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surface geometric structure,
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COMPARISON OF CLASSIFICATION ABILITY INDICES OF PARAMETERS CHARACTERIZING THE STEREOMETRIC FEATURES OF TECHNICAL SURFACES

The study examined the relationship between the values of two indices evaluating the classification capacity of parameters characterizing the stereometric features of technical surfaces. The values of 83 3D parameters characterizing the stereometric features for 22 surfaces created in various machining processes were taken into account. The examined surfaces differ significantly in the stereometric characteristics of the surface with the similar value of the St parameter. The variance and the geometric mean of ordered parameter values differences were used as the indices of parameters classification ability. In particular, the existence, type and strength of relationship between the adopted indices were evaluated, and the model of the relationship between the indices was determined using the least-squares method. A comparison of the results obtained with those obtained from the analogous evaluation for 8 types of theoretical distributions of parameter values was also carried out.

1. INTRODUCTION

The development of manufacturing technology results in the need to analyze and improve the quality of technical products. One of the basic issues related to the production of modern, highly specialized machinery and equipment is the assessment of the quality [*]of technical products and forecasting of their operational properties. The large importance of research in this area is related to the increase in the requirements for the accuracy of the manufactured components and their properties, including the strength associated with an increase in the loads to which the machine elements are subjected.

The conducted research led to the development of many new measurement methods and devices for their implementation. The large number of methods used significantly increased the number of parameters used [1]. One of the elements of technical products quality assessment is the analysis of surface topography, and in particular the stereometric features of the surface [1-3].

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The analysis of the stereometric features of the surface in precision machining is difficult, due to the small unevenness range of the analyzed surfaces [4]. Another difficulty is the selection of appropriate parameters to describe the surface topography [5-7]. More than three hundred standardized parameters are currently used to assess the geometric structure of the surface, both in 2D and 3D system. These parameters evaluate different elements of the examined surface or result from different approaches to the assessment of the same feature. The analyzes carried out show that some parameters are strongly correlated with each other. Failure to take into account these relationships when selecting the parameters used in the analysis may lead to duplication of the obtained information [5].

The number of parameters used for surface assessment should be small, with the complementarity of the set. This would enable an easy and comprehensive description of the analyzed surface. When selecting a set of parameters to be used, the purpose of the product should also be taken into account. No more than five parameters should be considered in the description of any type of surface. In industrial practice, only one selected parameter is often used to assess surface topography. This is undoubtedly a mistake, especially that the choice of the parameter used is usually determined by the ease of parameter interpretation or the worker's habits.

Therefore, one of the key issues in technical products quality assessment is the selection of an appropriate complementary set of parameters, ensuring the ease of interpretation of assessments for specific applications and surfaces, and the ability to effectively distinguish significantly different surfaces, which is referred to as the classification ability of the parameter. The problem of parameter set selection with high classification ability, easy to read and useful for selection of parameters and conditions of processing is schematically shown in Fig. 1.

