Microstructural phase differentiation of AA7075/ZrC composite using image processing of SEM micrographs

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Abstract. Image processing gives a more in-depth knowledge of the properties of various materials. The method employed in this study was an automated picture processing procedure to carry out quantitative microstructural characterization of AA7075/ZrC composites. Primary AA7075 matrix and secondary ZrC reinforcement phases were objectively divided, imaged and measured through images of the backscattered electron scanning electron microscopy (BSE-SEM). In order to be able to separate the matrix and the reinforcement in the entire area of the image, the methodology was based on Python-based libraries, like NumPy and OpenCV, to further improve thresholding, morphological filtering and create accurate color mapping. The calculations of the areas of pixels along with the Delesse principle of converting the data of two-dimensional images into volumetric quantities allowed the calculation of local ZrC volume fractions. The findings have shown that the reinforcement is not distributed all over the material but it is quite different in different regions. The non-uniformity herein emphasizes the need to carry out site-specific analysis in order to obtain structure-property relations in composite systems. Compared to manual methods, automated phase mapping and measurement proved to be faster, more consistent, and less prone to operator bias.

1 Introduction

Development of engineering materials has essentially revolutionized many of the technological fields opening up opportunities previously inaccessible to conventional metals and alloys. The introduction and widespread use of composite material is among the greatest advancements. The materials are designed by integrating two or more phases of the constituents- usually a matrix and a reinforcement- with dissimilar physical or chemical characteristics, leading to an additive increase in mechanical, physical and occasionally functional performance [1]. The aluminum matrix composites (AMCs) have gained importance especially in applications that require a compromise between light weight, high

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strength and superior wear resistance, including in automotive, aerospace and defence sectors [2].

The aluminum 7075 alloy matrix (AA7075) reinforced with zirconium carbide (ZrC) particulates is one of the prominent examples in this category. The reason behind the selection of AA7075 as a matrix is that it has a relatively low density, high specific strength, and is highly machinable; it is an alloy that is commonly employed in highly important structural parts where the issue of performance and weight reduction is of utmost importance. The introduction of ZrC-based ceramic reinforcements also increases the prospects of this system, which confer greater hardness, enhanced wear resistance, and enhanced thermal and chemical stability. This composite structure is very appealing in the situations when materials are subjected to harsh service conditions, and the necessity to introduce customized sets of mechanical and physical properties is severe [3].

The volume fraction of the reinforcement phase is a very important aspect that determines the properties of composite materials, especially particulate-reinforced metal matrix composites. The volume fraction, which is normally the ratio of the total volume of the composite that is occupied by the reinforcement, has a major effect on a wide range of mechanical responses. As an example, it has been shown in many studies that a significant increase in the volume fraction of reinforcement will tend to significantly increase hardness, yield strength, and wear resistance through the mechanisms of load transfer and inherent characteristics of the reinforcing phase. Considering the particular example of AA7075/ZrC composites, the increased ZrC content increases the resistance of the substance to plastic deformation and abrasion, which means that the material is more adequate to the high-stress and high-wear conditions [4].

Nevertheless, this correlation is not necessarily linear and always useful. Although the reinforcement content may be beneficial in the context of strengthening and stiffening the composite, they may also lead to the emergence of unpleasant phenomena, particularly when the volume fraction exceeds the optimal levels. Overloading of the ceramic particles may also cause agglomeration of the particles and hence uneven distribution in the matrix. This kind of clustering is associated with localized sites of stress concentration, which may trigger a microcrack and seriously deteriorate ductility, impact toughness and interfacial bonding properties. These may in turn encourage an early failure, a decrease in the overall component reliability and a reverse of the benefits that are being aimed to achieve by using composites. This spot analysis is important in the process of relating the microstructural features to localized variations in properties or failure modes. Reinforcement volume fraction is a metric that has been conventionally measured manually [5]. A micrograph (usually an SEM or optical image) is then analyzed by the operator in a typical workflow, which may involve counting or outlining particles, estimating their area or linear fraction, and statistically making inferences about the volume fraction, based on some assumptions. Although this method may be beneficial in terms of offering valuable information, it is also associated with serious disadvantages. Manual measurements are subjective by nature, and the outcome is not only different among the operators, but also among the repeated measurements of the same individual. It is a laborious, time-consuming procedure, which in many cases is not possible to analyze statistically significant numbers of images, or even follow changes due to a process in real time. Moreover, the manual method is inconvenient in large-scale industrial quality control programs or research programs with hundreds or thousands of samples [6].

