Automated Identification of Critical Malfunctions of Aircraft Engines Based on Modified Wavelet Transform and Deep Neural Network Clustering

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Abstract

The paper considers the issues of automatic classification of vibrational states of aircraft engine malfunctions based on the use of convolutional neural network processing of vibrational measurement data presented in spectral form and the knowledge of experts with experience in interpreting spectrograms characterizing the vibrational state of aircraft engines. The developed spectrogram analysis model allows the state monitoring of aircraft engines in automatic mode both during maintenance and in flight operation. The system is able to timely notify technical personnel or crew about the appearance of signs of emergency situations, as well as the type of possible malfunctions. It is shown that the main problem affecting the quality of detection of a potential turbine malfunction is a small sample of data corresponding to malfunctioning states. It is proposed to detect emission anomalies in a small sample by recognizing a modified wavelet transform and neural network clustering, which allows more complete formation of a training sample. The data samples used in training the neural network classifier during the experimental studies were generated on the basis of existing archive files containing complete aperture data from engine vibration sensors and information about malfunctions detected in them.

Keywords: big data, aircraft engines, gas turbine engines, intelligent system, software, deep learning, neural network, recurrent network, vibrodiagnostics, troubleshooting classification, wavelet transform, predicative analytics

1. Introduction

At present in the context of a reduction in the number of personnel, the maintenance staff of aviation equipment remains mainly maintenance specialists, while the number of qualified analysts-experts who are able to analyze spectrograms of data recorded by vibration sensors in continuous monitoring mode is decreasing. Thus, the urgent task is to develop the intelligent systems for monitoring the vibration state of aircraft engines and the detection of signs of malfunctions at an early stage.
regard, in recent years, special interest has been shown in the creation of monitoring and vibration diagnostics systems that not only provide for the detection of increased vibration activity of the turbine rotor or pumps, but also, based on the analysis of the obtained vibration information, make it possible to identify the causes of such vibration activity and formulate technical solutions and recommendations for its elimination [2, 3]. Monitoring the machines by the use of such systems is carried out in real time and is necessary to monitor continuously the machine vibration state, in particular, the vibration level of its main components and elements. Diagnosis of defects is carried out on the basis of pre-formed experimental databases and generalized knowledge bases that correlate an increased level of vibration activity with the provided it causes.

2. Turbine failure analysis

Fault analysis by spectrograms of a vibrational signal is one of the most accurate diagnostic methods, and, in connection with this, methods based on it are widespread [4, 5]. The formation of the algorithms set intended for a specific model for obtaining information in the form of diagnostic features is possible with the use of an orthonormal system of basic functions. The feature set is selected on the basis of its acceptability for solving diagnostic problems, the degree of reliability of diagnosis and is also limited by the capabilities of the calculator used — supporting the hardware multiplication, capacity, memory size and other factors. A set of orthonormal feature systems acceptable for spectral diagnostics are limited. The orthogonal trigonometric Fourier functions — the discrete and fast Fourier transform have the widest spreading. Non-trigonometric Fourier series are also common, Chebyshev orthogonal polygons and Walsh functions, in particular.

The tasks of vibro-acoustic diagnostics of gas turbine engines (hereinafter — GTE) can be divided into two groups. The first group of tasks is the determination of the technical condition of the engine and its elements (Figure 1), as well as the early detection of faults to ensure the required engine reliability and reduce costs associated with eliminating the consequences of malfunctions. These problems are solved at the operation stage, during bench tests, during fine-tuning and in production.

Figure 1. Installation points for vibration sensors.

The second group of tasks is about the assessment of the vibrational state of the engine and its elements in order to prevent malfunctions caused by vibrations (Figure 2). The vibrational state of the engine is defined the set of the parameters characterizing the vibration of the engine. The vibrational state can be determined for a given point the engine marked, a certain zone of diagram or the engine as a whole, as well as for a family of engines. The vibration state is determined for certain operating modes or for a set of engine operating modes, as well as for various operating conditions. Here are below the fault categories, which identify experts in the spectral characteristics of vibration signals.

Turbine rotor malfunctions: rotor imbalance, attachment failure, unacceptable runout of the rotor, unacceptable axial shift.
To assess the vibration velocity, the RMS of the vibration velocity is most often used — the root-mean-square velocity of the measured vibration velocity. The standards define a method of measuring the RMS — in the frequency range from 10 to 1000 Hz and a number of values of the RMS of vibration velocity: ... 4.5, 7.1, 11.2, ... — they differ by about 1.6 times. For units of different types and capacities, the value of norms of these series is set. When assessing the vibration state, one of the following parameters is:

RMS of vibration velocity in the frequency band 10–1000 Hz, Ve [mm/s];
RMS of vibration velocity in the octave frequency band, including the rotor speed, [mm/s];
Range of vibration displacement, [microns].