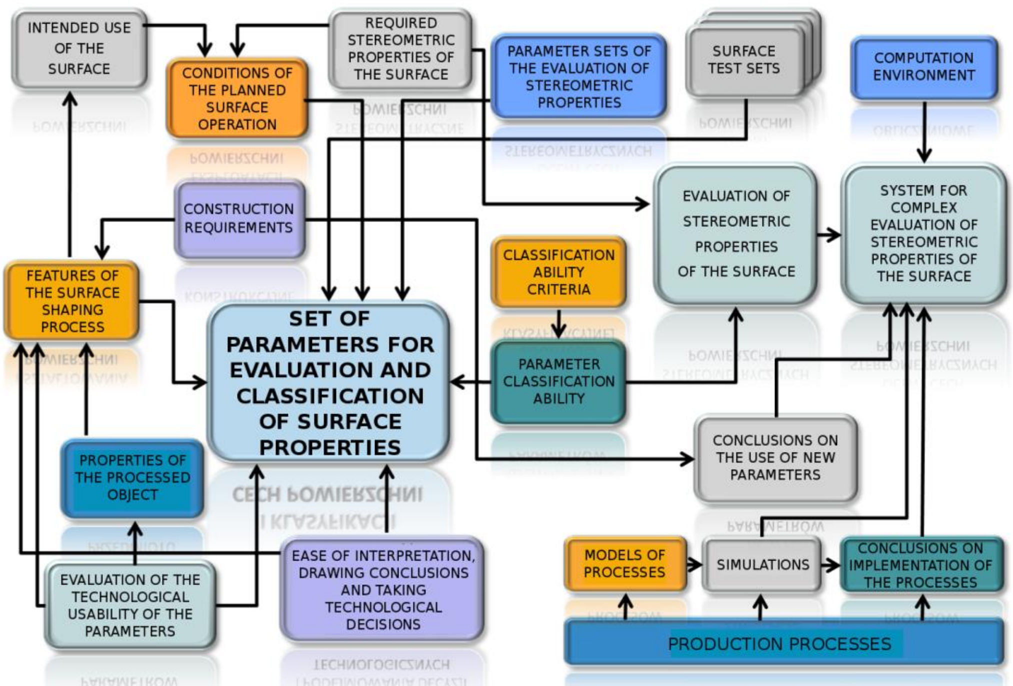

Fig. 1. Chart for methodology of the selection of parameter set with high classification ability [8]

2. PARAMETER CLASSIFICATION ABILITY

The classification issues are widely discussed in the literature, particularly in the technical and economic fields. Both general statistical tools, such as estimation, hypothesis verification and discriminant analysis [10], through methods directly related to technical object classification, to methods directly related to the quality analysis of technical products, including the method of classification ability of parameters evaluating topography characteristics of surfaces after processing, [1, 8, 10-14].

Many types of parameters based on the results of measurements of certain surface features are used to assess product surface quality. The parameters proposed in the literature do not allow for an unambiguous comparison of different types of surfaces. Moreover, many examples of completely different surfaces can be indicated, which are indistinguishable by commonly used parameters [2]. Therefore, the question arises about the choice of such parameters or their groups that will allow for the best classification of technical objects.

Applying the same parameters to assess surfaces with different topographical structures may lead to erroneous inference about the real state of the surface. This is especially noticeable for surfaces with low roughness parameters, where e.g. surface waviness, motif characteristics or other, play an increasingly important role in the surface assessment. The technological significance of individual parameters depends on the degree of correlation of their values and parameters describing the process of shaping the surface to be machined and the parameters describing the features of the tools and other processing features.

In order to enable the comparison of different parameters it is favorable to normalize these parameters. Certainly, this process has an effect on the distribution of each individual parameter, resulting in a loss of certain information on relationship between the dispersion measure and the position measure, which contribute a significant information on the classification ability of a parameter. In general, normalization can be performed using the following formula:

$$P_{j_i N} = \frac{P_{j_i} - P_{j\,\min}}{P_{j\,\max}},$$

where P_{j_i} is i-this value of parameter P_j, $P_{j_i N}$ the same value after normalization, whereas $P_{j\,\min}$ and $P_{j\,\max}$ are the respective lowest and highest values of the parameter P_j. After the normalization of the values of parameter P_j are without units and belong to the interval $\langle 0,1 \rangle$.

The classification ability of the parameter P_j increases as the distribution of probability of its value approaches uniform distribution. Thus, an ideal situation can be assumed, in which differences between the successive values of the parameter P_j for individual surfaces are equal, i.e. for each $i = 0,1,\dots,n+1$ we have $\Delta P_{j_i N} = P_{j_{i+1} N} - P_{j_i N} = \frac{1}{n+1}$, where n is the number of studied surfaces and $P_{j_{n+1 N}} = 1$.

