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Threshold-free method for determining the composition of a two-phase composite from an microscopy images

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A new method is proposed for estimating the quantitative analysis of the composition of two-component composites from an image. This method does not rely on a binarization threshold and offers greater accuracy compared to traditional methods that do. It is robust to contrast changes and performs well across a wide range of image contrasts.

Keywords: composite material, material analysis, computer modeling, computational methods, image analysis.

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Introduction

In modern materials science, the analysis of material composition is crucial for understanding their properties and potential applications. When studying two-component materials such as matrix-inclusions, accurately determining the quantitative content of each phase is paramount. Various physical methods are available for this purpose, including chemical analysis, X-ray diffraction, X-ray spectroscopy, scanning electron microscopy, and optical microscopy image analysis.

Recently, image analysis methods using optical or electron microscopy have emerged as valuable tools for quantitatively assessing two-component materials [1-7]. This approach offers several key advantages over other analytical methods, making it particularly effective in materials science practice. Microscopy can discern even the smallest material details and phases, enabling precise content determination. Moreover, it often eliminates the need for complex sample preparation, thus accelerating analysis and broadening accessibility to researchers. Image acquisition is rapid, facilitating analysis of large sample sets in short timeframes. Thus, the development of methods to quantitatively analyze material composition from images using computational capabilities is an urgent and practically significant task.

This paper focuses on two-component materials, known as "matrix-inclusions," where components do not dissolve or interact to form a third component and have distinct colors or brightness in microscopy images.

The method for assessing composite composition is based on mathematical fact that the ratio of areas occupied by components in a two-dimensional cross-sectional image correlates with their volumetric ratio (and consequently their mass ratio, given their densities).

Traditionally, this problem is tackled by determining the number of pixels corresponding to each phase. Each pixel's assignment is determined by various thresholding methods [8, 9], also referred to as segmentation, where pixel brightness is compared against a *threshold* value. Thresholds can be global [10], calculated for the entire image, or local [11], based on neighboring pixel values, useful for images with varying brightness. These methods are widely employed in software like ImageJ [12], SIAMS [13], and AMIS [14], particularly in metallography. However, these thresholding methods analyze images without considering the features of the underlying physical system.

Under ideal conditions, where each component of a two-component composite exhibits homogeneous optical properties and imaging conditions do not introduce distortions (such as variations in illumination nature or angle), the intensity histogram of the composite's image would display two distinct peaks at specific intensity values. In such cases, the quantity of each component is directly proportional to the height of its corresponding peak in the histogram, providing a comprehensive description of the composite's composition. However, due to numerous independent factors, physical quantities often exhibit a normal (Gaussian) distribution, as described by the central limit theorem. To address this variability without relying on a fixed threshold value, this study employs mathematical statistical methods that treat histogram peaks as discrete values “blurred” by normal distribution. This approach forms the foundation of the proposed method for estimating the composition of two-component materials, which *does not* use a threshold value at all.

I. Methods

The algorithms developed for this method utilize principles from probability theory, mathematical statistics (including normal distribution formulas), and numerical methods for solving nonlinear equations. Implementation was carried out in C++ using freely available tools: the Visual C++ 2022 compiler, wxWidgets for image processing, and ALGLIB for solving least-squares approximation problems via gradient descent.

For image preprocessing tasks, such as selecting specific areas of interest, IrfanView was employed.

The study utilized photographs of a matrix with the chemical composition Al-6.0Cu-0.4Mn (wt.%), chosen for its significant practical relevance, in particular high ductility, strength, heat resistance, and corrosion resistance. The matrix alloy powders were produced through argon melt spraying, while SiC powders with an average particle size of 14 μm served as reinforcing particles in the alumina-matrix composite. Experimental materials were obtained via hot extrusion of pressed billets, and their structures were analyzed using optical microscopy with a MIM-9 microscope [15].