Evaluation of the vibration state of any node of the mechanism is carried out by comparing the maximum of the parameters measured of this node with the normalized limit value.

Due to this way of assessing the technical condition for most types of engines the following rules are true:

If Ve not greater than approximately 5 mm/s, the state of the engine is considered to be normal. The engine can be operated without restrictions;
If Ve exceeding 5 mm/s, but not exceeding circa 12 mm/s, the state of the engine is considered to be acceptable. The
engine is operational, but needs repair. Operation of the engine is not recommended; if \( V_e > 12 \, \text{mm/s} \), the state of the engine is considered to be dangerous. Do not start the engine and eliminate defects as soon as possible.

The maximum value of the range of vibration displacement can be estimated by the formula:

\[
S_v = \frac{500 \times \text{[mm/s]}}{f \times \text{[Hz]}}
\]

where \( f \) — turbine rotor speed.

Below, here is a spectrogram by time. Data was obtained by the SlamStick diagnostic software on the outside of the aircraft when it rose from 23,000 feet to 40,000 feet. The temperature dropped from 14°C to 31°C (58°F to –24°F) during the test.

Evaluation of equipment condition by the general level of vibration is one of the simplest forms of technical condition assessment. The maximum value is used as a diagnostic parameter (Figure 4), the list of conditions (normal, permissible, dangerous) is used as the technical state classes, and the algorithm for comparing the diagnostic parameter with the normalized limit value is used as diagnostic algorithms.

4) In the spectrum of the envelope, they monitor the frequency components characteristic of this type of defect (tooth frequency). An increase in the modulation coefficient of the characteristic harmonic indicates the development of a defect.

3. Spectral response troubleshooting method

Algorithms have been developed for the spectral processing of multicomponent vibration signals based on a harmonic wavelet transform [5–7] which are consistent with the proposed model and allow estimating signal parameters in the time domain. To simulate GTE malfunctions a rotary stand with vibration sensors was developed (Figure 5).

The basic functions used in calculating the wavelet coefficients of the harmonic wavelet transform correspond in shape to the individual sections (both local and extended) of the vibration signals under study, which allows the use of harmonic wavelets to approximate these signals. The developed algorithms take into account the features of the considered vibrational signals and are implemented in 2 stages. At the first stage, the signal is cleared of noise using a modified threshold processing of wavelet coefficients, the use of which does not lead to a shift in the desired process boundaries. At the second stage, by selecting sections with insignificant wavelet coefficients, the signal is cleaned from noise to estimate the time boundaries of the established vibrational processes.
Due to the linearity property of the harmonic wavelet transform, the wavelet coefficients $a_{j\rho}(m)$ of the noisy signal $s(n)$ are represented in the form:

$$a_{j\rho}(m) = w_{j\rho}(m) + v_{j\rho}(m),$$

where $j$ is the level number of the wavelet decomposition; $m$ is the number of wavelet coefficient; $w_{j\rho}(m) —$ wavelet coefficients of the useful signal; $v_{j\rho}(m) —$ wavelet coefficients of the noise present in the analyzed vibrational signal.

The peculiarity of this representation is that the wavelet coefficients $a_{j\rho}(m)$, corresponding to the analyzed vibration process are complex. In this regard, their further threshold processing necessary to remove noise from the signal should be based on modified thresholds that take into account the distribution of noise over noise levels.

Due to the oscillating structure of the considered steady-state vibration processes (SSVP), the wavelet coefficients of the mixture of the steady-state vibration process and noise are approximately equal to the wavelet coefficients of the noise:

$$a_{\text{SSVP}}(m) \cong v_{\text{SSVP}}(m),$$

where $a_{\text{SSVP}}(m)$ are the wavelet coefficients of the mixture of the steady-state vibration process (SSVP) and noise; $v_{\text{SSVP}}(m) —$ wavelet coefficients of the noise component of the steady-state vibration process.

Vibration values $w_{j\rho}(m)$ are defined as follows:

$$w_{j\rho}(m) = G[a_{j\rho}(m), \rho],$$

where $G$ is the nonlinear operator of the modified soft threshold processing of the wavelet coefficients $a_{j\rho}(m)$; $\rho$ — the modified threshold values.