These constraints have prompted a shift to computerized, digital image processing methodology to microstructural analysis. The key benefits of processing the volume fraction measurement process using automation are based on the possibility to provide: Unbiased, operator-independent results: Software-based solutions eliminate the variability caused by human judgment, providing reproducible and objective quantification. High throughput and

scalability: Automated procedures can compute and analyse large data sets - batches of micrographs - in a fraction of the time that manual methods take, allowing feedback loops to be run quickly to control processes or optimise research. Real-time or near-real-time analysis: Automated routines are run on production lines or in research laboratories to aid in making immediate decisions and quick detection of defects, outliers, or process deviations. Flexibility and adaptability: Digital methods can be designed to be flexible in recognizing particular morphological properties, can work with varied image properties, and can be able to counteract changes in imaging conditions, and hence be useful in a wide range of composite systems [7].

Image processing methods which take advantage of software development, e.g. the OpenCV library in Python, Image Processing Toolbox in MATLAB, or open-source software like ImageJ, allow the segmentation of constituent phases based on contrast, morphology, and spatial distribution differences. Composite micrographs can be mapped to identify and quantify each phase by operations like thresholding, edge detection, and region labeling. The outcome is an extremely efficient method of finding the global and local volumes of reinforcements in the matrix. Such automated measurements can be plotted, statistically compared and related to other micro-structural or mechanical properties, which encourages a more in-depth view of the composites performance and informs further optimization of the material [8].

It is on this basis that the current research paper meets a crucial demand in the research and application of composite materials: automated determination of the local volume fraction of ZrC reinforcements in AA7075/ZrC composites through image processing of SEM micrographs. The study uses the latest digital analysis to work around the shortcomings of manual measurements to produce highly accurate, reproducible and consistent phase maps of whole micrographs. The work aims to make possible the rapid and objective measurement of composite microstructure by automation of the measurement process to enable the design, production and certification of advanced AMCs with predictable and optimized mechanical behaviour. This methodological development does not only increase the scientific rigor of composite characterization but improves as well the practicability of strict quality assurance protocols in manufacturing set-ups-a more critical issue as the use of metal matrix composites is on the rise [9].

2 Materials and methods

In this work, composites consisting of an AA7075 aluminum alloy matrix reinforced with zirconium carbide (ZrC) particulates were produced and assessed in terms of their microstructural characteristics. AA7075 was selected as the base matrix material due to its exceptional strength-to-weight ratio, coupled with its widely recognized engineering performance. ZrC particles were added as the reinforcement phase due to their intrinsic hardness and chemical stability, expected to provide improved wear resistance and mechanical strength to the composite.

The processing started with the accurate weighing and mechanical mixing of AA7075 powder with a calculated amount of ZrC particles to reach a homogeneous distribution of the reinforcement phase. The obtained powder mixture was further consolidated by using several techniques of powder metallurgy, either hot pressing or spark plasma sintering, followed by controlled cooling to obtain fully dense composite billets. Small specimens were sectioned for microstructural characterization from the consolidated billets and then systematically prepared by conventional metallographic procedures. The procedures consisted of sequential grinding with silicon carbide papers of increasing fineness, followed by polishing with diamond pastes to a mirror finish, and finally by appropriate etching procedures related to aluminum alloys. The microstructure was examined in an SEM equipped with a BSE

detector. This imaging mode was chosen because it provides good atomic number contrast; thus, the AA7075 matrix will appear darker, whereas the ZrC reinforcement phase appears brighter.

