



# Characterization of macrosegregation in eutectic alloys

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## ABSTRACT

An image processing method has been developed to characterize the macrosegregation on cross-sections of castings produced from eutectic alloys. The method utilizes a combination of image segmentation, pixel-to-pixel analysis and tessellation techniques to construct a quantitative map of the solute distribution over large samples. Compared with methods reported previously in the literature, the current method is robust and can be applied to samples with large irregular cross-sections. The accuracy and validity of the method has been assessed through a series of artificially designed micrographs. An example application to an A356 aluminum alloy sample casting with irregular cross-section is presented.

## 1. Introduction

During the solidification of multicomponent alloys, solute redistribution, occurring due to bulk and diffusional transport phenomena, can result in a defect called macrosegregation [1]. Macrosegregation occurs when the alloying elements are transported over length scales larger than the grain size [1]. This causes depletion or enrichment in solute levels within the casting. These changes in composition lead to variation in the microstructure and the mechanical properties within the casting. Since this phenomenon was first reported, many techniques have been devised to visualize the redistribution of solute at the macro-scale in order to study it. Traditionally, methods based on metallography have been used to assess segregation at the scale of the casting based on variations in the phase content. Unfortunately, these methods do not necessarily yield quantitative results suitable for numerical model validation. On the other hand, quantitative methods like EDX microprobe analysis are only capable of quantifying macrosegregation in small areas or volumes. The difficulty lies in the limited number of samples that can be taken from large cross-sections to create a segregation map [2]. This issue is especially prominent when experimental data from a large sample is being acquired, where a high level of accuracy is required [3,4].

The method proposed in this paper is able to overcome this issue by automatically creating an optimal map of segregation from a montage of optical images. This approach first utilizes a tessellation map overlaid on the image montage. Then, using a pixel-to-pixel analysis, the area fraction of the desired phase is calculated in each element. It should be noted that the spatial variation of segregation in contour maps is strongly dependent upon the number of 2D elements used to

evaluate the area fraction. For small numbers of elements, the generated contour map represents the area average of the desired phase across large areas and is therefore quite coarse. An increase in the number of elements reduces the size of each element to the point where each element may contain only one microstructural phase. In this case, the measured area fraction becomes a binary representation because it is either completely filled with one phase or not. Thus, a method called the Average Maximum Difference (AMD) has been developed to determine the optimal number of elements to accurately represent the spatial variation of segregation. After application of the AMD method, a contour map of segregation is generated. This work describes the AMD method before using artificial microstructures to assess it and provides a demonstration of its application to a casting.

## 2. Methodology

### 2.1. Analysis Procedure

The initial step to analyze the spatial variation of segregation in a sample is to construct an image montage of the microstructure over the entire area that is to be analyzed. This can be done through different techniques, the most common one being optical microscopy. In order to prepare a montage, the cross-sectional area must first be polished. Then, a sequence of images of the microstructure covering the entire surface of the sample cross-section should be acquired. Before constructing a montage, these images should be segmented into the desired phases. Several methods can be utilized to segment the images, such as the Gaussian Mixture Model, K-means and Markov Random Fields [5]. Although these methods are quite accurate, when it comes to a large set

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of images, they are not time-efficient [5]. The recommended method in this case is to use Otsu thresholding, then implement appropriate morphologies to eliminate the “salt and pepper” noise in images [5]. Fig. 1 shows a montage image of an A356 casting after segmentation, composed of ~6000 images.

In the second step, a tessellation map is overlaid on the montage in order to create a segregation map.<sup>1</sup> However, the final segregation map is sensitive to the mesh size. The optimal mesh size for the tessellation is determined by calculating a quantity referred to as the Average Maximum Difference (AMD) using a simple algorithm.<sup>2</sup> In this algorithm, the difference between the area fraction of the phase of interest in an element with its nearby elements using a specified kernel is first calculated. A kernel in this case is a square matrix centering around an element. The area fraction in each element calculated by counting the number of pixels of the desired phase and then dividing by the total number of non-black pixels (Eq. (1)).

$$f_i^e = \frac{n_i^e}{n_{tot}^e - n_{bk}^e} \tag{1}$$

where  $f_i^e$  is the area fraction of the desired phase  $i$  in element  $e$ ,  $n_i^e$  is the number of pixels in element  $e$ , where subscripts  $i$ ,  $bk$  and  $tot$  indicate the pixels of the desired phase, black pixels and the total number of pixels, respectively.

The maximum difference of each element with its neighbours is then determined by calculating the difference of the area fraction of each element with its adjacent elements (Eq. (2)) and selecting the maximum value (Eq. (3)).

$$D_i^e = |f_i^e - Ar_{f_i}^{kernel}| \tag{2}$$

$$MD_i^e = \max(D_i^e) \tag{3}$$

where  $D_i^e$  is an array of the difference values for an element  $e$ ,  $Ar_{f_i}^{kernel}$  is an array containing the area fractions for all the elements in the kernel centering around element  $e$ , and  $MD_i^e$  is the maximum difference of an element  $e$ .

