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DIAGNOSIS METHODS FOR MECHANISMS AND MACHINES BASED ON EMPIRICAL MODE DECOMPOSITION OF A VIBROSIGNAL AND THE WILCOXON TEST

Abstract. Methods for diagnosing mechanisms and machines based on the analysis of vibration signals are considered. In particular, the comparison of various algorithms for analyzing vibration signals in the time and frequency domains was made, methods for selecting diagnostic features and methods for secondary processing were analyzed. **The purpose of the study** is to develop algorithms for selecting the vibration signal envelope based on empirical mode decomposition and decomposition of the signal into intrinsic mode functions, algorithms for the spectral estimation of envelopes and to choose a criterion for making a decision on object classification. It is proposed to choose the non-parametric Wilcoxon signed-rank test to determine the statistical significance of the difference between the parameters of normal and faulty objects. The multichannel microcontroller system for collecting data from an accelerometer and transmitting it to a computer via a local Wi-Fi network, including a number of independent data gathering nodes connected to a common distributed computing system, has been developed and experimentally studied. The computer processing of the recorded vibration signals for serviceable and faulty mechanisms was performed, including data decoding, Hilbert-Huang transform, spectral analysis using the Welch and Yule-Walker methods, and the choice of a diagnostic feature that provides maximum reliability of recognition. Based on the **results of the work**, it was determined that the empirical mode decomposition makes it possible to obtain vibration signal envelopes suitable for further diagnostics. Recommendations are developed for choosing the intrinsic mode function and the spectral analysis algorithm, it is determined that the first intrinsic mode function is the most informative for the mechanism under study. In accordance with the Wilcoxon criterion, the degree of diagnostic reliability was numerically determined in the analysis of the spectral power density of the vibration signal and the amplitude of peaks, and the comparison of probabilities of error-free recognition for various modifications of the algorithm was made.

Keywords: vibration signal; spectral analysis; empirical mode decomposition; Hilbert-Huang transform; intrinsic mode functions; Wilcoxon test; accelerometer; microcontroller.

Introduction

The improvement of the efficiency, reliability and resource, as well as the safe operation of machines and mechanisms can be achieved primarily by periodically assessing their technical condition in order to identify defects in the early stages of their development. To solve this problem, a wide range of methods of non-destructive testing are used, primarily vibration diagnostics, a method for diagnosing technical systems and equipment based on the analysis of vibration parameters generated by operating equipment. It is the vibration signal, having sufficiently complete information about the operation of the unit and its elements, that can be a reliable indicator of its condition.

The first methods of vibration diagnostics, widely introduced into engineering practice, were the measurement of the maximum absolute signal value (Peak), the effective value (root mean square value, RMS) and the PEAK factor - the ratio of the Peak parameter to the RMS. The main disadvantage of these methods is the rather late detection of a fault, when the defect is sufficiently developed and is accompanied by a significant increase in the overall vibration level.

A set of methods for diagnosing defects in rotating equipment that use vibration signal spectra for analysis is more effective. Measurement of vibration signal spectra, including low and medium frequencies, as well as peak values and envelope spectra of high-frequency vibration in the rotational support of machine or mechanism, allows to detect most types of defects before they become dangerous.

There are a number of modifications of diagnostic methods for equipment based on the spectral analysis of vibration signals. The ratio of the vibration signal power in two fixed frequency bands can be calculated. The criterion for the technical condition of the unit is the ratio of these calculated capacities. Similarly, the ratio of the amplitudes of the spectral peaks in different ranges and the ratio of the PEAK/RMS spectrum in individual bands can be chosen as a diagnostic feature. At the same time, in most algorithms, the vibration signal is detected by a digital detector (the signal envelope is constructed), and the usual spectrum is taken from it, which is subsequently analyzed.

It should be noted that despite the large number of studies in the field of vibration diagnostics, a set of issues have not been sufficiently developed and require further improvement. Thus, the development of algorithms that allow reducing the influence of interferences, increasing the accuracy of measurements and the reliability of diagnostics of rotating units is relevant.

Overview of methods for diagnosing mechanisms and machines based on the analysis of vibration signals

A significant number of works of domestic and foreign scientists are devoted to the analysis of methods for detecting faults in drives, turbines, bearings and other mechanisms containing rotating parts. Thus, in analytical reviews [1, 2], the main algorithms for computer diagnostics of mechanisms and machines based on digital signal processing methods are identified.