Quantitative analysis of the volume fraction was done from a set of two representative BSE SEM images, acquired at locations carefully selected in order to capture typical microstructural features. These micrographs represented the input for digital image processing. After quality checking, images were cropped and their contrast enhanced, if necessary, in order to optimize the phase contrast. Fully automated image analysis was performed with Python, in particular by using its OpenCV and NumPy libraries, which guarantee that results are reproducible and operator-independent. Binary phase maps from grayscale SEM images were obtained by using intensity-based thresholding through the selection of a proper threshold value, either empirically or with the help of automated algorithms like Otsu's method, enabling the darker aluminum matrix to be differentiated from the brighter ZrC particles.

After thresholding, a color mapping procedure was performed: the pixels corresponding to the matrix were colored in green and the ones corresponding to ZrC were colored in red. Such an approach has allowed an easy differentiation between the two phases along the whole image without sacrificing any spatial information. The area corresponding to each phase was afterwards measured by counting the number of colored pixels representing the phase, according to the standard assumption that the analyzed two-dimensional microstructure is representative of the three-dimensional volume fraction.

In this way, each SEM image provided the volume fraction of the ZrC reinforcement in the AA7075 matrix. Results from both images were then used in statistical analyses that test the possibility of changes in the phase distribution between different areas in the composite material.

Representative processed images with clearly differentiated phases were prepared to include in the manuscript as a means of showing the efficacy of the segmentation and quantification workflow. In general, this automated image-based methodology allowed for a fast, objective, and reproducible way to identify phases and measure volume fractions in accordance with area in AA7075/ZrC composites; hence, supporting not only scientific study but also practical quality control in the production of advanced composite materials.

3 Results and discussions

The results of this study present the automated quantitative analysis of the phase composition in AA7075/ZrC composites based on two representative BSE SEM images, Figure 1 and Figure 2. These figures show not only the different microstructural features present across different regions of the material but also represent the foundational dataset for automated segmentation, phase discrimination, and volume fraction estimation. The key driver behind this study was to develop and apply a reproducible digital workflow for distinctly separating and quantifying the matrix and reinforcement phases, which would aid in making objective assessments of local variation of microstructure in the composite. The methodology was based on exploiting open-source and widely adopted Python libraries, specifically OpenCV and NumPy, for all image analysis and computation tasks, while matplotlib and PIL were used for visualization and figure development [10].

The workflow started by acquiring high-quality, backscattered electron (BSE) SEM images at appropriate magnifications to clearly resolve ZrC particulates within the AA7075 matrix. In these BSE images, differences in atomic number contrast led to obviously distinguishable regions where the lighter ZrC particles were bright against a darker AA7075 background. Images were carefully selected to include areas of high reinforcement density,

as seen in Figure 1, and more typical, dispersed microstructures, as seen in Figure 2, which provide an instructive comparison of phase distribution across the composite [11].

