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CLASSIFICATION OF METAL SURFACES FOR STATISTICAL PICTURE SIGNS OF A DISPERSION

The paper contains the results of investigation of statistical features based on dispersion and their comparison in conditions of using for metal surface classification. The partitioning of whole set of characteristic values into ranges, which correspond to separate types of metal alloys, is used for classification.

Keywords – image, surface classification, statistical features, dispersion, characteristic comparison.

Introduction

Research Texture plays an important role in image processing [1-6], in particular to study the structural features of machined surfaces using statistical techniques, namely the correlation matrix [1], the matrix of distances [2], the properties of fractals [3], the probability distribution of responses filter [4], the combined distribution of intensity values [5], the spatial distribution of gray levels [6]. Statistical characteristics associated with the parameters of the surface, and can be used for classification. Some methods are designed specifically for texture classification in general [3-4], or adapted specifically to the classification of surface material [5]. Also to assess the quality of the surface material used methods for detection and classification of defects [7].

The peculiarity of this paper is the comparison of simple statistical features of images based on the variance in the classification of various metal surfaces.

The aim is to compare the performance in terms of suitability for classification of metal surfaces and study their conditions of use. Distinction and classification of different types of alloys are subject to further evaluation as a model, finding and classifying defects in material.

1. Statistical features images of metal surfaces

In the analysis of images of metal surfaces should consider their features. First, differences in the structure and surface quality of processing clearly visible only under magnification, so the quality of images it is advisable to use an image obtained by shooting under a microscope. Second, the surface of most metals (except, for example, gold or copper) do not differ much in color. Thus, to analyze the metal surface is appropriate to use statistical features based on intensity in grayscale. Furthermore, algorithms using intensity are more versatile because they allow to work effectively with both color and monochrome input image.

If the input image is in color, the intensity for grayscale it becomes. Each pixel takes values from black to white, which is denoted as b - brightness. The range of all possible values of brightness is in the range 0 ÷ 255. To convert BT709 algorithm using the following coefficients R, G, B:

$$R = 0{,}2125;\ G = 0{,}7154;\ B = 0{,}0721; \tag{1}$$

As classification features can be used simple statistical properties, including dispersion [8,9]. To do this, the image is divided into some areas, such as columns and rows [8], vertical and horizontal fragments [9], vertical and horizontal segments [9] cell. Distributed dispersion characterizes the dispersion of pixel intensity in each such area image:

$$\bar{I}(s) = 1/k_s \sum_{i=1..k_s} I_i(s) \tag{2a}$$

$$E^2(I(s)) = 1/k_s \sum_{i=1..k_s} (I_i(s) - \bar{I}(s))^2 \tag{2b}$$

where k_s – number of pixels in the s-th image area, $I_i(s)$ – intensity of the i-th pixel in the s-th image area, $\bar{I}(s)$ – expectation of intensity in the s-th image area, $E^2(I(s))$ – variance of pixel intensity in the s-th image area.

Consider a distributed computation methods specified variance:

1. To calculate the variance of the columns of a distributed input image *X* is divided into equal-sized columns, where *X* - image width in pixels. Similarly, the image can be divided by line [8].
2. To calculate the variance of distributed vertical fragments input image is divided into n pieces vertical lines at intervals (step fragmentation) *d=X/n*, where *X* – image width in pixels. Similar images can be broken by horizontal fragments [9]. Thus, vertical fragment intervals *d=1* corresponds to the columns, and horizontal - row.
3. To calculate the variance distributed in segments, each segment s-th image is formed by the union of all the fragments of the first left to the s-th inclusive. [9] Thus the first segment corresponding to the first fragment, and the last - the whole image.
4. To calculate the dispersion of cells distributed input image is divided into *n* parts by vertical lines and horizontal lines *m* parts, as in fragmentation. Then the variance is calculated for each of the *n* × *m* cells.

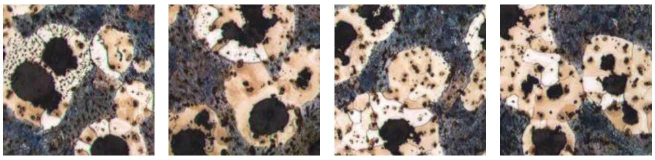
The result, in any of these four ways, there are some values of dispersion. And as a general numerical characteristics of the whole picture can be used such characteristics:

1. Mean variance - calculated by the formula (2a), resulting from the substitution of a number of values instead of intensity variance.
2. Dispersion variance - calculated by the formula (2), substituting the resulting series of values instead of intensity variance.
3. The amplitude variance - measured as the difference between the maximum and minimum number of elements in the resulting dispersion values.

