DECISION MAKING OF AIRCRAFT ENGINE BLADES CONDITION BASED ON BISPECTRAL ANALYSIS OF THE VIBROACOUSTICAL SIGNAL

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ABSTRACT. In this paper the simulation of vibroacoustical signals radiated by the engine turbine at the stationary vibration excitation is carried out for situations when all turbine blades have no defects and one blade has a small fatigue crack. Bispectral analysis is used for diagnostic information processing. It demonstrates that appearance and evolution of the fatigue crack in a blade change intensity of global and local extremums of bispectral modules. The results of bispectral processing and Probability Neural Network (PNN) are used to recognize of the turbine blades condition. The efficiency factor is used for precision analysis.

INTRODUCTION

Now the problem of prolongation of aircraft turbine engine working life and increasing their reliability is the issue of the day. This problem may be solved using effective methods and means of technical condition monitoring for those engine systems, units, and components which limit its working life to the utmost. These components are turbine and compressor blades which contain as usual the majority of engine strengthening faults caused by vibration.

Vibration and vibroacoustical blade condition monitoring and incipient strengthening faults diagnostics permit to avoid the engine destruction during it exploitation, raise reliability, and increase its working life. On the other hand, vibroacoustical methods provide the possibility to diagnose and non-destructively evaluate defects without disassembling an engine.

This work is dedicated to further development of low-frequency vibration and vibroacoustical diagnostic methods which are used for monitoring, diagnosis, and evaluation of small fatigue cracks in aircraft engine blades at an engine stationary and non-stationary operating modes. Low-frequency vibrating and acoustical noises (0-25 kHz) are considered as diagnosis information. These noises are radiated by blades of a rotor which rotates with steady or varying frequency.

PROBLEM STATEMEN

In order to develop a monitoring system it is necessary to solve some theoretical and applied problems such as processing of diagnostic information, diagnostic features extraction, and decision-making about technical condition of engine blades.

One of the effective methods used for signal processing is higher-order spectral analysis which is based on use of higher-order statistical characteristics [1]. This method has substantial advantages in comparison with the tradition spectral-correlation analysis. It reduces noise influence on diagnostic features and extracts combination and modulation frequency components which are statistically connected.

Recognition of test object condition using extracted diagnostic features during signal processing is the final procedure of a diagnostic process. In development automatic vibroacoustical monitoring system the problem of recognition can be solved using neural networks.

The aim of this work is efficiency analysis of bispectrums using neural networks for recognition of aircraft engine blade condition at stationary regimes.

SIMULATION OF VIBROACOUSTICAL SIGNALS

Simulation of output vibroacoustical signals is made according to the diagram demonstrated on "Fig. 1". The model of an aircraft engine turbine contains 21 blades and is presented by a control system consisting of dynamic units with parallel connection ($Z_i, i=\overline{1,n}$). As the input effect it is considered vibration rotor excitation P(t) at stationary operating mode. It is described by the model of a polyharmonic process:

$$P(t)=\sum_{i=1}^{n} P_i \sin\left(i2\pi f_p t+\varphi_{i0}\right), \tag{1}$$

where P_i, φ_{i0} are amplitude and starting phase of i-th harmonics accordingly; f_p is excitation frequency which corresponds to engine rotating speed.

Simulation is realized with following data: $P_1 : P_2 = 1 : 10^{-2}; f_p$ =125 Hz; n=2; φ_{i0} are random starting phases uniformly distributed in the range $[0;2\pi]$.

Defectless blades are described by the model of an linear oscillating system with natural frequency ω_* ($f_* = 600$ Hz). The pulse characteristic of it is:

$$g_*(t)=\frac{1}{\omega_*}\sin \omega_* t\ . \tag{2}$$

The model of a blade with a fatigue crack is presented by the model of an oscillating system with piecewise-linear characteristic of a recovering force. The pulse characteristic of a blade model is expansion in fourier series at harmonics of the cracked blade model base frequency ω_0 [2]:

$$g(t)=\frac{a_0}{2}+\sum_{k=1}^{K} a_k \cos k\omega_0 t\ , \tag{3}$$

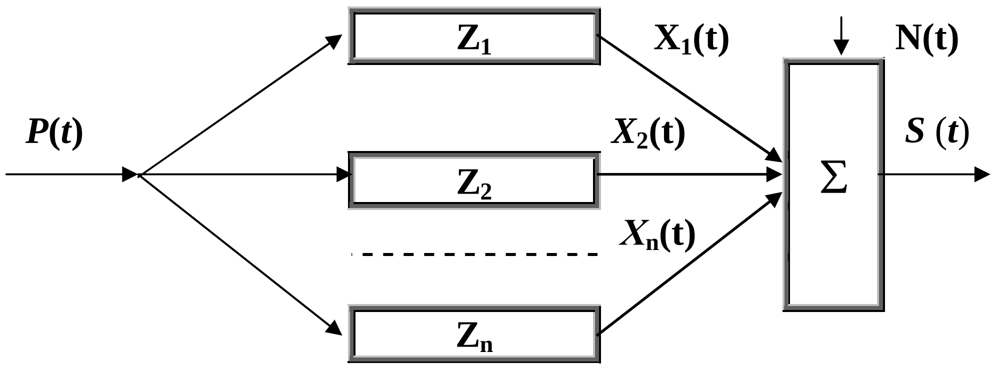


FIGURE 1. A diagram of vibroacoustical signals simulation.

where $a_0 = \dfrac{4(1-\varsigma)}{\pi\omega_*\varsigma}$; $a_k = \dfrac{4(1+\varsigma)^3(1-\varsigma)^2}{\pi\omega_*\varsigma[(\varsigma+1)^2 - 4k^2][(\varsigma+1)^2 - 4\varsigma^2 k^2]}\cos\dfrac{\pi k}{\varsigma+1}$;

$\omega_0 = 2\omega_*\varsigma/(1+\varsigma)$; $\varsigma = \sqrt{1-\vartheta}$; ϑ is a crack parameter, relative rigidity change.

The output signals X_i are defined by convolution of the input excitation (1) with the corresponding pulse characteristic (2) or (3). The convolution for each sampled reading is defined from expression:

$$X_{ij} = \Delta T \sum_{\mu=1}^{j} g_{j-\mu+1} P_\mu , \tag{4}$$

where ΔT is sampling period, j is a number of sampled reading.

Output signal S(t) is a sum of blade model responses in form (4) and stationary noise N(t). The characteristics of noise are set in such a way as to provide signal-to-noise merit $\rho = 10^1,..., 10^5$.

Simulation was accomplished in time frame 1c with the sampling period $\Delta T = 2\cdot 10^{-4}$ c providing total number of points N = 5000. Signals S(t) were found at mentioned above data and different intensity noise N(t) for defectless blades and for case one of the blades had a crack with parameter ϑ. Simulated vibroacoustical signals were processed using higher-order spectral analysis (bispectral analysis).

HIGHER-ORDER SPECTRAL ANALYSIS

It is known that spectral density of a stationary process $x(n)$ can be found using Fourier transform for autocorrelation sequence or autocorrelation function of a process [1]. The natural generalization of autocorrelation function are higher-order moments, and specific nonlinear combinations of these moments are cumulants.

The first order cumulant of a stationary process is its average value. Higher-order cumulants are invariant to average value change, therefore they can be found for processes with zero average value from the expression [3]:

$$C_{2x}(k) = E\{x^*(n)x(n+k)\}; \tag{5}$$

$$C_{3x}(k,l) = E\{x^*(n)x(n+k)x(n+l)\}; \tag{6}$$

$$C_{4x}(k,l,m)=E\{x^*(n)x(n+k)x(n+l)x^*(n+m\}-C_{2x}(k)C_{2x}(l-m)-C_{2x}(l)C_{2x}(k-m)- \\ -M^*_{2x}(m)M_{2x}(k-l) \quad , \tag{7}$$

where $E\{\bullet\}$ indicates ensemble averaging; * -is mark conjugating;

$M_{2x}(m)=E\{x(n)x(n+m)\}=C_{2x}(m)$ - for real-valued processes.

The autocorrelation function is a cumulant of the second order according to (5). Higher-order spectral characteristics can be found using Fourier transform for appropriate cumulants:

$$S_{2x}(f)=\sum_{k=-\infty}^{\infty}C_{2x}(k)\exp(-j2\pi fk), \tag{8}$$

$$S_{3x}(f_1,f_2)=\sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty}C_{3x}(k,l)\exp(-j2\pi f_1 k)\exp(-j2\pi f_2 l); \tag{9}$$

$$S_{4x}(f_1,f_2,f_3)=\sum_{k,l,m=-\infty}^{\infty}C_{4x}(k,l,m)\exp(-j2\pi f_1 k)\exp(-j2\pi f_2 l)\exp(-j2\pi f_3 m), \tag{10}$$

They are spectral density (8), a function of two frequencies - bispectrum (9), and a function of three frequencies - trispectrum (10). Whereas spectral density is the real nonnegative value, the bispectrum and trispectrum are complex quantities.