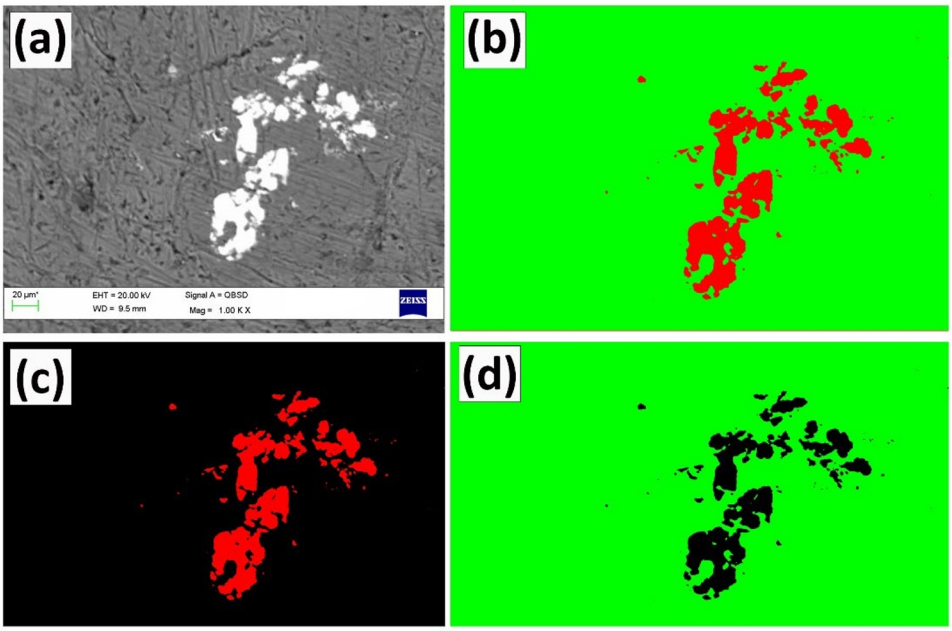

Fig. 1. Segmented SEM images showing (a) Original image (b) Combined layout mask (c) Matrix mask, and (d) Reinforcement mask.

When importing the SEM images into the analysis environment, the preprocessing involved converting them to a single-channel grayscale format when they were not already in that format. The histogram analysis of the image intensities was conducted afterward to ascertain the distribution of the pixel intensities and inform the threshold choice. The histogram of BSE SEM pictures is normally bimodal with the two peaks representing the primary and secondary phases of reinforcement, respectively. To choose the most objective way of threshold determination, the method of Otsu was used to divide the pictures, and it was supported by the usage of the cv2.threshold operation of OpenCV. In this method, the best threshold value that gives the lowest intra-class variance is computed to separate the pixel in the matrices (which are assigned with less intensity) and the ones that are used to represent the high-atomic-number ZrC particles (which are assigned with high values).

The binary mask of each image was obtained as a result of the thresholding operation and mathematically represented as:

$$M(x,y) = \begin{cases} 1 \; If \; I(x,y) \geq T \\ 0 \; If \; I(x,y) < T \end{cases} \quad (1)$$

where M(x,y) is the binary mask value at pixel (x,y), I(x,y) is the grayscale intensity, and T is the Otsu-determined threshold. Though quite effective for basic segmentation, this binary map may still contain noise in the form of isolated pixels or small gaps within larger features. In order to refine the integrity of the segmented features and further suppress the artifacts, a suite of morphological operations was employed, including dilation, erosion, and closing, using cv2.morphologyEx and related OpenCV functions [12].

With the binary mask obtained, a color mapping protocol was implemented in order to maximally interpret, not only for scientific scrutiny but also for broader communication. Pixels that correspond to AA7075 matrix with a value (0) in binary mask were mapped to a green channel (Red,Green,Blue value) and segmented ZrC reinforcement with a binary mask

value (1) were mapped to red channel (Red,Green,Blue value). This step immediately resulted in visual separation between the two phases and hence created the color annotated overlays which are presented here as the lower panels of Figure 1 and Figure 2. The clarity of these overlays made it possible to make qualitative measurements such as observing reinforcement clustering and particle morphology and size distribution, as well as providing a spatial map for accurate quantitative computation [13].

The quantitative analysis of the reinforcement content presented in the following stage of the results, using area fraction measurements, is based on the Delesse principle. This states that on any random section through a material, the two-dimensional area fraction occupied by a phase is proportional to its volume fraction in three dimensions for isotropic, homogeneously distributed structures. In this approach, direct counting of pixels was employed to assess the reinforcement content. The relation employed for the determination of the volume fraction of the ZrC phase, fv, was given by:

$$f_v = \frac{Number\ of\ pixels\ assigned\ to\ the\ ZrC\ reinforcement\ phase\ (N_r)}{Total\ number\ of\ pixels\ within\ the\ analyzed\ region\ (N_{total})} \quad (2)$$