Fig. 2 shows an element and its adjacent elements with three different kernels superimposed on them. A kernel with a width smaller than mesh size will only capture the element itself. On the other hand a kernel with a width larger or equal to the mesh size will capture three or more elements. In this research, a kernel with a width of 1.2 times the mesh size has been chosen. This is the smallest kernel that captures all the adjacent elements, while ensuring that only the adjacent elements are picked. Applying this process to the entire image, the maximum differences of each element and its neighbours are calculated. These maximum differences represent how sharply the area fraction is changing with respect to the neighbouring cells. By calculating the average of these values over the whole image, a single value, called the AMD, representing the overall change in the gradient can be calculated (Eq. (4)). This process can be repeated for different tessellations. The optimal mesh size to evaluate the spatial gradient of a sample is achieved when the calculated AMD is a minimum (Eq. (5)).

$$AMD_l^h = \sum_{e=1}^{N_h} MD_i^e / N_h \tag{4}$$

$$h_{opt} = x \ni (AMD_l^x = \min(AMD_l^h) |_{h=h_l}^{h_f}) \tag{5}$$

where  $N_h$  is the number of elements in the mesh with spacing  $h$ , and  $AMD_l^h$  is the Average Maximum Difference of mesh with spacing  $h$ . The subscripts  $opt$ ,  $l$  and  $f$  for  $h$ , indicate the optimal mesh size, the lower bound for mesh size and the higher bound mesh size for AMD analysis.

<sup>1</sup> Python package is available on Github: <https://github.com/wildthingz/MakeContour>.

<sup>2</sup> Python package is available on Github: <https://github.com/wildthingz/pyAMD>.

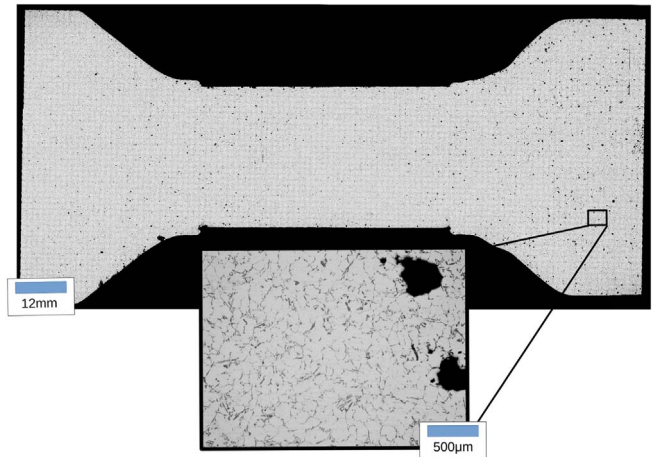


Fig. 1. An image montage of the microstructure in an A356 casting. Light and dark grayscales represent primary aluminum and eutectic phases, respectively, and black regions in the casting represent pores.

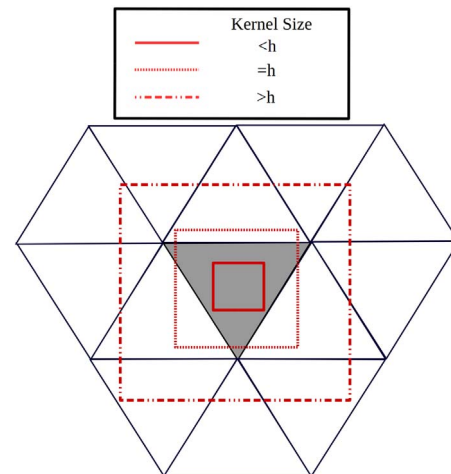


Fig. 2. An element with its neighbouring elements. Red boxes indicate the kernels overlaid on the mesh with three different sizes, where  $h$  indicates the mesh size. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

After the optimization stage, the image is divided into small triangular sections based on the determined mesh size. Subsequently, the area fraction of the desired phase is determined in each triangular section. The data then gets written into an input file for the Tecplot360 visualization software,<sup>3</sup> which can be used to visualize and further analyze the segregation map.

## 2.2. Artificial Microstructure

In order to assess this technique, a series of carefully designed, artificial microstructure images were generated and analyzed using the AMD method. To construct images with the area fraction changing in 1D, a python code was used to generate a number of thin rectangular images with constant area fraction. This was done by first initializing the matrix of values representing the image section with zeros and then populating the matrix with ones at random positions until the ratio of the number of ones to the total number of pixels met the criteria of the desired area fraction. The rectangular regions were then joined together to create a square region with a known gradient in area fraction. The same method has been used to create images with 2D area fraction

<sup>3</sup> Tecplot360 website: [http://www.tecplot.com/products/tecplot\\_360/](http://www.tecplot.com/products/tecplot_360/).

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