The question arises how to compare the classification ability of individual parameters. Since the sum of all value differences for the normalized parameter P_j is equal to 1, it is not possible to compare parameters according to the Loewner order [15]. However, it is possible to compare them using one-dimensional measures. Assuming that the measure of parameter classification capability is the degree of equalization of differences between successive values of the parameter, it seems appropriate to recognize the variance of differences ΔP_{j_iN} (denotes $Var(\Delta P_{j_iN})$) as a natural index allowing comparison of standardized parameters classification ability. If the values of differences are to be compensated, the variance will tend to zero.

The use of variance is, however, unfavorable due to the fact that it is the average value of square deviations, which entails all the disadvantages of the arithmetic mean. Another possible measure of classification ability is the geometric mean of the differences $Sg(\Delta P_{j_iN})$. In a situation where the differences of values are aligned, the geometric mean tends to the arithmetic mean, in this case $\frac{1}{n+1}$. From a mathematical point of view, the geometric mean appears to be a better index of value alignment. A certain drawback of the geometric mean is the fact that it is equal to 0, when one of the factors is equal to 0, regardless of the variability of the other values. A possible way out of the situation is to add a very small value to each ε. The value of ε should be taken so low that it does not significantly affect the geometric mean value (e.g. $\varepsilon = \frac{1}{1000n}$). More on this subject can be read in [9], and the selection of ε values was examined in detail in the paper [16].

The evaluation of classification ability of individual parameters can be carried out using the following methodology:

1. Selection of surface model set characteristic for a given processing type.
2. Determination of values of the considered parameters for all surfaces included in the test.
3. Normalization of parameter values to the interval $\langle 0{,}1 \rangle$.
4. Visualization of the normalized parameter values e.g. in a radar graph.
5. Sorting out values for each of the normalized parameters P_{jN} and determination of differences for the following values of individual parameters $\Delta P_{j_iN} = P_{j_{i+1N}} - P_{j_iN}$.
6. Determination of $\varepsilon \ll \Delta P_{j_iN}$ value for each i and correction of every $\Delta P_{j_iN} = 0$.
7. Determination of geometric mean $Wsk_{\text{klas}_j} = \left(\prod_{i=1}^{n}\left(\Delta P_{j_iN} + \varepsilon\right)\right)^{\frac{1}{n}}$, for all ΔP_{j_iN} for each P_j.
8. Value $0 < Wsk_{\text{klas}} < \frac{1}{n+1}$ is the index for classification ability of the parameter P_j. Classification ability increases with the value Wsk_{klas}.

In further considerations we will assume that all P_j parameters are normalized.

3. COMPARISON OF GEOMETRIC MEAN AND VARIANCE AS INDICES OF PARAMETER CLASSIFICATION ABILITY EVALUATION

The aim of the study was to examine the variability of variance and the geometric mean ΔP_{j_i} for various 3D parameters assessing the roughness of the surface created in various machining processes. In addition, the study examined the existence of a relationship between both indices of classification ability and a model of this relationship was determined. The obtained results were also compared with the analogous ones obtained for theoretical data generated for 8 types of distributions of parameter value differences [10].

Data containing values of 83 parameters for 22 surfaces were used for the analysis. All the surfaces considered, although were formed in various machining processes and differ significantly in the stereometric features of the surface, have approximately the same value of the St parameter. The 22 surfaces included 7 surfaces after abrasive machining, 7 after erosion treatment, 3 abrasive smoothed surfaces, 2 with high porosity, 2 after exploitation wear and 1 with regular topography [8]. The values of 83 3D parameters characterizing the stereometric features of the surface were determined for the described surfaces (Table 1).

Table 1. List of used 3D parameters [8]