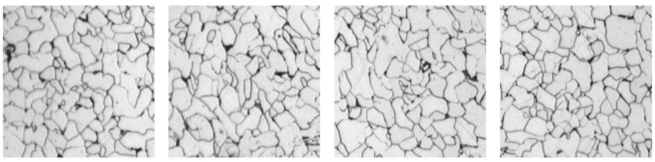
Thus, the combination methods of calculating the dispersion 4 and 3 overall numerical characteristics get 12 image characteristics of a dispersion.

2. The results of the classification of surfaces with different characteristics

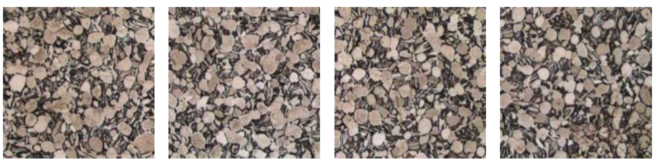
For input images taken photos surface of metal alloys made under a microscope with 20x magnification. Size Photos - 300 × 300 pixels, each of which represents a square surface of side 187,5mkm. All four samples taken four different surfaces are shown in Pict.1. - Gray cast iron (a) steel St37 (b), titanium BT6 (c), Inconel 792 (d).



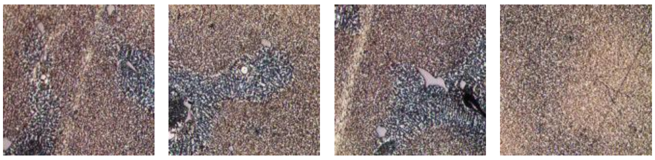
(a)



(b)



(c)



(d)

Pict. 1. Images surface of metal alloys with a 20-fold increase

To investigate the characteristics of the image based on variance and identify the most suitable for the classification of surfaces, a series of experiments. For each of the 16 images of surfaces shown in Pict. 1. Calculated all 12 characteristics, and the results are grouped according to these characteristics. In calculating the variance of distributed fragments and segments the image is divided into 10 fragments (fragmentation step - 30 pixels) when calculating the dispersion of cells distributed image divided mesh 15 × 15 to 225 square cells (size 20 × 20 pixels). Thus, distributed dispersion for all methods except cells were calculated twice (horizontal and vertical) to obtained results allowed to estimate characteristics regardless of image orientation.

Each experiment mentioned characteristics for different samples of alloy combined into one range. For characterization could be used as a classification attribute, you need to ranges of values for different alloys do not overlap each other.

As a result of experiments carried out revealed that a complete classification of the set of surfaces can be applied only variance variance distributed through cells. The corresponding value characteristics and their ranges are given in Table 1. Rounded to the range 10^5.

Table 1.

Dispersion distributed variances in cells

Alloy	**Gray cast iron**	**Steel St37**	**Titanium BT6**	**Inconel 792**
Sample №1	2’229’995	1’154’452	725’139	437’084
Sample №2	2’291’441	1’605’382	742’369	415’060
Sample №3	3’193’452	1’398’365	757’441	371’893
Sample №4	2’661’398	1’181’823	541’519	220’271
Value Range, 10^6	2,2..3,2	1,1..1,7	0,5..0,7	0,2..0,5

Thus, using data ranges, samples of metallic alloys can be automatically proklasyfikovani by calculating the dispersion variance distributed through cells. In addition, the presence of bands, which do not get any value from the set of alloys (eg, $0{,}7\times10^6..1{,}1\times10^6$ або $1{,}7\times10^6..2{,}2\times10^6$), makes it possible to use this feature and for more than four different types of surfaces.

Also, the experiments revealed that partial classification (without distinction of color alloys - titanium and Inconel 792 BT6) can be used mean values averaged variance: the columns and rows, or fragments or segments. Mean values averaged variances in columns and rows and their ranges are given in Table 2. The range rounded to 10^2.