Temporal methods include analysis of the maximum and effective value of the vibration signal and the PEAK factor. In addition, many works analyze the statistical characteristics of vibration signals: standard deviation, skewness, kurtosis, higher order moments.

Methods based on the analysis of a vibration signal in the frequency domain are more common. In addition to the classical spectral analysis based on the Fourier transform, have recently been used methods of analyzing vibration signals, which provide greater accuracy and clarity of diagnostics: short-term Fourier transform [3, 4] with display of results in the form of spectrograms, Wavelet analysis [5], Wigner- Villa transform [6], bispectral analysis [7].

The factor limiting the application of this set of methods is the presence in the spectrum of harmonics caused by the engine speed, noise and artifacts created by data acquisition systems from the unit under study, and other interferences. These harmonics can mask spectral peaks important for diagnostics and make it difficult to isolate faulty mechanisms.

To a large extent, this problem is eliminated by calculating the spectrum not from the signal itself, but from its envelope. At the same time, in many works [8, 9] it is proposed to use the procedure of Empirical Mode Decomposition (EMD) to select the envelope. EMD decomposes the signal into intrinsic mode functions (IMF) that can be used as vibration signal envelopes.

Various methods of secondary processing of the obtained spectra and various decision rules can be used. Thus, in [8], the wavelet transform is additionally calculated from the high- and low-frequency spectral coefficients, and the multi-scale entropy IMF is calculated in [9]. In many works, neural networks [10], as well as singular value decomposition [11], are used to make a decision about the serviceability of the unit after calculating the EMF.

Unfortunately, in most of the known works the statistical significance of the results obtained is not assessed, and the choice of spectral frequencies, for which diagnostics is made, is carried out according to empirical formulas for the mechanical characteristics of bearings and other units, which may reduce the reliability of recognition.

The purpose of the paper is to develop algorithms for constructing envelopes of vibration signals and their spectral estimation, to choose a method for assessing the reliability of diagnostics and to experimentally study the proposed algorithms in order to determine the optimal parameters of the algorithm and the probability of correct classification.

Selection of vibration signal envelopes using the EMD method

The analysis of the spectrum of vibration signals in many cases is difficult due to the predominance of harmonics in the spectrum, which correspond to the frequency of drive rotation and are multiples of it. So, in Fig. 1 the spectrum of vibrations of a mechanical unit rotated by a synchronous engine with a frequency of 50 Hz is given. It is obvious that the selection of harmonics that provide amplitude diagnostics, that correspond to natural vibrations of bearings, blades, gears and other mechanical objects, is largely difficult.

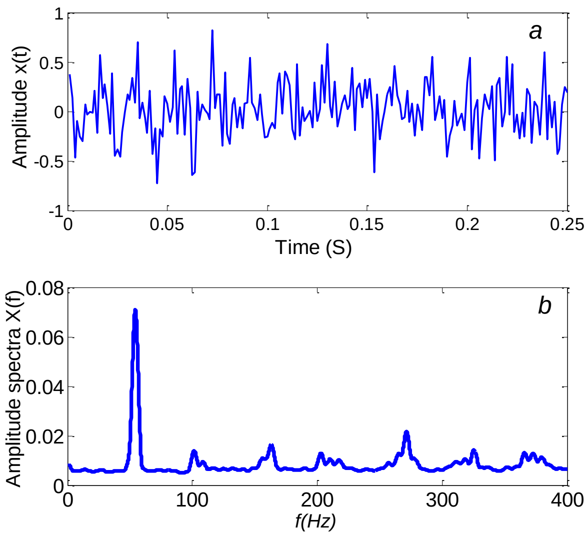

Fig. 1. Vibration signal (a) and its spectrum (b)

The analysis of the vibration signal envelope which will allow to reduce the influence of the engine speed and other interfering influences, can be more effective. There are a number of methods for constructing an envelope, however, as shown in [8, 9], the most effective method for analyzing vibration signals is the empirical mode decomposition method. The method was proposed by N. Huang in [12] and, as well as the Fourier transform and wavelet analysis, has found wide application in digital signal processing.

