the definition of its operating states. The recordings were recorded in the Laboratory of Electrical Machines at the Institute of Electronic Systems of the Faculty of Electronics of the Military University of Technology using the SZUAa54a induction motor. The feature extraction process involved the generation of spectral descriptors. The method of decision trees and the k nearest neighbor method were used as the classification algorithm. The proposed method gives an efficiency of 95.53%.*

Streszczenie*. W ramach eksperymentów przeprowadzono badania mające na celu wykrycie stanu maszyny elektrycznej. W pierwszej kolejności zaprojektowano stanowisko laboratoryjne do badania sygnałów akustycznych. Proces ten obejmował m.in. dobór maszyny elektrycznej, układu obciążeniowego, urządzeń pomiarowych, urządzenia rejestrującego oraz określenie jego stanów pracy. Nagrania rejestrowano w Laboratorium Maszyn Elektrycznych Instytutu Systemów Elektronicznych Wydziału Elektroniki Wojskowej Akademii Technicznej przy użyciu silnika indukcyjnego SZUAa54a. Proces ekstrakcji cech obejmował generację deskryptorów widmowych. Jako algorytm klasyfikacji zastosowano metodę drzew decyzyjnych oraz metodę najbliższego sąsiada. Proponowana metoda daje sprawność 95,53%. (****Analiza możliwości wykorzystania sygnału akustycznego do detekcji stanu maszyny na bazie generowanego przez nią dźwięku****).*

Słowa kluczowe: diagnostyka, sygnał akustyczny, ekstrakcja cech, detekcja stanu maszyny
Keywords: diagnostics, acoustic signal, feature extraction, machine condition detection.

Introduction

Technical diagnostics deals with the evaluation of the technical condition of the machine by testing the properties of the processes that take place on the machine [1]. One of the most important diagnostic tasks in relation to the machine analyzed is the possible early detection and accurate recognition of emerging damages. The need to diagnose devices is stimulated by the general development of technology, i.e. the increasingly complex structure of systems, where one failure can cause huge material or financial losses. Repairing a machine costs less when the failure is detected earlier, which is why it is so important to quickly detect a device malfunction. 2:3]

An acoustic signal is a signal used by scientists in a very wide spectrum. It can be used, among others, to recognize the identity of people, musical genres, road surfaces, dangerous events, or medical conditions. The spectrum of applications is expanding practically every day and is limited only by the ingenuity of the human mind. One of the possibilities of using an acoustic signal is to detect the condition of the machine based on the sound it generates.

The article presents the study of acoustic signals from a selected electrical machine to recognize its condition. For this purpose, the authors designed a station for recording acoustic signals. The next step was to collect research material that was used to analyze the recorded signals using digital signal processing techniques and methods. Frequency analysis was used mainly. In the last part of the research, a methodology was proposed to classify the sound of an electric machine, taking into account previously performed experiments. The recognition results were analyzed using a global recognition error.

Related research

To recognize machine damage, methods dedicated to the construction, manufacture, and operation phases of machines are used. The most important methods use thermal analysis [4], acoustic analysis [5,6], vibroacoustic analysis [7,8], infrared analysis [9], as well as examination of machine electrical signals [10,11], machine magnetic field [12], ultrasound generated by machines [13], wear products contained in lubricating or hydraulic oils of machines [14,15].

A review of the literature on the recognition of the pre-failure state of a machine based on the acoustic signal generated by it shows the use of various methods by researchers: *Fast Fourier Transform, Mel-Frequency Cepstral Coefficients, Gaussian Mixture Models*, Higher-order statistics, Convolution Neural Network. [16-23]. The preliminary research results obtained so far confirm the validity of the use of these methods to recognize pre-failure conditions of electrical machines [16]. Different types of damage to electrical machines cause characteristic changes in the signal spectrum. For example, bearing wear can generate sounds at certain frequencies. Measuring current and voltage in electrical machines in combination with sound analysis can provide comprehensive information on the condition of the machine. Changes in sound characteristics can correlate with fluctuations in these parameters, which can indicate problems with the wind or power supply. Changes in the amplitude of certain frequency bands can also indicate damage such as rotor imbalance, bearing failure, or winding problems [16].