Table *2.*

Середні значення розподілених дисперсій по стовпцях і рядках

Alloy	**Gray cast iron**		**Steel St37**		**Titanium BT6**		**Inconel 792**	
	the columns	the rows	the columns	the rows	the columns	the rows	the columns	the rows
Sample №1	4406	4314	1625	1677	2954	2974	2679	2697
Sample №2	4285	4312	1946	1959	3218	3209	3652	3618
Sample №3	5009	5131	1904	1934	3299	3340	3448	3575
Sample №4	5055	4110	1879	1905	2970	2959	2804	2808
Value Range	4100..5200		1600..2000		2900..3400		2600..3700	

As can be seen from the results, ranges of values for titanium and Inconel 792 BT6 overlap, so this characteristic can not be used for their distinction. Similar results were obtained for the mean values and variances distributed in fragments and in segments.

For other characteristics intersect three or more ranges, so these characteristics to classify data alloys practically unusable.

3. Research dispersion variances distributed through cells

To investigate the conditions for the application of distributed dispersion variances in cells for the classification of surfaces, a series of additional experiments that allow you to identify the dependence of the number of cells and the multiplicity of image magnification under a microscope.

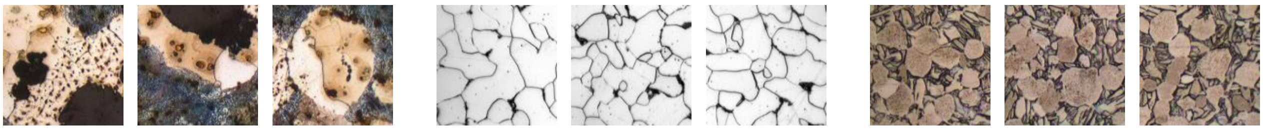
To study the dependence of the number of cells per input images are the same image taken with a 20-fold increase, as in the previous experiments (Pict. 1). Ranges of values of each metal alloys obtained by different numbers of cells are given in Table 3. The range rounded to 105 range that do not overlap with any other range for a given number of cells marked in gray.

Table 3.

Range of dispersion for images with 20-fold increase

Size grid	Number of cells	Value Range, 10^6			
		Gray cast iron	Steel St37	Titanium BT6	Inconel 792
2×2	4	0,1..0,4	0,0..0,2	0,0..0,1	0,0..0,2
5×5	25	2,3..3,0	0,0..0,3	0,0..0,2	0,1..0,3
10×10	100	2,6..3,5	0,5..0,9	0,2..0,5	0,1..0,4
15×15	225	2,2..3,2	1,1..1,7	0,5..0,7	0,2..0,5
20×20	400	1,9..2,6	1,4..2,1	0,8..1,2	0,2..0,5
50×50	2500	0,7..1,3	1,7..3,0	1,2..1,7	0,5..1,1
100×100	10000	0,2..0,6	1,0..2,0	0,6..1,1	1,0..1,7

To study the dependence of the multiplicity increase for incoming images taken photos surface of metal alloys made under a microscope at 50-fold magnification. Size Photos - 300 × 300 pixels, each of which represents a square surface of side 75mkm. All three samples taken on three different surfaces are shown in Pict. 2. - Gray cast iron (a) steel St37 (b), titanium BT6 (c).



(a) *(b)* *(c)*

Pict. 2. Images surface of metal alloys with 50-fold increase

Ranges of values of each metal alloys obtained by different numbers of cells are given in Table 4. The range rounded to 10^5. Ranges that do not overlap with any other range for a given number of cells highlighted in gray.

Table 4.

Range of dispersion for images with 50-fold increase

Size grid	Number of cells	Value Range, 10^6		
		Gray cast iron	Steel St37	Titanium BT6
2×2	4	0,1..1,9	0,0..0,4	0,0..0,2
5×5	25	1,0..3,2	0,8..1,8	0,0..0,3
10×10	100	1,5..2,5	1,8..3,0	0,4..0,6
15×15	225	1,2..2,0	2,0..3,5	0,5..0,8
20×20	400	0,8..2,0	2,2..3,5	0,6..0,9
50×50	2500	0,4..1,2	1,3..2,1	0,5..0,8
100×100	10000	0,2..0,4	0,5..0,8	0,1..0,3

As seen from the results, all ranges of dispersion distributed variances in cells not intersect only at partition image grid 15 × 15. The last experiment confirms that this is also true for images obtained under different increase.

Conclusions

Investigated by simple implementation and time to obtain statistical features based on variance and by comparing them in terms of suitability for image classification metal surfaces.

Established that for this type of image as classification criteria most appropriate to use variance variance distributed through cells. The optimal grid size for splitting the cells is 15 × 15 and does not change depending on the multiplicity increase under a microscope. Under these conditions, a complete classification of possible sample surface by type alloy.

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