The EMD method is a part of the Hilbert-Huang transform and is an iterative computational procedure, as a result of which the signal is decomposed into empirical modes or intrinsic mode functions. Each intrinsic mode function must have the following properties:

1. The number of extreme points (highs and lows) and the number of zero crossings differ by no more than one.

2. The average value, which is determined by two envelopes - upper and lower, is equal to zero.

The essence of the EMD method lies in the sequential calculation of empirical modes $c_j(t)$ and remainders $r_j(t) = r_{j-1}(t) - c_j(t)$ and the representation of the analyzed signal $x(t)$ in the form:

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t), \tag{1}$$

where n is the number of empirical modes that is determined during the calculations.

The algorithm includes the following steps:

1. The extrema of the signal $x(t)$ located between each two successive sign changes are found.

2. By approximation with a cubic spline or due to another method, two envelopes - the lower $q(t)$ and the upper $p(t)$ are constructed.

3. The average value $m(t) = (q(t) + p(t))/2$ and the difference between the signal and its average value are

calculated: $h_{1,1}(t) = x(t) - m_{1,1}(t)$. The first index in the formula denotes the number of the intrinsic modt function, the second one is the iteration number during its calculation.

4. It is determined whether the resulting difference satisfies the above definition of an empirical mode. For this, the following condition must be checked:

$$S_{j,k} = \sum_{i=1}^{N}\left(h_{j,k}(t_i) - h_{j,k-1}(t_i)\right)^2 \Big/ \sum_{i=1}^{N}\left(h_{j,k-1}(t_i)\right)^2 < \varepsilon, \quad (2)$$

where i is the number of the discrete signal sample, N is the number of samples in the signal feagment, ε is the given error.

5. If the condition (2) is satisfied, the process stops. If the condition is not satisfied, the transition to step 1 is performed and the previous operations (searching for extrema, constructing envelopes, calculating the average and its subtraction) are repeated for the obtained difference $h_{1,1}(t)$.

The procedure for constructing the first approximation of IMF1 for the fragment of a vibration signal is shown in Fig. 2.

Thus, the so-called sifting process is performed with the assignment of h1, k(t) = $h_{1,k}(t) = h_{1,k-1}(t) - m_{1,k}(t)$ at each step. After the condition (2) is reached, the final value of the first IMF $c_1(t) = h_{1,d}(t)$ is determined, where d is the number of iterations.

As soon as the empirical mode, denoted by $c_1(t)$, is selected, the iterations stop. The remainder $r_1(t) = x(t) - c_1(t)$ is calculated and the whole algorithm is repeated again, but for the function $r_1(t)$. The number of algorithms passes that determines the amount of empirical modes n in the sum (1) is either set in advance, or the decomposition process continues until the remainder $r_n(t)$ turns out to be a monotonic function or has a conditioned small number of extrema. The process of decomposition of a vibration signal into empirical modes is shown in Fig. 3 (the first 8 IMFs are shown).

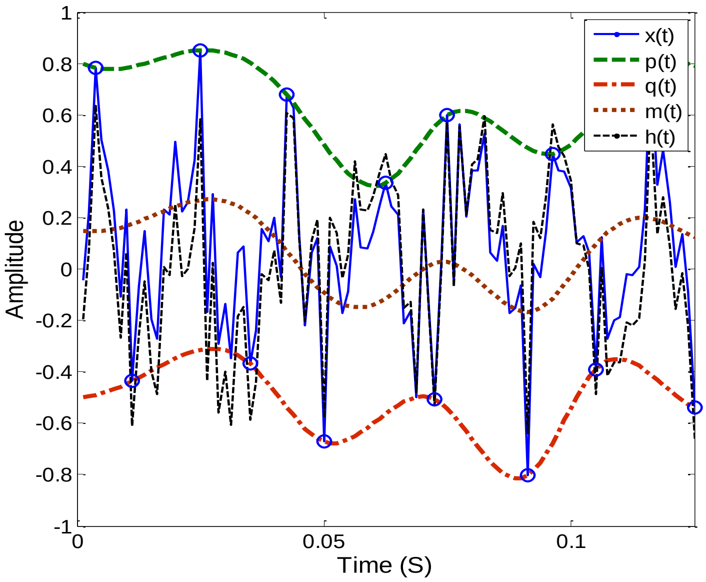

Fig. 2. Construction of the first approximation $h_{1,1}(t)$ of a vibration signal