Contribution

The main aim of our research is to develop an automatic diagnostic system capable of discovering not only the occurrence of the fault, but also the type of fault. In our considerations, we have focused on several essential cases of the machine damage most often met in practice.

Fault recognition is treated as identification of the pre-failure state of the device, and in terms of data analysis, it is treated as a problem of pattern recognition.

The main advantages of this type of technology are low invasiveness and low cost. In addition, this type of analysis ensures earlier and faster detection of defects in the machine. It is characterized by an equally high sensitivity and allows for the identification of detailed information about the fault [16]. In the accepted reasoning, the occurrence of a prefailure state is interpreted as a threat of machine failure. Repairing a machine costs less when the failure is detected earlier, which is why it is so important to investigate pre-failure conditions.

Design of a laboratory station for registration acoustic signals

To design a system for recognizing the prefailure state of a machine based on the sound it generates, an acoustic signal database is necessary. For this purpose, the authors proposed a draft of the workstation, which included the selection of an electric machine, the selection of a recording device, the definition of machine operating states, and the selection of appropriate recording conditions for them. The recordings were recorded in the Laboratory of Electrical Machines of the Institute of Electronic Systems of the Faculty of Electronics of the Military University of Technology using the SZUAa54a induction motor. This model was chosen due to the fact that this type of machine and the nature of its operation allows us to simulate many different states of machine operation. The basic parameters of this machine are a power of 3kW, at 1430 rpm. The power factor cosφ is 0.8.

The design of the measuring station defined as part of the work must take into account both the electrical connection and the use of sound recording devices for the machine. The practical implementation of the proposed solution is presented in Fig. 1.

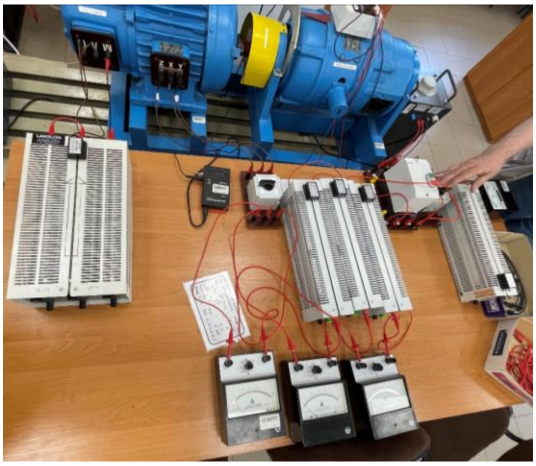

Fig. 1. Physical implementation of the concept of a station for recording acoustic signals for selected pre-failure states of an electrical machine

The acoustic signals were recorded using the Audacity software using a microphone on a portable computer. The research material consisted of samples recorded with a sampling frequency of 44.1 kHz and a resolution of 16 bits. The distance between the dictaphone and the tested machine was approximately 1 m. The signals were recorded in a lossless format.wav. The length of each recorded signal is in the range of 10 to 15 seconds. These signals were used to conduct experiments that were the basis for analysis in terms of the search for unique features that differentiate individual states of the machine.

One of the most important tasks in the development of the concept of the measuring station was to determine the operating states of the machine. The proposed stand allows measurements to be carried out in the following types of work treated as separate classes within the developed system:

- *Class1*: Acoustic signal of the machine in no-load state, at 780 rpm - no fault
- *Class2*: Acoustic signal of the machine in the non-load state at 1485 rpm. - no fault
- *Class3*: Machine acoustic signal with single phase asymmetry – operation at rated voltage
- *Class4*: Machine acoustic signal with loose motor foot screw – no-load operation
- *Class5*: Acoustic signal of the machine with loose motor foot screw – operation at rated load
- *Class6*: Machine acoustic signal with loose motor housing pin - no-load operation
- *Class7*: Acoustic signal of the machine with a loose motor housing pin - operation at rated load

The Class1 and Class2 states are the state without the machine fault. Class3- Class7 states reflect pre-failure states that can occur in the machine due to simulated mechanical damage in its construction. In the long run, these conditions can affect the condition of the machine and cause it to be damaged.