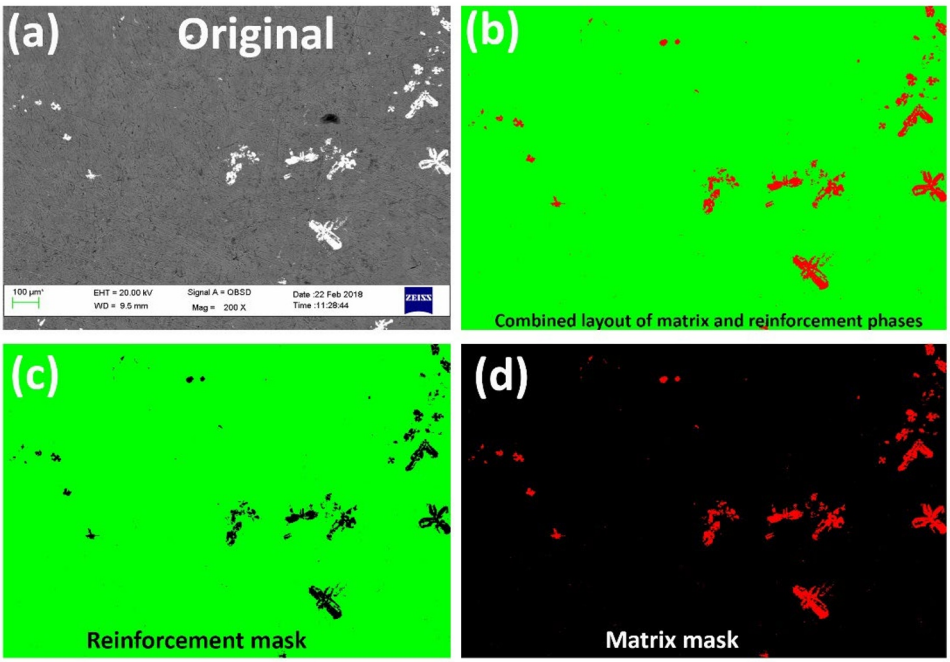

Fig. 2. Another Segmented SEM image showing (a) Original image (b) Combined layout mask (c) Reinforcement mask, and (d) Matrix mask.

This is a simple but powerful computation, which was possible due to the NumPy array manipulation and Boolean masking features, which offered a strong and scalable estimate of the local reinforcing content of each image. Figure 1, which shows a reinforcement-rich region, showed that the calculated fv was greater compared to Figure 2, which represents a more characteristic or dilute microstructure. These findings show directly the ability of automated measurements to record real and consequential heterogeneity in composite microstructure- heterogeneity that may be obscured in traditional bulk measurements or even by subjective and selective manual measurements [14].

The statistical aspect of the findings was also taken care of by comparing the values of the area/volume fraction that was obtained in both images. This methodology can be easily

extended to more regions of view and so can be used to comprehensively characterize the statistics in spite of limited sample size in this demonstration being two regions. The volume fraction mean values, range, and standard deviations can also be determined in multiple images or regions as a rigorous measure of microstructural uniformity, which is a direct predictor of mechanical performance and reliability in composite applications.

A more in-depth analysis of the working process shows that there are clear benefits compared to the old manual work. First, automation saves time significantly in the analysis process; individual images can be analyzed in seconds after optimization of the parameters, unlike in hours that it may take to count points or trace them manually. Second, objectivity and reproducibility of the approach is too strong: threshold selection by Otsu method, rather than subjective operator, reduces the influence of the human factor and inherently normalizes the output of different images and users. Third, the entire workflow, including the import of images and their preprocessing, thresholding and morphology, and finally, color mapping and the number of pixels, is transparent and can be modified with all operations encoded in Python scripts to be adapted to later and be viewed as an open system [15].

The quality and versatility of the open-source libraries used increases the rigor of this approach. OpenCV was used as the central processing unit of image processing, such as image reading, thresholding and morphological filtering. NumPy offered outstanding computational throughput of pixel-wise operations and statistical analysis of masks and matplotlib and PIL provided the ability to export the results in high-quality visual formats that can be published and presented.

