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Experimental Methods for Image Analysis of Two-Phase Metallic Microstructures

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Experimental Methods for Image Analysis of Two-Phase Metallic Microstructures

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| 14. ABSTRACT In many engineering alloys, there are two phases at room temperature: alpha and beta. Traditionally, the process of categorizing visual features of the microstructure by phase has been performed manually according to ASTM International (or other) standard methods for counting and measuring microstructural elements. The benefit of this approach is that humans can recognize phase patterns relatively easily. Still, the work is tedious and puts practical limits on the quantity of data available for analysis. However, much current research involves digital image processing. Many of the current automated methods can easily create large amounts of data but sometimes at the cost of quality because almost all automatic processes to improve clarity, vary brightness, or highlight edges reduce the amount of information in the image. Here, the researchers employed a combination of machine learning and standard image processing techniques to provide large quantities of high-quality data. By training a segmentation classifier on features from several images, the researchers could delineate between the alpha and beta phases with higher accuracy than previously used operations and collect the size, shape, and orientation data desired. | | | | | | |
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1. Introduction

Digital, computer-based image analysis offers a relatively new avenue for material science research with distinct advantages for the quantity and types of data that are easily accessible. However, it also introduces some unique challenges because machines do not recognize patterns the way humans do, which sometimes leaves computers blind to certain features. Why then is it worth creating computer programs to simulate human pattern recognition and then have a computer quantify the observed patterns? Simply put, image analysis presents a new frontier for microstructural analysis of materials. Typically, a sample must be pulled apart, crushed, indented, or otherwise disfigured to estimate the ultimate compressive strength or hardness of a metal (or other material property). Not surprisingly, microstructural features are significant determinants for these mechanical properties; work correlating grain size to mechanical properties has been expanding since the 1950s with the discovery of the Hall–Petch Relation (Hansen 2004). While most of the testing for the methods described herein was performed on titanium alloy Ti-6Al-4V, the goal of the research was to develop a process to generate data that could be correlated to mechanical performance for many different two-phase materials.

2. Experimental Procedure

Images were taken at 1500× magnification using a backscattered electron (BSE) detector for average atomic number contrast on a Phenom XL scanning electron microscope (SEM), powered at 15 kV with Image Mode current density. The field of view was nearly 180 μm to a side, as shown in Fig. 1a. The images were fully processed within ImageJ using native functions and plugins available through the Fiji build version of that software (Schindelin et al. 2012). Analysis fell into three stages: 1) machine learning segmentation, 2) linear intercept analysis, and 3) “projected grain” analysis.

- 1) Images were segmented into alpha and beta phases using Fiji’s “Trainable Weka Segmentation” plugin (Arganda-Carreras et al. 2017). The plugin was initially designed to differentiate between cell groups/types for life science applications. However, using a visual analysis method proved very useful in the beginning to isolate grains for analysis. Essentially, a user opened an image representative of the image set, highlighted an area, and identified that area as being either alpha or beta. After multiple sample areas had been highlighted and identified (either from the same image or from multiple images), the classifier was trained and then applied to a more extensive

image set. The result was a set of binary images divided by phase into two colors (Fig. 1b).

- 2) Once the images were segmented, linear intercept analysis was performed on the images to reveal some general trends in the microstructure. Two types of image analysis were performed. The first was an automated adaptation of the ASTM method for grain size analysis: A series of randomly oriented lines of equal length were drawn on the image. The number of grain intercepts were counted, as shown in Fig. 1c. The total line length is divided by the number of intersections to reveal a mean linear intercept distance, which is a metric of grain size (ASTM 2013). The second analysis method was not directly derived from any specific ASTM method but was much more exhaustive. Evenly spaced lines were drawn across the image from edge to edge and overlaid on the segmented image such that the beta grains broke up the lines. Each line was then measured, and the length and orientation were saved. The process was iterated with lines drawn from 0° – 175° in 5° intervals. (A representative angle is shown in Fig. 1d.) The most significant advantage of the data from these two linear intercept methods is that they were based entirely on positively identified features in the original sample. However, while linear intercept analysis provided some helpful generalizations about the size of alpha sites and any preferred direction of grain orientation, unfortunately this method only provided two data types for analysis: line length and angle. That data is of limited value without further investigation.
- 3) The images underwent an areal analysis of individual grains through Fiji, which yielded many different data types (grain area, perimeter, Feret diameter, and Feret angle). The biggest hurdle to clear for this type of analysis was that it required every grain to be fully enclosed. Since the beta phase fully surrounded very few alpha grains, grain boundaries needed to be interpolated or projected on the alpha phase to create distinct grains for analysis. The option employed was an adjustable watershed algorithm. This algorithm connected beta grains to fully isolate individual alpha grains based on assumptions of average grain size acquired during linear intercept analysis.