It was determined that the processing of noisy vibration signals set octave filters, harmonic respective wavelet transformation, the standard noise deviation (SND) for each successive level of decomposition is reduced in time compared to the previous one. The following expression was obtained for calculating the thresholds:

$$\rho_j = \frac{\sigma_q}{\sqrt{2^{j/2}}} \cdot \sqrt{\ln N},$$

where $\sigma_q$ is the estimate of the standard deviation of the noise component at the thinnest level of decomposition (this level, due to the pronounced oscillating structure, contains the largest share of noise) with the number $q = \log_2 N - 1$; the threshold $\rho_j$ is applied to the real and imaginary parts of the wavelet coefficients.

The expressions for calculating the modified wavelet coefficients (taking into account the found thresholds) and the signal cleared of noise have the form:

$$\hat{w}_{j\rho}(m) = \begin{cases} a_{j\rho}(m) - \rho_j, & a_{j\rho}(m) > \rho_j; \\ 0, & \rho_j < a_{j\rho}(m) \leq \rho_j; \\ a_{j\rho}(m) + \rho_j, & a_{j\rho}(m) \leq \rho_j, \end{cases}$$

$$\hat{s}(n) = W^{-1}[\hat{w}_{j\rho}(m)],$$

where $\hat{w}_{j\rho}(m) —$ modified wavelet coefficients; $\hat{s}(n) —$ signal cleared of noise; $W^{-1}$ is the inverse harmonic wavelet transform operator; $\rho_j = \frac{\sigma_q}{\sqrt{2^{j/2}} \sqrt{\ln N}}$. The $\sigma_q$ estimate is determined in accordance with the least squares method or median estimate (normalized median of the absolute deviations of the wavelet coefficients from their median).

After obtaining an estimate of the vibration signal, sections with insignificant wavelet coefficients at the thinnest level of the wavelet decomposition are selected. Modified wavelet coefficients $\hat{w}_{j\rho}(m)$ of the vibrated signal cleared of noise are considered insignificant if they satisfy the condition:

$$|\hat{w}_{j\rho}(m)| < \eta, \quad q = \log_2 N - 1,$$

where $\eta \approx 10^{-3}...10^{-5}$.

Otherwise, the wavelet coefficients are significant and correspond to a transient or shock process. According to the results of segmentation in wavelet field it is generated an $A_j$ wavelet coefficients set at the subtle level of decomposition:

$$A_j : [\hat{w}_{j\rho}(m)],$$

where $n_r, n_i, ..., n_{r_{\text{last}}}, n_{i_{\text{last}}}$ are the boundaries of the established vibrational processes in the space of wavelet coefficients.

The found boundaries of insignificant sections are recalculated into the time domain, and thereby the vibrational signal is segmented.

To evaluate the signal parameters characterizing the potentially dangerous resonance phenomena and the energy properties of mechanical vibrations, a computational algorithm based on wavelet-smoothing [5, 6] Fourier periodograms [6] of steady-state vibration processes has been developed.

When developing the algorithm, it was taken into account that the processes under study have a continuous spectrum, an irregular structure, and distributed local features in the frequency domain, including the most important of them — resonance peaks. In addition, the algorithm allows us to use not only the samples of the signal in the time domain, but also the samples of its DFT (discrete Fourier transform) or the samples of its Fourier periodograms coming from the object.
via telemetric communication channels as initial information for estimating the parameters of a multicomponent vibration signal.

4. Implementation using a neural network

Convolutional Neural Network (CNN) [7] is a class of models that successfully solve the problem of modified wavelet transform. Convolutional neural networks are part of the “deep learning” machine learning paradigm, which has proven itself very well in various tasks. The principle of its use is the sequential use of convolution operations and the choice of the maximum value (max-polling [8]).

At first, the neural network classifier was trained with tuned wavelet coefficients [9, 10]. Recurrent layers highlight the spectrogram feature space, which allows finding a suitable critical cause of the defect and displayed on the spectrogram.

At the output there will be a vector $k_1, ..., k_n$; the coefficients $k_n$ are the correlation coefficients with clusters of spectrogram images of individual GTE nodes, produced the neural network (Figure 6).

![Figure 6. Configuring neural network classifier layers and spectrogram input.](image)

To train the layers of a neural network without a teacher, gradient minimization of error is used. Recurrent auto encoders allow you to work not with a single input vector, but with the time sequence of vectors. The number of vectors in the sequence is set by the parameter val_acc (validation data vector) and val_loss (loss data vector) (Figure 7) [11, 12].