Architecture of proposed system

Any recognition system whose methodology uses digital signal processing consists of two processes: the pattern creation process and the identification process. The process of recognizing the sound of an electrical machine is the same as the process of identification. In general, the methodology of such a procedure consists of 3 stages, Fig. 2.

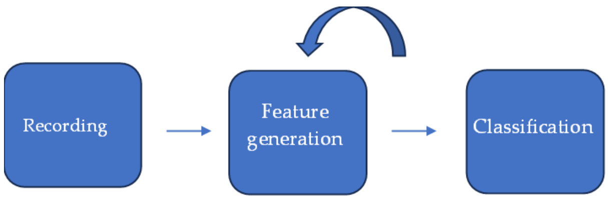

Fig. 2. Architecture of the proposed system

The first stage is the recording of the sound signal. In the next stage, the signal is analyzed, and its parameters are extracted and selected, which will allow efficient recognition of the machine condition. The last stage is classification, i.e. the result of the test, which allows a diagnosis to be made on the basis of the recorded signal.

From the point of view of designing any recognition system, the most important stage of work is the extraction and selection of features from the recorded signals. The purpose of this procedure is to select parameters that will fully characterize the collected signal and facilitate further observations when selecting them to determine the final feature vector. In order to obtain a numerical representation of these parameters, it is necessary to use appropriate sound signal processing algorithms, which will allow to obtain the so-called characteristics of a given object/model.

To extract the parameters that enable the description of a given acoustic signal, Matlab software was used. The project decided to use the *audioFeatureExtractor* framework, part of the *AudioToolbox Library*, which is a special tool for extracting sound features and analyzing sound signals. The planned experiments focused on analyzing the spectrum of the acoustic signal generated by the machine in a given state. To this end, spectral descriptors were defined using the classical linear frequency scale. These descriptors describe in detail the spectrum of the acoustic signal generated by the machine, providing complete information about the frequency range of the analyzed signal. Table 1 presents a list of extracted descriptors. The feature extraction scheme is shown in Fig. 3. A more detailed description of all descriptors can be found in [24, 25].

Based on the applied procedure, 7 features were defined for each of the machine states.

Fig. 3. Architecture of the proposed system

Tab. 1. List of extracted descriptors

Akronim cechy	Angielska nazwa cechy
c_1	*Spectral Centroid*
c_2	*Spectral Kurtosis*
c_3	*Spectral Crest*
c	*Spectral Decrease*
c_5	*Spectral Flatness*
c_6	*Spectral Spread*
c_7	*Pitch*

The last stage is the selection of a classification method in the recognition system. For this purpose, it is necessary first to determine the number of models representing a given class. Initially, the number 100 was assumed to be the number of models representing a single class. However, this number turned out to be too small in the initial experimental studies because for such a defined problem, it is required to model the class with more models. The number of feature vectors, i.e., the number of models, also defines the size of the matrix that will be created in the further process, which translates into a different data processing time in the selected software. It was decided to define 500 trait models, or 500 trait vectors, to make the learning process more accurate and more accurate. For each of the signals recorded for the above-mentioned machine operating states, feature vectors corresponding to each class have been generated. The classification method was used the *decision trees* and *the k nearest neighbor*.

The output of the system should decide whether the machine is in normal state or damaged. In the case of damage, the system should qualify it as one of the classes of damage mentions above.

Results analysis

The extracted descriptors, together with the calculated numerical values for the acoustic signals, provide the basis for evaluating the suitability of their use for machine condition detection. Research was carried out in two stages. The first was the comparison of the numerical values of the selected signal descriptors and the analysis of changes in the values of the selected parameters over time. The authors used the results of these analyses for the stage of feature selection, i.e. the selection of the most representative features in order to define the final feature vectors and subject them to experimental tests for selected classification methods.

Figs. 4,5,6 show examples of changes in selected spectral parameters (c_1,c_2, c_7) for the Class2 normal operating state, and the pre-failure Class5 and Class7 states. On the above waveforms, you can easily notice clear differences in the course of changes in the selected parameters. The most significant differences can be observed in the case of changes in the value of spectrum kurtosis (c_2) and the fundamental frequency of the spectrum (c_7) characterizing a given state of the machine.