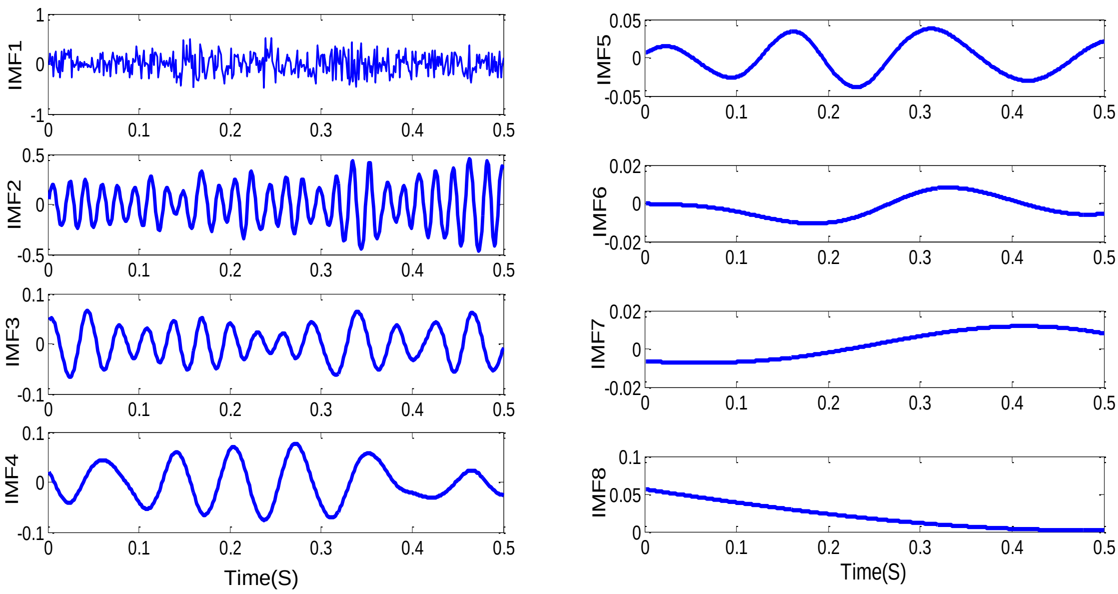

Fig. 3. Decomposition of a vibration signal into internal mode functions IMF

Validity estimation of diagnostic features

After selecting the envelope of a vibration signal using the empirical mode decomposition or another method, the question of choosing the diagnostic feature that provides, the most reliable separation of serviceable mechanisms and machines from defective ones, becomes relevant. The review of existing works showed that the spectral analysis of a signal envelope demonstrates the best results.

In this case, the comparison of the energy of the spectrum attributable to different frequency ranges is most often made, as well as the analysis of the amplitude and location of the spectral peaks. At the same time, the best diagnostic feature is the one that provides the maximum statistical significance of the difference between the samples of serviceable and defective mechanisms. To check the degree of difference between the samples, one or another statistical criterion should be chosen, that is, the rule by which the differences between two measurement samples will be checked. Since the power spectral density is distributed according to a law different from normal, it is advisable to choose one of the nonparametric criteria.

On the other hand, it is not always possible to obtain a significant number of measurements, especially for faulty objects. In this case, the Wilcoxon signed-rank test is most often used. The test is used to detect differences between the medians of two dependent samples with data distribution other than normal and the number of measurements in the samples from 5 to 25.

Checking the significance of the difference between the samples according to the Wilcoxon test is performed in the following order

1. Samples of parameters are formed for normal $\{x_1, x_2 \ldots x_N\}$ and faulty $\{y_1, y_2 \ldots y_N\}$ mechanisms.
2. Differences between the elements of the first and second sequences $\Delta_i = x_i - y_i$ are obtained.
3. A «typical» shift (positive or negative), corresponding to the expected sign of the parameter difference in the samples for the faulty and normal mechanisms, is selected.
4. The absolute values of the differences Δ_i, are ranked, and a lower rank is assigned to the smaller value.
5. T_{emp} **-** the sum of ranks corresponding to shifts in an atypical direction, is obtained.
6. From the tables of the Wilcoxon distribution for the obtained T_{emp} and the sequence size, the value of the probability P_0 of making a false positive decision is determined.
7. The significance level α is chosen (usually 0.05 or 0.1). If $P_0 \leq \alpha$, we conclude that the medians of the samples $\{x_i\}$ and $\{y_i\}$ are significantly different and the shift to the «typical» side is significantly dominant.

