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ELF を用いて作製した Fe-Cu 合金球の凝固組織の解析

Analysis of Solidification Microstructures in Fe–Cu Alloy Spheres Fabricated Using an Electrostatic Levitation Furnace (ELF)

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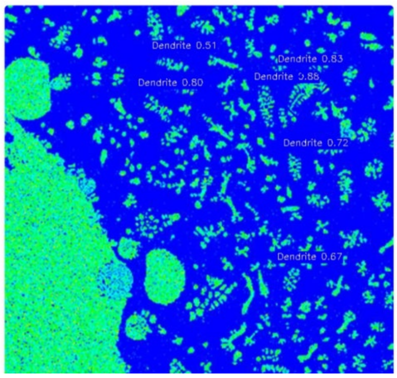

Abstract: In Fe-Cu alloys, the existence of a metastable solubility gap just below the liquidus line has been suggested. Verification of this requires rapid quantification of a large number of microstructural images. This study aims to apply deep learning to EPMA cross-sectional images to achieve automatic detection and measurement of Fe dendrites precipitated in the Cu phase. Fe–Cu alloy spheres of multiple compositions were produced using ELF containerless solidification under low gravity conditions. The cross-sectional EPMA images were divided into 640-pixel squares, and 150 images were selected that showed a wide area of the Cu phase and contained large dendrites. All images were annotated with oriented bounding boxes (OBBs) using Label Studio, and YOLOv8x was trained on 100 images (50 for training and 50 for verification), with the remaining 50 images used for inference. The inference results detected an average of 4.06 dendrites per 320 μm square, with an average confidence level of 78.2%. The detection targets were generally 20–50 μm in size, and particles with a long axis >50 μm could also be extracted when there was little overlap. On the other hand, micro-particles smaller than 10 μm were not detected, which is thought to be due to confusion with spherical small particles.

Keywords: Machine learning, Microstructure, Metastable phase,

1. introduction

In the evaluation and analysis of microstructural characteristics, recent advances in computer vision (CV) and machine learning (ML) have brought about new methods for extracting information from microstructural images [1)]. Fe-Cu alloys are eutectic alloys with a nearly horizontal liquidus line over a wide composition range in the alloy phase diagram. Fe-Cu alloys exhibit two-phase separation upon undercooling, suggesting the presence of a metastable solubility gap just below the liquidus line [2)]. To observe and analyze this phenomenon in experimental samples, it is necessary to analyze a large number of microstructure images. As a CV method capable of performing this analysis rapidly, the creation of weights using deep learning and subsequent inference using those weights is useful. In this study, cross-sectional EPMA images of Fe-Cu alloy spheres with multiple composition ratios solidified in a low-gravity environment using ELF were incorporated into deep learning to create weights capable of recognizing dendrites. The aim was to detect, measure, and illustrate Fe-precipitated dendrites from random EPMA images and to process microstructural observations at high speed.

2. Experimental method

Fe-Cu alloy ball samples prepared by the ELF were polished, and images observed and photographed by EPMA of multiple cross sections were divided into 640-pixel squares. The scale of these images was 0.5 (μm) per pixel.

Among the cross-sectional images created, 150 images were selected that contained a large area where the Cu main phase occupied most of the screen and Fe dendrites were formed within the Cu main phase. These images were annotated using the open-source data labeling tool Label Studio, and a dataset in oriented bounding box (OBB) format was constructed.

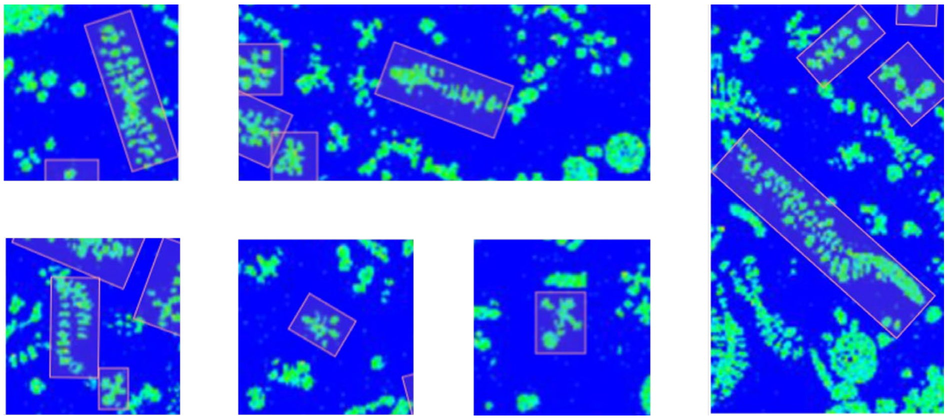

Figure 1. Annotation in Label Studio

Although the shapes of the dendrites observed in the cross-sections varied, in order to maintain the quality of the annotations, we excluded those that were independent of their surroundings and those that were so small that their arms were crushed.

We divided 100 of these images into 50 for training and 50 for verification, and used Ultralytics' deep learning platform “Ultralytics” to train the YOLOv8x model and obtain new trained weights for dendrite detection. For the remaining 50 images, we performed inference to determine the positions of dendrites using these weights. Training and inference were performed on a workstation (Lenovo ThinkStation P520c, CPU: Intel Xeon W-2123 @ 3.60GHz ×8, memory: 32GB) running Ubuntu 22.04.5 LTS.

3. Experimental Results and Discussion

The following is an example of an image in which dendrites were detected.

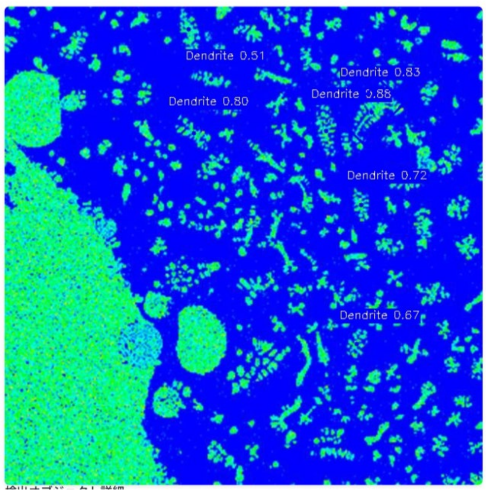

Figure 2. Detection image of a 320 [μm] square section

As shown in the image, typical large dendrites were detected. Fifty images were processed, and the average number of detections per image was 4.06, with an average confidence level of 66.9%.

The detected particles were approximately 20 (μm) to 50 (μm) in size. The shape was predominantly short-armed with many small particles, similar to the shape shown in the upper left of Figure 1. Even large particles with a long axis length exceeding 50 (μm) were detected if there were no overlapping particles in the surrounding box, but conversely, fine dendritic particles smaller than 10 (μm) were not detected. This is thought to be because they could not be distinguished from normal spherical small particles, which are excluded during deep learning, and were therefore excluded from detection.[)].

References

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