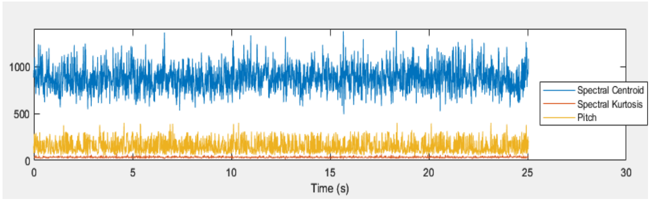

Fig. 4. Course of changes in selected spectral parameters (c_1, c_2 and c_7) for the Class2 operating state.

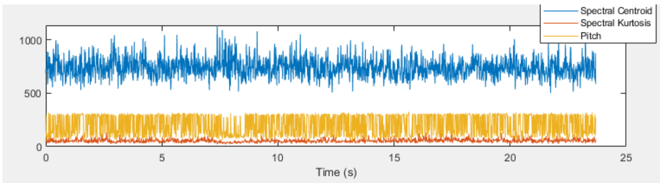

Fig. 5. Course of changes in selected spectral parameters (c_1, c_2 and c_7) for the Class5 operating state.

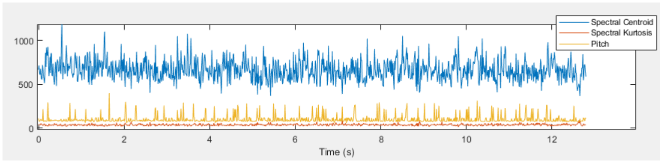

Fig. 6. Course of changes in selected spectral parameters (c_1, c_2 and c_7) for the Class7 operating state.

The first stage of the experiments contained all the descriptors in the resulting feature vector. *Cross-validation* techniques were used in the classification process. It consists of dividing the available data into a training set and a test set. At the beginning, the entire data set is randomly divided into equal parts of K, of which 1/K is the test set and the rest is the training set. This process is repeated K times so that each piece of data acts as a test set. In the case of classification methods, the following variants were used for the analysis:

- *Decision tree* (maximum number of divisions: 2,,3,5,8,13,20)
- *Methods k nearest neighbors* (k=1,2,5,10,25,50)

Table 2 presents the results of the algorithms used, along with their parameters. It can be noted that the efficiency of recognition of individual classes for both methods remains at the level of 91-95%, which is a very good result, giving a good chance of correct signal classification. Among the methods used, the best results were achieved for the following methods. *Fine Tree (*number of maximum divisions: 3) *and k-nn (*k nearest neighbors equal to 25*).*

Tab. 2. Results of the effectiveness of the recognition of proposed classification methods

L.p.	Method	Effectiveness	Time	Parameter
1	Fine Tree	91,73%	5,61s	number of divisions:2
2	Fine Tree	92,80%	0,84s	number of divisions :3
3	Fine Tree	92,53%	4,26s	number of divisions :5
4	Fine Tree	92,60%	2,06s	number of divisions :8
5	Fine Tree	92,53%	4,31s	number of divisions:13
6	Fine Tree	92,07%	2,14s	number of divisions:20
7	k-nn	92,73%	4,43s	k = 1
8	k-nn	91,73%	2,17s	k = 2
9	k-nn	93,93%	4,06s	k = 5
10	k-nn	94,07%	3,07s	k = 10
11	k-nn	94,13%	2,20s	k=25
12	k-nn	95,53%	4,55s	k=50

Fig. 7 shows: a graphical *matrix of errors* for both classification methods. The *confusion matrix* arises from the intersection of the predicted class and the actually resolved class. This is the primary tool used to evaluate a classifier. On its basis, the effectiveness of the algorithm is defined as the number of all correctly diagnosed cases in all tested cases within the proposed diagnosis concept.