Asymmetry parameters and coefficients of excess(normalized values) are widely used to solve diagnostics and NDE problems. They are invariant regarding transference and scale, characterize the symmetrical and normal distribution deviation of an analyzed process, and can be found from (6) and (7). Higher-order spectral characteristics are the most appropriate to process complicated nonlinear processes which are the additive mixture of non-Gaussian process and Gaussian noise [1,3]. This is typical for vibroacoustical processes arising from a working aircraft engine.

Higher-order spectral analysis was applied to get bispectral module estimators. They are presented in following forms: 1) three-dimensional images characterizing bispectrum module dependence on frequencies f_1 and f_2; 2) multicolored contour plots which are certain configuration lines represented various received estimates and differed in intensity and geometrical adjectives; 3) diagonal sections characterizing bispectral module dependence on frequency along symmetry line of 3-D images. The listed above results of bispectral signal processing for a turbine with a cracked blade (ϑ=0,05) are shown on "Fig. 2".

As the results of diagnostic information processing demonstrate, appearance and development of a crack in the engine turbine lead to change of global and local extremums intensity of bispectral module estimators. The values of these estimators can be found from the diagonal sections ("Fig. 2,c,d"). Influence of the additive Gaussian noise on global maximums intensity is low (decrease no more than 4%), while the values of local maximums increase by 12%. The relationship between a crack generalized parameter ϑ and obtained bispectral estimators is illustrated in Table 1 by the relative values of averaged intensity of global I_g/I_g^* and local I_l/I_l^* maximums, and also by the ratio of extremum values I_g/I_l . $I_{g(l)}$ and $I^*_{g(l)}$ are values of diagnostic features at a crack presence and absence accordingly.