Experimental study of the developed method

To select the parameters of vibration signals that provide reliable diagnostics of machines and mechanisms, an experimental facility, shown in Fig.4, was built.

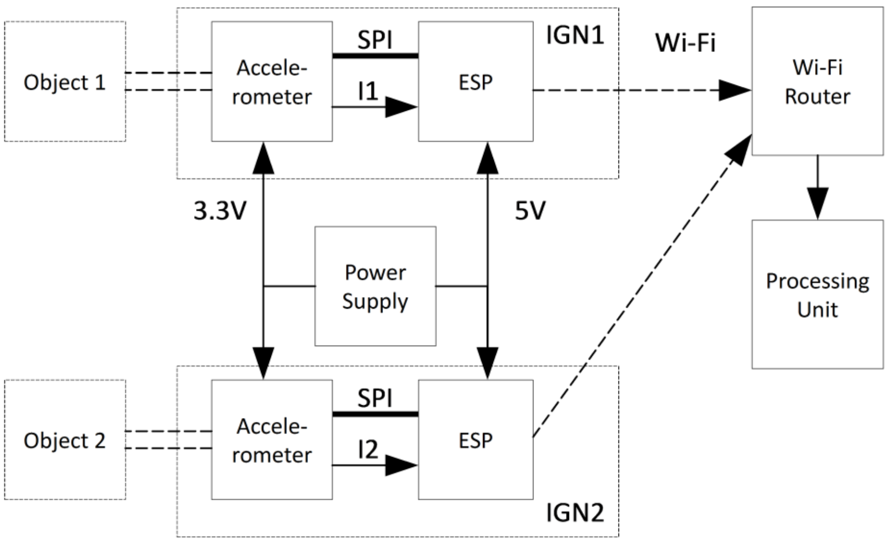

Fig. 4. The scheme of a facility for data acquisition: IGNn - nth Information Gathering node, In - nth Interrupt signal (Buffered Data Ready), ESP - Node control microcontroller with WiFi support

The facility consists of independent Information Gathering nodes (IGNs), which are connected to a common distributed computing system. Each node consists of an accelerometer and a microcontroller with support for a wireless data transfer protocol. The accelerometer is fixed directly to the object from which the data is taken. Data transfer is carried out using a high-speed SPI bus. The read data is placed in the internal buffer of the accelerometer, after it is half full, an interrupt is called, according to which the microcontroller reads the accumulated data and sends them wirelessly to the processing module. This approach allows the use of high sampling rates (up to 3.2 kHz) due to the parallel operation of the accelerometer (data acquisition) and the microcontroller (data transmission). In general, the system supports an easy way to extend the inspected objects by adding a new node.

IGN uses the ADXL345 as an accelerometer, and the microcontroller for data acquisition and transmission — ESP8266 [13]. After starting IGN, it searches for an available local Wi-Fi network and connects to it. IGN receives an IP address on the local network. After that, the data transfer protocol is configured: the SPI bus is initialized in the FULLDUPLEX mode, MASTER: the number of data bits is 8, the divider is 8, which gives a frequency of 80 MHz [14]. The GPIO pin of the microcontroller is configured to «data ready» "" interrupt input signal from the accelerometer, which activates the procedure for reading data from the accelerometer buffer.

Next, the accelerometer is directly configured, the Bandwidth Rate register is set to 0x0E, which gives a polling rate of 1600 Hz, the number of interrupt samples is set as 16, which is half the ADXL345 hardware buffer [15].

After setup, the interrupt mode is set to fill the buffer and the accelerometer is turned on to work in continuous mode.

The IGN software operates in an asynchronous mode, after receiving an interrupt signal from the accelerometer, data is read through three channels, the obtained values form a single data packet and are sent to the processing unit (the central computer of the system).

Each packet is prefaced with the following information:

1. the number of a package for synchronization;
2. the number of a package to restore the contiguous sequence;
3. countdown of the start time of data acquisition;
4. duration of data reading.