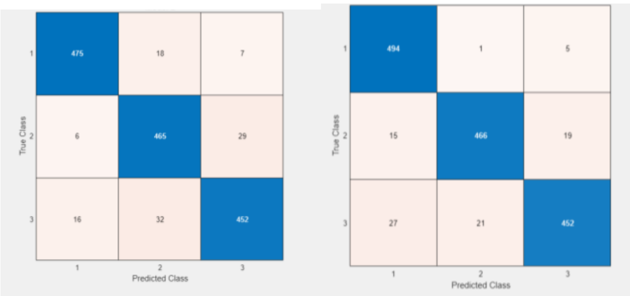

Fig. 7. Confusion matrix for the analyzed classification methods (left; Fine Tree, right k-nn method)

To reduce the dimensionality of the feature vector describing a given class, the author decided to conduct a trial of three samples with the use of the selected features based on previously conducted analyses of changes in the values of descriptors. 3 experiments will be carried out, in which the set of parameters describing the sound model was changed:

- I attempt - features: C_1, C_2, C_3, C_4, C_5
- II attempt – features: C_4, C_5, C_6, C_7
- III attempt - features C_1, C_3, C_5

The results for all 3 trials are presented in Table 3.

Tab. 3. Results of the effectiveness of the recognition of proposed classification methods

L.p.	Method	Effectivenes s	Time	Parameter
I próba	Fine Tree	90,33%	3,69s	ilość podziałów: 3
	KNN	92,18%	1,94s	ilość podziałów: 25
II próba	Fine Tree	85,40%	4,46s	ilość podziałów: 3
	KNN	89,60%	1,72s	ilość podziałów: 25
III próba	Fine Tree	77,33%	4,10s	ilość podziałów: 3
	Fine Tree	84,56%	2,35s	ilość podziałów: 25

Reducing the number of features that describe a given model of the machine condition did not result in an increase in the effectiveness of their recognition. In the case under analysis, the use of a seven-element vector describing a given model is definitely a more effective solution. It is also worth noting that the k-nn method achieves much better results than the Fine Tree method. This may be due to the recognition algorithm on which this method is based. The optimum number of neighbors is 25 with 500 models for each machine operating condition. This number of models provides a very detailed representation of the data in space. Ultimately, the proposed concept is based on the use of seven spectral descriptors and the nearest-neighbor method with the number k = 25.

Summary

The purpose of the research carried out by the authors was a parametric analysis of audio signals to determine patterns to recognize the operating state of the machine. To achieve the intended goal, it was first necessary to create a station for the generation and recording of acoustic signals. The authors recorded a total of 14 signals, for seven states of machine operation – 7 to learn the system and 7 to check its correctness. The collected database of acoustic signals allowed us to carry out an analysis in order to search for differences between the recorded signals. This step, called the descriptor extraction process, is necessary to define the last stage of the work, which was to propose a recognition algorithm. The study extracted spectral descriptors. The next step in creating a classification system is to select a classification method. The author decided to use the KNN algorithm, i.e. k nearest neighbors, mainly because of its effectiveness and simple scheme of operation. The proposed method gives a recognition efficiency of 95.53% using the number of neighbors *k=25.*

The effectiveness of similar solutions in this range ranges from 67.39-100% for 1-5 second samples and from 90.9-100% for 3-5 second samples in [26]. Another research shows that the efficiency of the recognition of the acoustic signal of the direct current motor was in the range of 83.3-96.7% [27]. In general, comparison of this type of research is very difficult to carry out due to the lack of publicly available databases. [16]. Different conditions for signal recording, the multitude of machines, differences in the length of recorded signals, all this limits the possibility of comparing individual test results.

Sound analysis as a tool for diagnosing the condition of electrical machines is becoming increasingly popular. The use of various acoustic methods, such as spectroscopy, frequency analysis, artificial intelligence, and time-frequency signal analysis, allows for early detection of machine failures.

The creation of a comprehensive tool to identify the operating status of a given electrical machine seems to be very desirable. The experiments conducted outline the further direction of research, which will allow the use of acoustic diagnostics supported by artificial intelligence methods to accelerate the diagnosis of a given device and thus reduce the costs of its possible repair. In addition, the acoustic signal-based method can be used in conjunction with other diagnostic methods. In this way, it can improve the diagnostics of electric motors. The proposed system can be used to detect problems in the initial phase before a failure becomes serious. This makes it possible to detect the problems that may be difficult to spot with traditional monitoring methods.

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