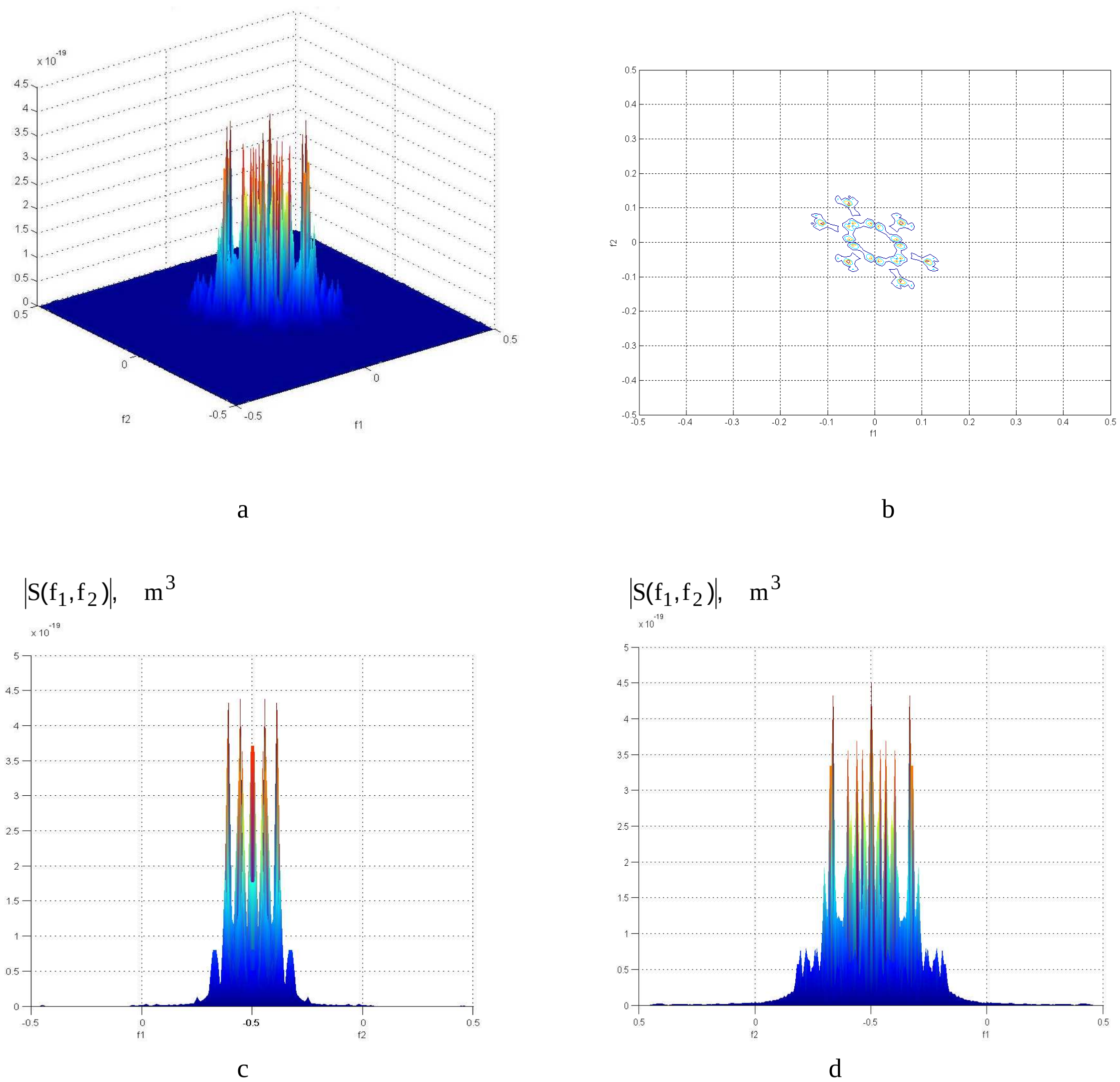
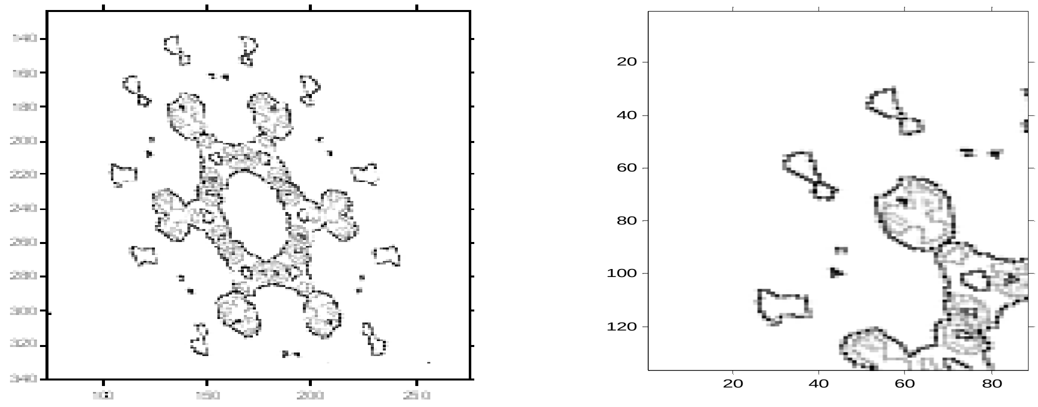


FIGURE 2. The results of bispectral signal processing for the turbine with a cracked blade (ϑ=0,05): a) three-dimensional image; b) multicolored contour plot; c) and d) - diagonal sections.

Diagnostic features change at initiation and starting development of a crack (ϑ<0.07) is not regular. The ratio of bispectral module extremum values I_g / I_l is the most sensitive to a crack parameter change.

TABLE 1. Diagnostic features dependence on a crack parameter .

ϑ	0	0.01	0.03	0.05	0.07	0.1
I_g / I_g^*	1	0.93	0.91	0.95	1.03	1.2
I_l / I_l^*	1	0.89	0.88	0.91	0.89	0.9
I_g / I_l	1.21	1.26	1.24	1.26	1.38	1.58



a b

FIGURE 3. The image with shade of gray (a) and its fragment (b).