Symbol of the parameter	Unit	Context	Description
A1	$\mu m^2/mm$		relative area of summits
A2	$\mu m^2/mm$		relative area of valleys
Dw	μm	h = 0.2 St	average length of summits
Dw/Sw	μm/μm	h = 0.2 St	the ratio of the average length of the summits to the average width of the summits
Lw		h = 0.2 St	number of summits
Lwjd	1/mm	h = 0.2 St	number of summits per mm of the length
Lwjp	$1/mm^2$	h = 0.2 St	number of summits per mm^2 area
Ow	μm	h = 0.2 St	average distance between the summits
Pw	μm^2	h = 0.2 St	average area of summits
S5p	μm	slash = 5%	height of 5 surface summits
S5v	μm	slash = 5%	height of 5 surface valleys
S10z	μm	slash = 5%	height of 10 surface points
Sa	μm		arithmetic mean deviation of the surface
Sal	μm		fastest decay autocorrelation length
Sbi			bearing index
Sci			core fluid retention index
Sda	μm^2	slash = 5%	surface area of closed valleys
Sdc	μm	p = 10%, q =80%	surface section height difference
Sdq			root-mean-square slope of the surface
Sdr	%		developed interfacial area ratio
Sds	$1/\mu m^2$		density of summits of the surface
Sdv	μm^3	slash = 5%	volume of closed valleys
Sfd			fractal dimension of the surface
Sha	μm^2	slash = 5%	surface area of closed summits
Shv	μm^3	slash = 5%	volume of closed summits
Sk	μm	Gaussian filtering, 0.8 mm	kernel roughness depth (roughness depth of the core)
Sku			kurtosis of the height distribution
Smc	μm	p = 10%	inverse field surface material ratio
Smmr	μm^3		mean material volume ratio
Smq		Gaussian filtering, 0.8 mm	relative material content on plateau and depressions transition
Smr	%	c = 1 μm under the highest peak	bearing area ratio at a given depth

Smvr	μm		mean void volume ratio
Sp	μm		maximum height of summits
Spc	1/μm	slash = 5%	area peak count
Spd	$1/\mu m^2$	slash = 5%	density of summits of the surface
Spk	μm	Gaussian filtering, 0.8 mm	reduced peak height (roughness depth of the peaks)
Spq		Gaussian filtering, 0.8 mm	slope of the regression line in plateau area
Sq	μm		root-mean-square (RMS) deviation of the surface
sqrt(Pw) /Ow	μm/μm	h = 0.2 St	ratio of the element of mean summits area to the mean distance between summits
Sr1	%	Gaussian filtering, 0.8 mm	upper material ratio
Sr2	%	Gaussian filtering, 0.8 mm	lower material ratio
Ssc	1/μm		arithmetic mean summit curvature of the surface
Ssk			skewness of the height distribution
St	μm		total height of the surface
Std	°		surface texture direction
Str			texture aspect ratio of the surface
Sv	μm		maximum depth of valleys
Svi			valley fluid retention index
Svk	μm	Gaussian filtering, 0.8 mm	reduced valley depth (roughness depth of the valleys)
Svq		Gaussian filtering, 0.8 mm	slope of the regression line in valleys area
Sw	μm	h = 0.2 St	average width of summits
Sxp	μm	p = 50%, q = 97.5%	extreme height of the summit
Sz	μm		ten Point Height of the surface
Vm	$\mu m^3/\mu m^2$	p = 10%	material volume at a given depth
Vmc	$\mu m^3/\mu m^2$	p = 10%, q = 80%	material volume of the core
Vmp	$\mu m^3/\mu m^2$	p = 10%	material volume of peaks
Vv	$\mu m^3/\mu m^2$	p = 10%	void volume at a given depth
Vvc	$\mu m^3/\mu m^2$	p = 10%, q = 80%	void volume of the core
Vvv	$\mu m^3/\mu m^2$	p = 80%	void volume of valleys
σ(sqrt(SPw) / sqrt(Pw)		h = 0.2 St	ratio of the standard deviation of the square roots of the summit areas to the square root of the mean summits area

An analysis of the variability and relationship of the geometric mean and the variance of parameter value increments for the theoretical data from 8 types of distribution of normalized parameter increments is presented in the paper [10]. The results obtained then are shown in Fig. 2. On the basis of Fig. 2, it can be concluded that there is a strong linear inversely proportional relationship between $Var(\Delta P_{j_i})$ and $Sg(\Delta P_{j_i})$.

Analogous analysis of the real values of 83 parameters investigating the stereometric features of the 22 surfaces gave similar results. The relationship between the variance and the geometric mean of the increments of individual parameters for the analyzed data is presented in Fig. 3.