After each stage of training, the quality of training achieved at this stage was checked. For this, sets of input data that were not involved in the training were presented at the network inputs [13, 14]. After that, the probability (share) of correct and false recognition (classification) of the input data sets was calculated and a table of the maximum probability of incorrect classification depending on the number of the training stage was compiled [15]. Training is considered successful if the reliability of the classification of faults is at least 0.95.

![Figure 7. The scheme of training layers of the neural network classifier.](image)

When considering Figure 4, four clusters with deviations from the norm can be distinguished. In two clusters, it is clearly seen that the dispersion will not exceed 0.2. Such clusters reveal groups of vibration accelerations in the spectrogram, which clearly indicate the effect of thermal expansion of the rotor.

![Figure 8. Visualization of vibration acceleration vectors in hidden space using t-NSE.](image)

In Fig. 5, the vibration acceleration vectors are represented in a hidden space using t-NSE, it is also possible to distinguish 4 main clusters corresponding to critical vibration states. Two
clusters closer to the center contain data sets corresponding to vibrations associated with thermal expansion of the rotor. 

The method was tested in the analysis of the spectral characteristics of vibration parameters measured during the operation of the developed stand, simulating the malfunction of the gas turbine engine. For various turbine generator failures, vibration signals were obtained, to which the fast Fourier transform was applied. As a result, signal spectra (spectrograms) were obtained for each type of fault. Informative diagnostic features represent the amplitude of the spectrogram at given frequencies.

After each stage of training, the quality of training achieved at this stage of training was checked by presenting input data sets that did not participate in the training to the inputs of the simulation stand. After that, the probability (share) of the correct and false recognition (classification) of the input data sets was calculated and a table of the maximum probability of incorrect classification depending on the number of the training stage was compiled. Training is considered successful if the reliability of the classification of faults is at least 0.95.

To evaluate the accuracy of the forecast, we calculate the coefficient of determination of \( R^2 \) and the average absolute error (MAE). Mean Modulus of Deviation (MAE — Mean Absolute Error or MAD — Mean Absolute Deviation):

\[
MAE = \frac{1}{m} \sum_{i=1}^{m} |a_i - y_i|, \tag{9}
\]

where \( a_i \) is the predicted result, \( y_i \) is the actual result, \( m \) is the sample size. \( R^2 \) is the variance fraction of the dependent variable.

It was calculated the value of the reliability of detection of the predicted malfunction and the indicators of the accuracy of the forecast (table 1).

| №№ | Fault signal | Validity of definition | Operand function | \( R^2 \) | MAE |
|---|---|---|---|---|---|
| 11 | «Rotor imbalance» | 0.95 | HEAT DEFLECTION ROTOR GTE | 0.86 | 730 |
| 22 | «Rotor imbalance» | 0.98 | GTE ROTOR IMBALANCE | 0.81 | 620 |
| 33 | «Loosening the mounting of the support nodes» | 0.98 | TOUCHING IN THE OPPOSITE PART OF THE SUPPORT NODES | 0.94 | 650 |
| 44 | «Rotor imbalance» | 0.96 | ENGINE SHAFT ROTOR CURVING | 0.86 | 620 |
| 55 | «Damage to babbit loose leaves» | 0.98 | BEARING SHAFT IN BEARING | 0.88 | 690 |
| 66 | «Increased clearance of rotor bearing» | 0.97 | VIBRATION LEAP | 0.71 | 870 |
| 78 | «Increased clearance of rotor bearing» | 0.99 | BEARING VIBRATION MEASUREMENT CHANNEL MALFUNCTION | 0.9 | 640 |

Based on the analysis of the reaction of the vibration analysis system, it can be concluded that the application of the module for forecasting the category of malfunction of a gas turbine engine is effective.

For this input, the reliability of the fault classification was calculated. The reliability of the classification of malfunctions according to the parameters of the absolute vibration of the bearings of the GTE bearings was at least 0.95.

5. Conclusion

Thus, an approach to the analysis of aircraft GTE malfunctions based on spectral characteristics is proposed. For analysis, we used a modified wavelet transform apparatus using a neural network of the recurrent autoencoder type. As a result, the neural network has learned to identify clusters with critical vibrational states at a time interval of more than 24 hours. When new data appears, the prediction module will establish a data cluster with a dispersion of no more than 0.2 and determine the type of predicted malfunction.

This approach and methods have their limitations, studies of which can be the subject of further search and experiments, including those used with other non-destructive testing means of rotor assemblies [16].

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