Surface microgeometry monitoring of large-sized aircraft elements

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Abstract. The article is devoted to the assessment of the surface microgeometry of structural elements of an aircraft with a significant surface area. A statistical method for assessing the surface quality using correlation methods for analyzing random processes is presented. An example of processing results is given.

1. Introduction

One of the tasks solved during the design and operation of an aircraft is to ensure its aerodynamic characteristics, flight safety and fuel economy [1]. The microgeometry of the aircraft structural elements surfaces has a significant influence on these characteristics. The aircraft surfaces structure is largely determined by the widespread use of polymer and composite materials in aircraft construction. The surface microgeometry also depends on the surface protection against the external environment (multilayer, erosion-resistant, fabric-film, paint, varnish and other coatings). At the same time, the current methods for assessing the characteristics of surfaces are based on the analysis of small areas, which results are extrapolated to the entire rest of the surface [2]. Such an assumption in the surface survey fails to identify defects located outside the area being evaluated. The overwhelming majority of primary measuring transducers (mechanical, optical, eddy current, magnetic, etc.), used to control the deviation of the geometry of surfaces, have largely exhausted their capabilities to improve the accuracy [3]. Therefore, it is promising to improve algorithms for computer processing of measurement data.

2. Statistical method for assessing surface quality

Since the microgeometry of surfaces is a realization of a random process, statistical methods of analysis of random processes can be used for processing. The feasibility of implementing this approach has been convincingly proven in radio engineering [4, 5]. Reasoning by analogy, it can be assumed that, for example, correlation processing of measuring signals [6] can significantly increase the metrological characteristics of monitoring systems.

The aircraft outer surfaces defects may be classified as follows:

- roughness, that is, a collection of surface irregularities with relatively small steps;
• dirt, that is, particles of solid substances (dust, sand, etc.) adhering to the surface, the distribution of which is irregular;
• microcracks formed during the operation due to aging and erosion, which are depressions with relatively large steps;
• waviness, that is, macroroughness on a surface, characterized by smooth transitions from protrusions to depressions;
• protrusion or sinking of the heads of rivets, bolts, screws;
• protrusion of welded seams, dents of resistance welding, skin tightening along riveted seams;
• ledges and gaps along sashes, hatches, etc.

Roughness and waviness have the greatest influence on the quality of the aircraft surface [7, 8].

The control of the microgeometry of the aircraft surface, based on the use of correlation analyses, is advisable to be carried out using paired optical means that can provide the required speed. In the case when a defect appears on the surface, the statistical characteristics in this zone will be different than that of a normal quality surface, which will cause a change in the correlation function of the signals of the two sensors. Therefore, by successively comparing the correlation functions of the measurement signals corresponding to the control of neighboring areas of the surface, it is possible to estimate the degree of its homogeneity and manifestation of defects [8].

Let the generated measuring signal $S(x)$ represent the sum of the signals $y(x, \lambda(x))$, depending on one parameter $\lambda(x)$, characterizing the surface structure (for example, the height of irregularities), and stationary white noise $n(x)$:

$$S(x) = y(x, \lambda(x)) + n(x), \quad 0 \leq x \leq L$$

(1)

In this case, the assessment of the change in the structure of the signal $y(x, \lambda(x))$, caused by the presence of a surface defect, is largely determined by the accuracy of its estimation. For the criterion of the accuracy of the estimation of random signals, it is advisable to use the maximum of the posterior probability of the value of the parameter $\lambda(x)$ [8].

In this case, if $\lambda(x)$ over the observation interval $(0 \leq x \leq L)$ is a simple Markov process, then for surface elements $x$ and $x + \Delta x$ located close to each other (with $\Delta x$ much smaller than the size of the surface defect), the posterior probability density $f_{\lambda}$ for the values of the parameter $\lambda(x)$ on these two adjacent intervals is [4]:

$$\frac{\partial f_{\lambda}(x, \lambda)}{\partial x} = \frac{1}{2} \cdot \frac{\partial^2}{\partial \lambda^2} \cdot [Q_2(\lambda)f(x, \lambda)] - \frac{\partial}{\partial \lambda} \cdot [Q_1(\lambda)f(x, \lambda)] + [F(x, \lambda) - \bar{F}(x, \lambda)] \cdot f(x, \lambda),$$

(2)

where: $F(x, \lambda) \approx \frac{2}{N_0} \cdot S(x) \cdot y(x, \lambda)$; $N_0$ — spectral density of white noise; $\bar{F}(x, \lambda)$ — average value on sites; $Q_1$, $Q_2$ — coefficients describing the "behavior" of the parameter $\lambda(x)$;

$$Q_1(l) = \lim_{l \to 0} \frac{(\lambda_j - \lambda)^2}{l} \quad ; \quad Q_2(l) = \lim_{l \to 0} \frac{(\lambda_j - \lambda)^2}{l}.$$

Thus, the accuracy is determined by the value $\lambda_{\text{opt}}(x)$, corresponding to the maximum of the posterior probability distribution (2), and by the variance of this distribution. The practical implementation of algorithm (2) can be very difficult due to the inaccuracy of the real values of the input parameters. At the same time, if we assume that the posterior probability density is Gaussian, that is,
then it is sufficient to estimate only the mean value \( \lambda(x) \) and \( \sigma^2(x) \), which characterize the confidence interval of the posterior distribution. In this case, expression (2) can be reduced to the form [4, 8]

\[
\frac{d\lambda(x)}{dx} = Q_1(\lambda) + \sigma^2 \cdot F'(x, \lambda),
\]

\[
\frac{d\sigma^2}{dx} = 2\sigma^2 \cdot Q_1(\lambda) + Q_2(\lambda) + \sigma_0^4 \cdot F''(x, \lambda).
\]