To compare the results obtained using the developed method with existing threshold methods, we utilized the Otsu method [16, 17], gradient method [18], Bradley method [19], and Sauvola method [20].

II. Results

The method is predicated on the typical histogram character of image data from matrix-composite systems, which often exhibits two distinct peaks (as depicted in Fig. 1). It is assumed that these histogram peaks follow a Gaussian distribution, a hypothesis supported by experimental evidence—approximate curves of normal distribution (shown in magenta) were obtained via least squares fitting.

Thus, we can treat the histogram peaks as two normal distributions of pixel brightnesses — for dark and light areas — and instead of counting absolute numbers of pixels estimate the *ratio of the* "dark" and "light" pixels, which we assume to be equal to the ratio of the areas under the Gaussian curves. The pixels these two curves are ignored; we treat them as a kind of "transient noise".

The algorithm processes images with clearly distinguishable peaks by first constructing a standard brightness histogram and smoothing it with 3–5 points to reduce noise. Next, it identifies two maxima on the histogram as points where adjacent points to the left and right have lower values.

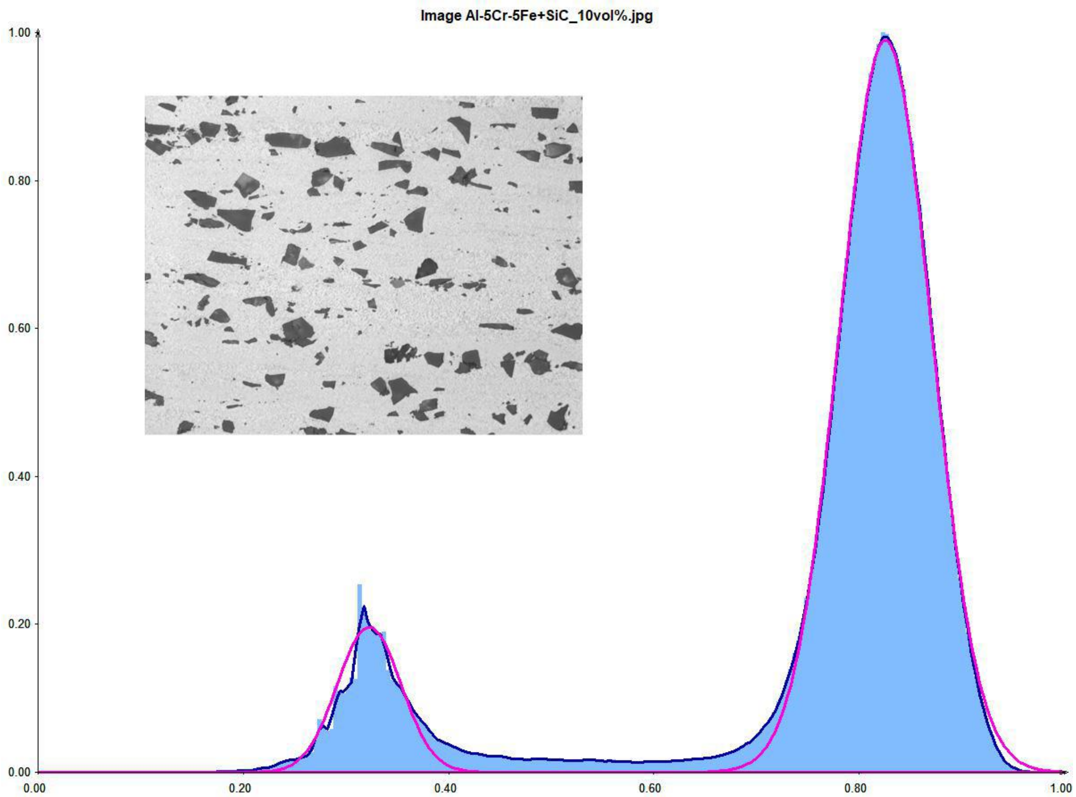

Fig. 1. Histogram of brightness for an image depicting the Al-6Cu-0.4Mn matrix with 10 vol.% SiC inclusions.