The packet is transmitted over a wireless communication channel using the UDP protocol. In addition to data packets, the module sends packets with system information: communication level, supply voltage and other information about the IGN status. Such packages allow to monitor the serviceability of all IGNs and perform synchronization in case of transmission errors or unit shutdown (restart).

The central computer of the system receives and stores information coming from the units, and also monitors the status of the units. When the control software of the central computer starts, a local area network is created, after which the computer goes into the standby mode for switching on the modules. When the next module is turned on, a section with a unique identifier (module identifier, date, time) is created in the database, in which the data packets coming from the module, as well as its status, will be recorded.

The system has been tested with two modules, each of which was connected with its own source of data (vibrations) - bearings located on the motor shaft. Both modules were connected to a common network through a router.

The same network includes a central computer with control software. After turning on the system and the electric motor, the data were taken for a certain time and placed in the database on the central computer, after which they were further processed.

The signals taken from normal and damaged mechanisms were subjected to empirical mode decomposition in order to obtain envelopes in the form of intrinsic mode functions. For the obtained IMF envelopes, the spectral analysis was performed both by the Welch periodogram method and on the basis of autoregression models using the Yule-Walker equations [16].

For various IMFs, the location and amplitude of the spectral peaks, as well as the distribution of the power spectral density along the frequency axis, were analyzed. T

he preliminary analysis showed that the energy spectrum of the IMF1 function turned out to be the most informative. Typical curves of the power spectral density IMF1 of normal and faulty gears are shown in Fig. 5.

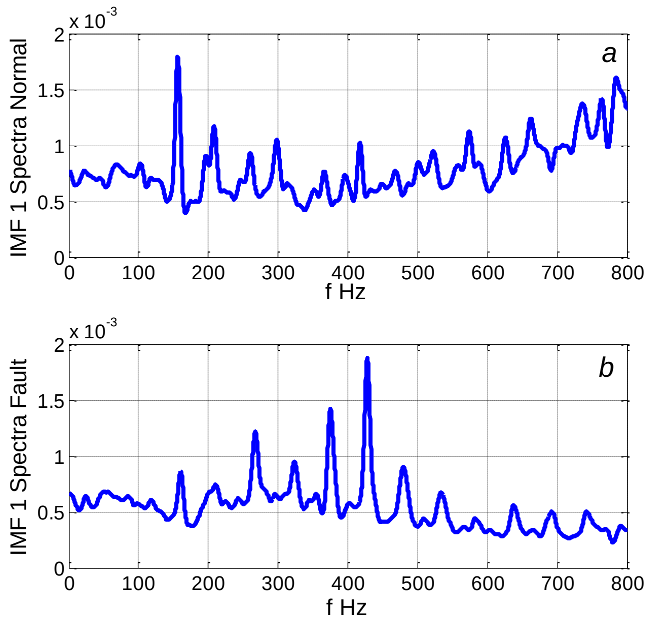

Fig. 5. Power spectral density IMF1 of normal (a) and faulty (b) gears

It was determined that for a normal gear, most of the energy of the IMF1 spectrum is in the range of 100-300 Hz, the maximum spectral peaks are also located there. At the same time, the faulty gear has a rise in the spectrum in the range of 300-500 Hz. Thus, it is suggested to choose $d_1 = E_1/E_2$, $d_2 = A_1/A_2$ as diagnostic parameters, where E_1, E_2 are the energy of the spectrum, A_1, A_2 are the amplitude of the maximum peaks in the bands of 100–300 Hz and 300–500 Hz, respectively. It is assumed that for a normal mechanism the condition $d_1 < d_{1m}$, $d_2 < d_{2m}$ is satisfied. In the presence of a fault, $d_1 > d_{1m}$, $d_2 > d_{2m}$, respectively, where d_{1m} , d_{2m} are medians of the sample.

The reliability analysis of the selected criterion was made. For this, a number of serviceable mechanisms and a number of mechanisms with malfunctions were selected (the blades are bent or rub against the body, the knife has fallen off or vibrates, etc.). Based on the results of the experiment, the Table 1 was constructed.