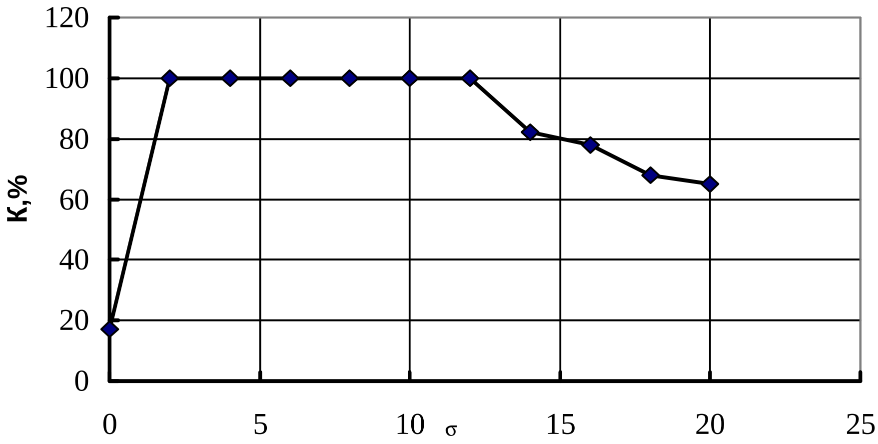
RECOGNITION OF TURBINE BLADE CONDITION

Recognition of turbine blade condition is carried out with neural networks using contour plots (outline pictures) of bispectral module estimators. The contour plots can be found transforming multicolored images ("Fig. 2,b") in images with shade of gray ("Fig. 3,a"). Then from each image with shade of gray is taken a fragment of its diagonal section ("Fig. 3,b").

Further, the received fragment is transformed in numerical matrix. The elements of this matrix are numbers from 0 to 255. Finally, matrix columns are converted in a vector which is supplied at the input of a neural network. There were used in twenties learning and test sets to solve a problem of recognition.

Classification of turbine blade condition was carried out using a two-layer stochastic neural network [4]. It has low learning time, possibility to learn with a null error, and high accuracy of recognition linearly inseparable types of a test object condition. The first layer consists of 20 neurons. As a second layer it is used so called a competitive layer from 2 neurons. These neurons determine correct solution probability - the input vector belongs to a faulty type or not. Such classification is based on Bayes methods and needs probability density estimate for a condition type. For that, set of learning vectors are used. Every vector is described by Gauss function with a center in the point corresponded to this vector. The sum of named functions according to the whole available set of learning vectors is probability density of input vectors for each condition types. The value of the Gauss function mean-square deviation σ specifies width of the neurons activation function and define their influence on a probability density estimate sum. This implyies that the parameter σ influences on a classification result. Therefore its value is determined mostly experimentally.

Effectiveness of turbine blade condition classification by Probability Neural Network (PNN) was judged by the coefficient K. This coefficient is a value of correct classification probability expressed in percentage terms. Relationship between the coefficient K and the influence parameter σ for test set images is shown on "Fig. 4". As can be seen from a given plot, PNN recognizes the test images correctly in the range of the parameter $\sigma = 1.5, \dots, 12$. Analysis of the coefficient K dependence on a number of objects of learning set images



FIGUR 4. Dependence of correct recognition probability on the influence parameter of a neural network.

demonstrates that it is enough to provide the learning set from no less then 8 images for each condition type to correct recognition.

So, in spite of diagnostic features irregularity and little changes at turbine blade condition changing from defectless to faulty one, PNN provides correct classification of diagnostic object condition.

CONCLUSIONS

1. Simulation and higher-order spectral analisys of vibroacoustical signals radiated at stationary mode by an engine rotor with defectless and cracked blades indicate changing of global and local intensity extremums of a bispectrum module at initiation and initial development of a fatigue crack.
2. Application of a stochastic neural network provides test object condition classification using results of bispectrum analisys (the crack parameter was ϑ=0.005,…,0.1).
3. Received results are new and justify efficiency of test object condition recognition using results of higher-order spectral analisys. These resalts can be used to create a vibroacoustical monitoring system for aircraft engine rotor components.

REFERENCES

1. Collis, W.B. White, P.R. and Hammond, J.K. , *Mechanical Systems and Signal Processing*, **12(3)**, 375-394 (1998).
2. Bouraou, N.I., Marchuk, P.I., and Tyapchenko, A.N., "Condition Monitoring Diagnosis Method of Aircraft Engine Rotating Details", in *Proceedings of the 15th World Conference on Non-Destructive Testing*, AIPnD, created by NDT net, Italy, Rome, 2000, 11p.
3. Brillinger, D., *Ann.Math.Stat*, **36,** 1351-1374 (1965).
4. Sankar, K.Pal. and Sushmita, M., *IEEE Transaction on Neural Networks,* **3, #5,** 683-696 (1992).