The joint solution of the last equations gives an optimal estimate of \( \lambda(x) \). The assumption of a normal distribution \( f_\lambda(x, \lambda) \) will be justified at large signal-to-noise ratios for which the condition

\[
\sigma_2(x) \mid \Delta \lambda, \Delta \lambda \parallel \frac{y(x, \lambda)}{\partial y(x, \lambda)}.
\]

When assessing the quality of the surface microgeometry, it is proposed to use one generalized parameter — the correlation function between adjacent areas of the surface or the controlled area and the sample.

The scheme for the formation of such an assessment of the quality of the wing surface is shown in Figure 1. The structure of the aircraft surface is represented by a random spatial process \( S(x) \), the parameters of which are measured in zones \( x_1 \) and \( x_2 \) by sensors \( A_1 \) and \( A_2 \) at a fixed distance ("step"), which have the corresponding output signals \( S_1(x) \) and \( S_2(x) \).

When step-by-step movement of the primary measuring transducers for a time sufficient for signal processing using a computer, auto- or cross-correlation functions are determined, which are the "carrier" of detailed information about the structural properties of the surface, and about the statistical characteristics of the signals \( S_1(x) \) and \( S_2(x) \) and interference.

The results of the parameter estimation are used for detection and recognition of measuring signals carrying information about the actual surface structure. This method of processing the received measurement signals should allow to detect the presence or absence of a defect.

If we assume that the measuring signal for the surface, with the required degree of quality, is known, then the implementation of the defect detection rule leads to a scheme for detecting the known signal \( S_0(l) \) against the background of noise \( n(l) \), where \( l \) is the distance between the sensors [8].

This method of surface quality control uses an integral assessment of the characteristics of microroughnesses from statistical surface profilograms. For this, non-contact and contact methods can be used, for example, the method of interference of the incident and reflected light flux, raster and reflectometric methods, the method of diagnosing with a light beam, etc.
To increase the reliability of control, it is advisable to proceed from one-dimensional to two-dimensional correlation functions [8].

To determine the two-dimensional correlation function in the field of interaction of the primary measuring transducer with the surface, a strip with a width of $N$ pixels is allocated and a digital reference pattern of size $N \times N$ is attributed to the center of this strip. Then the reference pattern and the highlighted band are sent to the correlator. As a reference pattern, both the previous value of the $S(x)$ signal and the signal from the reference surface can be used. When the reference pattern is virtually moved along the selected strip with a certain step and each alignment with the current fragment of the image, the correlator calculates the number of matching pixels between them. This sum is considered as the autocorrelation coefficient. To obtain the normalized value of the autocorrelation coefficient $K$, the resulting sum is divided by the area of the control sample. The found $K$ values are stored in the computer memory. After completing the calculation of the autocorrelation coefficients of the first band, the next band is controlled in the same way as the previous one, but shifted by a few pixels. In this band, the previous reference pattern is used to calculate the autocorrelation coefficient and the steps are repeated, etc. Thus, after processing the entire surface, a matrix of autocorrelation coefficients or a two-dimensional discrete autocorrelation function is formed. It is used for quantitative assessment, on the basis of which it is possible to reliably recognize the deviation of the studied surface from the norm with a given probability. For the autocorrelation matrix, the average value of the autocorrelation coefficient $K_{\text{mean}}$ is determined. Then, the found $K_{\text{mean}}$ value is subtracted from each element of the autocorrelation matrix and the sum of all differences in absolute value is calculated. This sum is then divided by the size of the autocorrelation matrix $D$:

$$U = \frac{\sum_{i=1}^{D} |K - K_{\text{mean}}|}{D}.$$

The thus obtained estimate of $U$ can be considered as the average amplitude of the variable component of the two-dimensional autocorrelation function. The calculated value of $U$ with a given probability $P$ is used to determine the confidence interval in which this random variable falls. Then, using the found boundaries of the confidence interval, the parameters of the controlled surface are estimated [8].

3. Surface scan results.

Thus, the use of algorithms for correlation processing of the measurements of the aircraft surface structure increases the reliability of control without changing the design of the used measuring instruments. For example, the PIK-30M interference computer profilometer [6] makes it possible to measure fragments (up to 150 mm) of large parts with a surface reflection coefficient of more than 4% and a radius of curvature from 1.5 to 8 meters. Figure 2 shows the characteristic changes in the values of the correlation functions of the measurement signals obtained by scanning samples with a “rough” roughness (sample 1) and a “smoother” surface (sample 2).

![Figure 2](image.png)

**Figure 2.** Graphs of changes in the normalized correlation signals of the investigated surfaces.
4. Conclusion
Thus, the use of correlation algorithms for processing the measurement data increases the reliability of surface monitoring using the currently available technical means. In addition, using ultrasonic or magnetic sensors, it is possible to detect not only surface, but also subsurface defects, and find the relationship between them. The presented approach to surface quality monitoring is applicable for implementation both in manufacturing conditions and in aircraft operating conditions.

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