Two approximations of the Gaussian curve are constructed based on the peak maxima

$$f(x) = c_1 e^{-\frac{(x-c_2)^2}{c_3}},$$

while the area under the curve, which participates in the calculation of the quantitative composition of the composite, is equal to

$$S = \int_{-\infty}^{+\infty} c_1 e^{-\frac{(x-c_2)^2}{c_3}} dx = c_1\sqrt{\pi c_3}$$

Figure 2 shows histograms and calculation results for the Al-6Cu-0.4Mn matrix with SiC inclusions at 5, 10, 15, and 20 vol%, respectively. Table 1 presents results calculated using the proposed method and, for comparison, common binarization methods (Otsu, gradient, Bradley, and Sauvola). As shown in the table, the proposed method yields results closest to experimental values across all samples. This trend persists even for the last image, where Fig. 2 indicates a poorly defined and noisy "dark" peak, necessitating increased smoothing point counts.

It's noteworthy that changes in image contrast theoretically constitute an affine transformation of the histogram, ideally preserving the calculated ratio under the curves. Observed deviations primarily stem from the histogram's discrete nature and slight alterations in maximum peak heights due to applied smoothing during peak identification.

Table 2 displays the results of composition calculations using different methods for the original image

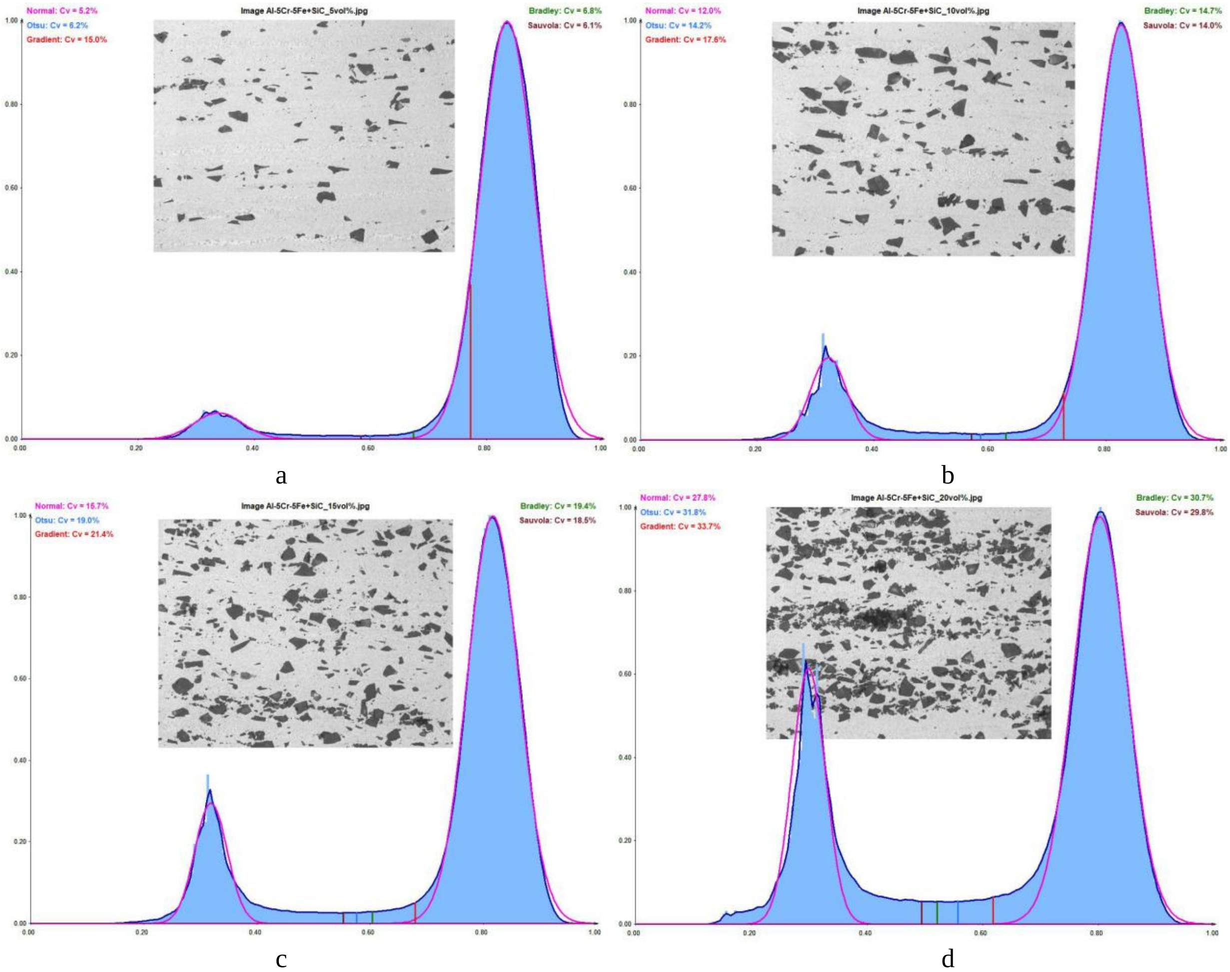

Fig. 2. Histograms, image examples, and calculation results for the composition of the Al-6Cu-0.4Mn composite with varying amounts of SiC inclusions using the proposed method and standard binarization methods. Amount of SiC, vol.%: a — 5, b — 10, c — 15, d — 20.

Table 1.

SiC contents in the Al-6Cu-0.4Mn composite with different volumes of SiC inclusions by the proposed method and standard binarization methods

SiC content, vol.%.	Gaussian curve (this work)	Otsu	Gradient	Bradley	Sauvola
5%	5.2	6.2	15.0	6.8	6.1
10%	12.0	14.2	17.6	14.7	14.0
15%	15.7	19.0	21.4	19.4	18.5
20%	27.8	31.8	33.7	30.7	29.8

Table 2.