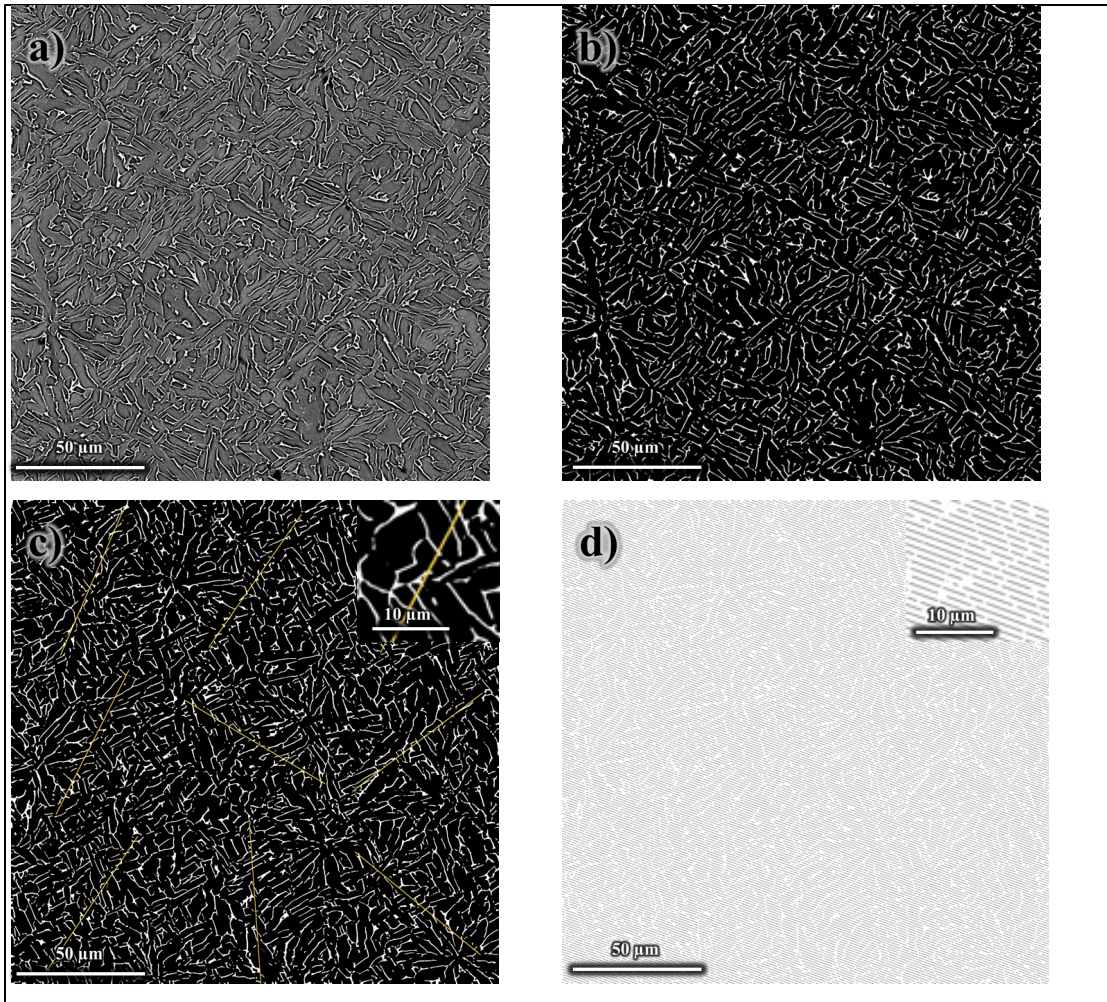


Fig.1 Images of Ti-6Al-4V alloy microstructure, showing the process of image segmentation and analysis for automated quantification of microstructure. a) Original BSE image of Ti-6Al-4V microstructure used for automated image analysis and quantification. b) Segmented $\alpha+\beta$ image generated using Fiji's "Trainable Weka Segmentation" plugin. c) Example of overlays used in the automated linear intercept method of interphase distance analysis. d) Example of cord-lengths used in "projected grain" analysis.

Using this two-stage analysis system provided a greater degree of confidence in the results of the areal analysis (Method 3) without limiting the data types to the only two available in linear intercept methods (Method 2). This helps future researchers in their ability to find more meaningful quantitative microstructural data, which aids in the search for correlations between the microstructure and mechanical properties.

3. Results and Discussion

By far, the most sensitive task of the research was segmenting the images consistently. Variations in SEM imaging settings, image location on a sample, and

sample processing history created visual variations, making it more difficult for the classifier to segment the images properly. After attempting to train a general classifier that would work on images taken with various imaging settings and processing histories, the research team found the classifier to be both inefficient and inaccurate due to visual inconsistencies in the regions selected to train the classifier. Ultimately, the best approach to create consistent results proved to be training a classifier on several images of samples with the same processing history and then applying the classifier to an image set captured with very similar or identical imaging settings. Additionally, by minimizing redundancy in training data, the memory use and computing time were reduced substantially.