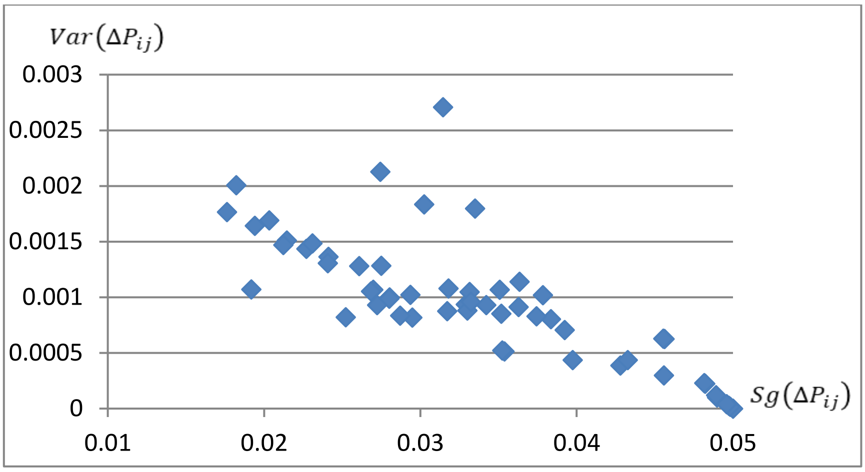

Fig. 2. Dependency of *Var* (ΔP_{j_i}) on $Sg(\Delta P_{j_i})$ for 8 types of distribution

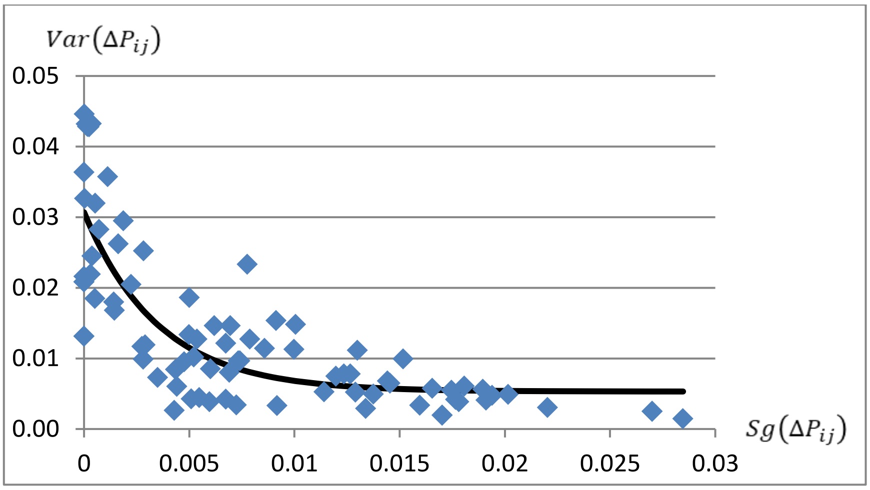

Fig. 3. Dependency of of *Var* (ΔP_{j_i}) on $Sg(\Delta P_{j_i})$ for values of 83 parameters and the exponential model curve with respect to data

Figure 3 shows that there is a strong exponential relationship between the geometric mean of the increments of the parameter values and their variance. The model of this relationship determined by the method of least squares takes the form of

$$Var(\Delta P_{ij}) = 0{,}0053 + 0{,}0254\ exp\left(-282{,}0836\ Sg(\Delta P_{ij})\right).$$

The model determination coefficient is approximately R^2 =0.6563. Thus, in about 66% the above model explains variability of $Var(\Delta P_{ij})$ treated as a function of $Sg(\Delta P_{ij})$. The curve of the model with respect to the values obtained is presented also in Fig. 3.