Impact of contrast reduction on composition calculation results for the Al-6Cu-0.4Mn composite with 10% SiC inclusions

Contrast reduction, units.	Gaussian curve (this work)	Otsu	Gradient	Bradley	Sauvola
0	12.0	14.2	17.6	14.7	14.0
25	12.2	14.3	19.3	14.6	13.8
75	11.8	14.5	27.1	14.1	11.8
100	11.2	14.6	33.3	12.8	—

and images with reduced contrast (achieved by reducing contrast in the IrfanView program by 25, 75, and 100 units). This demonstrates that the method not only exhibits the highest accuracy but also maintains stability in the face of contrast variations, performing well across a wide range of image contrasts.

These comparative results demonstrate that for the non-universal cases of image analysis, such as determination of composition, taking into account the specifics of the physical system underlying the image pays off by increased accuracy of the analysis.

Conclusions

The proposed novel method for quantitatively assessing material composition from images, which entirely avoids the use of threshold values, demonstrates superior accuracy compared to traditional binarization methods.

This method is particularly suitable for determining the quantitative composition of two-component composites due to its enhanced accuracy and stability, providing consistent results across varying image contrasts.

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Безпороговий метод визначення складу двофазного композиту за мікроскопічними зображеннями

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Запропоновано новий метод оцінки кількісного аналізу складу двокомпонентних композитів за зображенням, що не використовує порогового значення бінарізації і має більшу точність порівняно з традиційними методами бінаризації з використанням порогового значення. Метод є стійким щодо зміни контрасту і добре працює в широкому діапазоні контрастності зображень.

Ключові слова: композиційний матеріал, аналіз матеріалу, комп'ютерне моделювання, обчислювальні методи, аналіз зображень.