Once segmentation was complete, the linear analysis methods provided some basic information about the microstructure. The linear intercept method was an ASTM standard method of measuring grain size. The overlay method confirmed the trends of the linear intercept data and showed any preferential grain orientations. An advantage of these intercept methods was that they were, computationally, incredibly cheap. So, even though each line drawn had a degree of error associated with it, thousands of lines creating tens of thousands of data points could be accrued in very little time to establish statistically valid generalizations, following the principle of “do more, less well” (Friel et al. 2000). However, both of these methods were limited by one critical factor: They did not account for alpha–alpha grain boundaries when counting intercepts. The result was that for materials in which the alpha phase is not well dispersed, the reported intercept distances are really the distance between phase boundaries, not necessarily grain boundaries. Without a doubt, this was the single most significant limiting factor to the validity of the grain size estimates of the linear analysis. It was also the primary motivator for the use of a watershed algorithm to enclose the grains. However, future research could reach into a few different areas to mitigate limitations from this computational analysis.

The linear analysis data provided a helpful tool in confirming or rejecting the validity of the data provided by areal analysis. Areal analysis, as stated previously, offered a wide variety of data types and was necessary to establish a more comprehensive picture of the microstructure of a given sample. As much data as the areal analysis offers, it did have one major drawback: All of the connections made by the watershed were algorithmic conjecture. There are thousands of grains in a given image, and errors in the watershed process would cause a systematic, large-scale skewing of the results. However, if the analytical methodology is consistent between images and samples, the results should have been equally skewed in all examples and at least provide large quantities of comparative data for analysis between samples.

4. Conclusions

Machine learning shows great promise in metal micrograph image analysis, as it simulates human-like pattern recognition but can process data much more rapidly and consistently than manual procedures. Additionally, it provides a definite advantage in segmenting alpha and beta phases over simply thresholding the images based on grayscale value since alpha and beta regions are frequently visually distinct but not wholly composed of different grayscale values. Linear intercept analysis is a long-accepted method of grain size analysis. Its application in Ti-6Al-4V at minimum provides helpful generalizations about alpha colony size and the presence or absence of preferential grain growth directions. Since areal analysis offers many more data types than linear analysis, accurate areal analysis is likely the key to connecting the microstructure of samples to mechanical properties as a particular data type (average grain diameter, for instance) or a combination of factors (e.g., grain area and roundness) may be found to have a solid correlation to one or more mechanical properties. For metal micrographs where grains are entirely surrounded by a separate phase or the grain boundaries are otherwise visually apparent, attaining accurate areal data is relatively straightforward. Still, for samples with visually indistinct grain boundaries, a watershed algorithm is the best way the researchers found to separate individual grains for analysis.

5. Future Work

For the phase of areal analysis, the most immediate next step is optimizing the watershed process. Adjusting the watershed attempts to balance the number of “basins” so that as many alpha-alpha grains are traced out while minimizing the number of erroneous lines drawn. Adjusting the watershed tolerance can reduce the number of errors created by the process in images of Ti-6Al-4V. It remains to be seen if there is any clear correlation between optimal watershed tolerance and data from the linear intercept method(s). Still, the researchers are hopeful such a correlation can be found and employed to improve analytical consistency across data sets.

Other avenues for improving the quality of the analysis can be found in both the experimental and computational domains. On the experimental side, the original images could be improved by using an optical microscope (exploring different lighting conditions) instead of an electron microscope. Additionally, there are a wide variety of surface treatment techniques (e.g., sample etching) that could improve the visibility of the grain boundaries to the segmentation process. On the computational side, the possibilities are much more expansive. Many features

within Fiji were never explored in this current study and their use may be helpful for future research.

Due to the time limitations of the research project, many future applications and potential advancements were not fully explored. For instance, as mentioned, most of the testing took place on images of Ti-6Al-4V. However, the process could easily be applied to other two-phase metals (or other materials with visually distinct microstructural elements). Initial testing performed on tungsten heavy alloy sample images showed that the linear analysis methods could identify grain size and directionality for these materials. Equally promising is the prospect of using the machine learning segmentation tools to find other microstructural features beyond the division of the image by phase.

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List of Symbols, Abbreviations, and Acronyms

| | |
|------|---|
| Al | aluminum |
| ASTM | ASTM International, formerly American Society for Testing and Materials |
| BSE | backscattered electron |
| SEM | scanning electron microscope |
| Ti | titanium |
| V | vanadium |

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