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Grain boundary detection in microstructure images using computational intelligence

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Abstract

Two computational intelligence approaches, a fuzzy logic algorithm and a neural network (NN) algorithm, for grain boundary detection in images of superalloy steel microstructure during sintering are presented in this paper. The images are obtained from an optical microscope and are quite noisy, which adversely affects the performance of common image processing tools. The only known way to accurately determine the grain boundaries is digitizing by hand. This is a very time-consuming process, causes operator fatigue, and it is prone to human errors and inconsistency. An automated system is therefore needed to complete as much work as possible and we consider a fuzzy approach and a neural approach. Both methods performed better than the widely available standard image processing tools with the neural approach superior on images similar to those trained while the fuzzy approach showed more tolerance of disparate images.

Keywords: Grain boundary detection; Fuzzy logic; Neural networks; Image processing

1. Introduction

1.1. Sintering

Sintering is a process of forming objects from metal, ceramic or composite powders by applying heat at a temperature below the material's melting point for a certain period of time. To achieve parts with excellent creep life, fatigue resistance, high strength and durability, sintering is accompanied by high pressure (hot isostatic press or HIP), which greatly improves the final product but also increases the cost of manufacturing significantly. Hipping is a near-net shape manufacturing process. More than 97% of the raw material is used in the final product [11]. The compacted powder deforms during the sintering and

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hipping processes. This deformation is difficult to estimate because it is often anisotropic shrinkage, meaning, the deformation is not uniform in every direction [1]. Anisotropic shrinkage results in functional degradation of the product, proportional to the amount of deformation. If the shrinkage in the final product is overestimated, raw material will be wasted. If it is underestimated, the final product will be useless and may be scrapped. The mechanics of sintering have been studied for a long time and there are two different types of models: macroscopic and microscopic. Macroscopic models cannot represent the complex three-dimensional mechanics of particles and therefore are incapable of making accurate deformation predictions, resulting in high scrap rates. The microscopic approach has roots in sintering theory and concentrates on the local behavior of particle necks [1]. A better understanding of micro-structural mechanics will allow development of good prediction models for final product size estimation, which will increase production efficiency. Microscopic images of sintered material, taken during the sintering process, are very useful in understanding the dynamic behavior, or rearrangement of metal powder particles. In this study, the digital images of interest are the microscopic images of the sintered specimen. These images are to be used for the analysis of particle rearrangements, or particle cluster formations, and for calculations such as grain size distributions. Understanding how the metal particles behave individually and as a group will help explain the sintering phenomena. The first step of these analyses is the detection of grain boundaries, that is, converting the image to a binary grain boundary map.

1.2. Digital image processing

A gray-scale digital image is composed of discrete points of gray tones, or brightness, rather than continuously varying tones. A natural image is divided into a number of individual points of brightness, and in addition, each of those points is described by a digital data value. Each brightness point is a pixel of the digital image. A pixel is the most basic element of any digital image. The pixels of an image form a rectangular array. Each pixel has a coordinate (x, y) that corresponds to its location within the image, x being the vertical component, and y the horizontal component. In general (0, 0) is the upper left corner of the image. For 256 gray-tone images, a pixel can have one of the 256 brightness values, ranging from 0 to 255. Black is represented by 0, and white is represented by 255.

Image processing is the management or manipulation of the image data to meet a user's needs [12]. Two different purposes of image processing can be stated as; improving the visual appearance to a human viewer, and preparing images for measurement of the features and structures present. The latter is the group that the algorithms presented in this study fall into. Modern fast computers with high memory capabilities are able to handle large amounts of data, which is usually needed for image processing applications. Image processing does not reduce the amount of data present but simply manages or rearranges it.

1.3. Problem definition

The images that are studied in this paper are of a magnified specimen. An optical microscope was used to acquire the images and the resulting images have sizeable variation of brightness and contrast within the image itself, along with high noise levels and local imperfections, which complicate the processing. Despite being easily identifiable by the human eye, it is almost impossible to accurately extract grain boundaries using readily available conventional tools, e.g. edge detection or threshold filters, in commercially available image processing software. A special tool is therefore needed for effective grain boundary detection.

The example image given in Fig. 1 clearly shows the uneven brightness and insufficient contrast. High level of noise and local imperfections can also be observed. There are several sources of local imperfections including optical problems (e.g. uneven lighting, physical obstructions) and external conditions such as dust in the environment. Noise, which is present throughout the entire image, is usually caused by the equipment and environment properties that are inherent to the experiment setup. For these images, a traditional or simple thresholding interval image processing approach performs very poorly. In the simple thresholding method, the user defines, or selects interactively, a certain threshold value, or a threshold interval. The pixels of the digital image with