It can be concluded from the analysis of the correlation between the considered classification ability indices, that there is a negative relationship between them. Thus, for observations for which the geometric mean values are lower, the variance values are higher. On the other hand, for smaller $Sg(\Delta P_{j_i})$ values it is possible to obtain higher values of $Var(\Delta P_{j_i})$. Other ranges of both indices were obtained for real data. Especially the range of variance is significantly different. This results from the sensitivity of the indices under consideration, and in particular the variance, to the number of low values of parameter value increases [17].

Strongly asymmetrical distributions predominated for real data, in which the number of low increments was significantly higher than in the theoretical data. When comparing the change in classification indices ratios in both analyzes, the geometric mean can be considered as a better indicator. This is due to its higher resistance to the number of small increments. This confirmed by the conclusions obtained in [10], where the geometric mean was rated as a better indicator of classification ability.

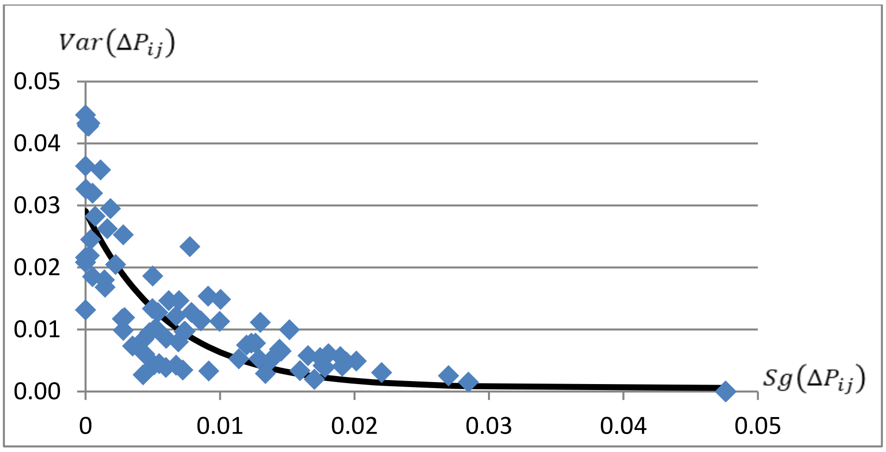

Fig. 4. The exponential model in relation to the data expanded by 21 zero points

As mentioned previously, the parameter classification ability would be ideal if its values were evenly distributed. In a situation where all increments of parameters would be equal, the geometric mean would be equal to the arithmetic mean, and the variance would be 0. In order to correct the obtained model of the relationship between the geometric mean and the variance of parameter increments so that the point with $Sg(\Delta P_{j_i}) = \frac{1}{21}$ and $Var(\Delta P_{j_i}) = 0$ coordinates would be taken into account, an additional point with such coordinates was introduced with the weight 21 was introduced for further analysis. This aimed to force a significant approximation of the determined regression curve to this point. The result of this treatment, together with a graph of the exponential model obtained by the least squares method, is presented in Fig. 4.

After correction, the model of the relationship between the geometric mean of the increments of the parameter values and their variance determined by the least squares method takes the form of

$$Var(\Delta P_{ij}) = 0{,}0003 + 0{,}0283\, exp\left(-139{,}6117\, Sg(\Delta P_{ij})\right).$$

The model determination coefficient is approximately R^2 =0.8025. Thus, in more than 80% the above model explains variability of $Var(\Delta P_{ij})$ treated as a function of $Sg(\Delta P_{ij})$.

4. CONCLUSIONS

In summary, it can be concluded that $Var(\Delta P_{j_i})$ and $Sg(\Delta P_{j_i})$ can be used to assess the classification ability of parameters. This confirms the existence of a strong statistical relationship between these indices. However, on the basis of both theoretical analysis of the differences presented in [10], and also on the basis of the analysis carried out for real values of 3D parameters evaluating stereometric features for the considered surfaces, it can be concluded that the geometric mean is a better index of the classification ability of technical parameters. This is due to the smaller influence of outstanding values on $Sg(\Delta P_{j_i})$ than on $Var(\Delta P_{j_i})$. This applies in particular to the strong influence of the number of small increments of parameter values on $Var(\Delta P_{j_i})$.

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