Table 1 – **The values of parameters d_1 and d_2 for normal and faulty mechanisms**

Number of the experiment		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Normal	d_1	0.8802	0.8116	0.9186	0.8708	0.9431	1.0941	1.2093	0.9088
	d_2	0.5728	0.5849	0.6558	0.5700	0.8984	0.5359	1.0234	0.7364
Faulty	d_1	1.0997	1.3728	1.1572	1.1311	0.8858	1.4555	1.1118	1.2915
	d_2	1.0744	1.1489	0.9601	1.5420	0.5973	2.0527	1.0064	0.9265

The analysis of the given data in accordance with the Wilcoxon test criterion showed that the probability of false acceptance of the hypothesis about the difference in the medians of the samples of the d_1 parameter is 0.0391, the d_2 parameter is 0.0547. Thus, the probability of correct classification of mechanisms by comparing the energy of the spectrum is $P_e = 1 - P_0 = 0.9609$, by comparing the peak amplitude $P_p = 0.9453$.

At the same time, checking the spectra of other IMFs and comparing other frequency ranges did not allow to distinguish vibration signals with a probability higher than 0.9218.

It is obvious that the proposed methodology can be successfully applied to diagnose any other mechanisms for which parameters that provide the highest possible diagnostic reliability, can be selected.

Conclusions

1. The spectrum of a vibration signal contains harmonics of significant amplitude, corresponding to the engine speed and multiples of it, and in its original form cannot be used to diagnose mechanisms.

2. Empirical mode decomposition provides vibration signal envelopes suitable for diagnostics by spectral analysis or otherwise.

3. The proposed microcontroller data acquisition system makes it possible to record a vibration signal with a sufficient sampling rate and, at the same time, easily increase the amount of inspected objects.

4. To determine the reliability of diagnostics, it is advisable to use the Wilcoxon test, which allows to process small samples containing measurements distributed according to a law different from normal.

5. By comparing the energy of the spectra of the intrinsic mode function IMF1 of a vibration signal in different bands and the amplitudes of spectral peaks, the reliability of diagnostics is 0.9609 and 0.9453, respectively.

6. It is advisable to further develop the proposed algorithms in order to ensure the detection of a specific defect.

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Методи діагностики механізмів і машин на основі емпіричної модової декомпозиції вібросигналу і теста Уілкоксона

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Анотація. Розглянуто методи діагностики механізмів та машин на основі аналізу вібросигналів. Зокрема, виконано порівняння різних алгоритмів аналізу вібросигналів у часовій та частотній області, проаналізовано методи виділення діагностичних ознак та методи вторинної обробки. **Метою дослідження** є розробка алгоритмів виділення огинаючої вібросигналу на основі емпіричної модової декомпозиції та розкладання сигналу на внутрішні модові функції, алгоритмів спектрального оцінювання огинаючих та вибір критерію для ухвалення рішення про класифікацію об'єкта. Запропоновано вибрати непараметричний тест Уілкоксону для визначення статистичної значущості різниці між параметрами справного та бракованого об'єктів. Розроблено та експериментально досліджено багатоканальну мікроконтролерну систему знімання даних з акселерометра та передачі в комп'ютер по локальній мережі Wi-Fi, що включає ряд незалежних модулів збору даних, з'єднаних у загальну розподілену обчислювальну систему. Виконано комп'ютерну обробку знятих вібросигналів для справних та несправних механізмів, що включає декодування даних, перетворення Гільберта-Хуанга, спектральний аналіз методами Уелча та Юла-Уолкера та вибір діагностичної ознаки, що забезпечує максимальну достовірність розпізнавання. За **результатами роботи** визначено, що емпірична модова декомпозиція дозволяє отримувати огинаючі вібросигналів, придатні для подальшої діагностики. Розроблено рекомендації щодо вибору внутрішньої модової функції та алгоритму спектрального аналізу, визначено, що максимально інформативною для досліджуваного механізму є перша внутрішня модова функція. Відповідно до критерію Уілкоксона чисельно визначено ступінь достовірності діагностики при аналізі спектральної щільності потужності вібросигналу та амплітуди піків та проведено порівняння ймовірностей безпомилкового розпізнавання для різних модифікацій алгоритму.

Ключові слова: вібросигнал; спектральний аналіз; емпірична модова декомпозиція; перетворення Гільберта-Хуанга; внутрішні модові функції; критерій Уілкоксона; акселерометр; мікроконтролер.