It is worth mentioning that the current methodology also offers more comprehensive information on the microstructure-to-property paradigm. The ability to objectively and locally measure the volume fraction of reinforcement allows correlation of material behavior (like hardness, strength, wear behavior, or ductility) with certain microstructural characteristics. Indicatively, it is a known fact that areas possessing increased ZrC content will exhibit increased hardness and wear resistance, though it may be more prone to microcrack formation when agglomerates exist, which is directly observable by comparing Figures 1 and 2 in their raw and processed state. Similarly, the capability to swiftly handle several areas or entire-sample montages aids mesoscale research and provides the capability to follow compositional consistency throughout fabrication or subsequent post-processing interventions.

Limitations of the methodology, clearly acknowledged in the discussion, pertain to the two-dimensional nature of the SEM imaging and statistical assumptions of the Delesse principle. In the case of particles showing pronounced anisotropy, preferred orientation, or non-random distribution-for example, due to processing gradients or aligned fibers/platelets-more sophisticated stereological or tomographic approaches may be necessary to avoid systematic error. On the other hand, while automated thresholding is quite powerful for clear bimodal histograms, for images with considerable phase overlap and low contrast situations, the Otsu-based schemes may pose challenges and more advanced, possibly machine learning-based segmenting schemes are required.

It should be noted, however, that bearing the above-mentioned limitations in mind, the importance of the findings and the workflow from Figures 1 and 2 remain extremely high. This automated reproducible pipeline of microstructural phase separation and quantification brings energy to basic research due to the path it offers to statistically significant unbiased studies of microstructure. More importantly, practical engineering will be made possible through high throughput quality control and batch inspection. The visualization aspect also contributes to this, through the mapping of green matrix and red reinforcement in a very clear way, communicating the results to both technical and general audiences.

In terms of processing as well as application, these results show the need for local microstructural analysis. The great differences between Figures 1 and 2, obtained from different regions of the same or similar samples indicates that a local evaluation of the reinforcement is necessary for the prediction of mechanical properties, and also for the optimization of process parameters. If applied in production circumstances, this capability would allow fast feedback about mixing homogeneity, sintering effectiveness or the success of strategies for particle distribution - all of paramount importance in the robust production of advanced composites. In summary, the approach for automated segmentation and analysis, developed and demonstrated in this work, allows effective and efficient differentiation of the matrix and reinforcement phases in BSE SEM images (Figures 1 and 2) based on objective volume fraction estimation by pixel-based area calculation.

Combining optimum phase contrast by BSE imaging with image processing using OpenCV and NumPy and color mapping for visualization provides a very effective toolkit both for scientific investigation and industrial application. The method is extensible not only within the AA7075/ZrC system but also to a broad range of composite and multi-phase materials, promising a new standard in microstructural quantification and reinforcing the role of digital techniques at the interface of materials science and engineering practice.

4 Conclusions

- An automated image processing workflow in Python was successfully developed and applied to segment and differentiate the primary (AA7075 matrix) and secondary (ZrC reinforcement) phases objectively in the BSE SEM images recorded from AA7075/ZrC composites.
- The method used with thresholding and morphological operations was done by the OpenCV and NumPy libraries and allowed distinguishing between matrix and reinforcements clearly, visually, and quantitatively, as depicted in Figures 1 and 2.
- By using pixel-based area measurements coupled with the Delesse principle, the local volume fraction of the ZrC reinforcement was rapidly and effectively quantified in two representative BSE SEM images.
- Processed, color-mapped images showed substantial local variations in reinforcement distribution; this emphasizes the need for local assessment of composites in understanding microstructure-property relationships.
- Reproducibility, consistency, and lack of subjective bias were ensured in this fully automated script-based approach.
- It is scalable to large datasets and can serve as a basis for the manipulation of other composite systems and imaging conditions for further microstructure characterization and quality control tasks.
- The capability of estimating the local volume fraction of the reinforcements correctly and efficiently allows more accurate modeling and prediction of composite mechanical properties.
- The established workflow provides the basis for integration with larger automated processing pipelines, potential machine learning-based segmentation, and high-throughput materials analysis.

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