# Application of Deep learning to the segmentation of synchrotron X-ray tomography data of multiphase metal matrix composites

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**Keywords:** Synchrotron X-ray tomography, Deep learning, Segmentation, Metal matrix composite

**Summary:** The 3D microstructure of an Al alloy matrix composite with two ceramic reinforcements was investigated by synchrotron X-ray tomography. A deep learning algorithm was used for the segmentation of four different phases. We show that convolutional networks with the U-Net architecture are able to solve complex segmentation tasks with small amount of training data.

#### 1. INTRODUCTION

Cast near eutectic Al-Si alloys with addition of transition elements such as Cu, Fe and Ni are commonly used materials in the automotive industry for engine pistons production. The microstructure of these alloys is characterized by a 3D interconnected network formed by eutectic and primary Si and several Ni-, Fe-, and Cu-rich aluminides embedded in the Al matrix [1]. In order to improve the strength and creep resistance of these Al-Si alloys, additional ceramic reinforcements such as short fibers and particles are used [2]. It has been shown that the mechanical behavior of such composites strongly depends on the orientation of the fibers, the spatial distribution of the particles, individual volume fractions of all reinforcement phases, as well as on their morphology and interconnectivity [2, 3]. It is therefore of high interest to use all this information as an input to micromechanical models, in order to improve their performance in predicting the mechanical properties of the material. The most suitable tool to provide this kind of information is X-ray computed tomography (CT) because of its 3D nature. However, image segmentation of the CT data, especially in the case of multiphase materials, remains a highly challenging task. Ceramic reinforcements, as well as some intermetallic phases (IM), have similar X-ray linear attenuation coefficients, and hence similar gray level in reconstructed CT data (Figure 1a). This makes a threshold-based segmentation of individual phases simply impossible (Figure 1b). Moreover, high interconnectivity and clustering of all phases also excludes the application of shape-based classification.

At the same time, rising interest in deep learning-based (DL) segmentation algorithms is observed for non-medical CT data analysis [4]. Therefore, in this work we use synchrotron CT to investigate the 3D microstructure of an Al alloy matrix composite reinforced with both Al<sub>2</sub>O<sub>3</sub> short fibers and SiC particles, and we show the application of an advanced DL method for segmentation of all phases present in this multiphase material.

## 2. EXPERIMENTAL

Cylindrical samples with a diameter of 1 mm were prepared from the bulk material using electrical discharge machining with the planes of randomly oriented Al<sub>2</sub>O<sub>3</sub> fibers perpendicular to the rotation axis. Synchrotron X-ray CT experiments were carried out at the BAMline (BESSY II, HZB Berlin, Germany). The energy of the monochromatic X-Ray beam was set to 25 keV, and an effective pixel size of 0.44µm was achieved using an optical detector system with a CCD camera and a 10x objective. 2400 projections were acquired with an exposure time of 3 s per projection. The reconstruction of 3D volumes was performed by an in-house developed software based on Paganin's phase retrieval method and the filtered back-projection algorithm. Prior to segmentation, the noise in the reconstructed CT data was suppressed by the application of a non-local means filter.

For segmentation, a 2D fully convolutional network with U-Net encoder-decoder architecture implemented in FIJI ImageJ was used [5]. The network was trained with manually annotated CT slices. The amount of training data used was different for every phase and depended on the contrast and the similarity of different objects belonging to the same class. In case of fibers and SiC particles, high segmentation accuracy was achieved using one manually segmented CT slice of 2000x2000 pixels as training data, while for Si and IMs a section of 500x500 pixels was sufficient. The network was trained with 5000 epochs. The segmentation of the reconstructed volume was performed slice by slice.

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## 3. RESULTS AND CONCLUSIONS

The results of the DL segmentation are presented in Figure 1d. In comparison to a manually annotated slice (Figure 1c, note that this CT slice with manual annotations was only used for evaluation of the DL segmentation and not for training of the DL model), only few not properly segmented objects were found (marked by black circles). A qualitative analysis of the DL segmentation (Figure 1e) shows that most objects, except a few fibers, are detected, and the difference against manual annotations occurs only at the object's borders.

For quantitative assessment of the U-Net segmentation result, we used the Intersection over union (IoU) parameter (see Table 1). IoU is a common evaluation metric to assess the performance of convolutional networks in semantic segmentation tasks. It measures how well the segmentation matches the ground-truth annotations and is defined as the ratio between the intersection of DL and manual segmentations and their union (IoU=0: no overlap; IoU=1 perfect match). As a ground-truth, the manually segmented slice of 600x600 pixels was used. At the current stage of DL development, values of IoU higher than 0.7 correspond to acceptable segmentation results [4]. For all segmented phases, IoU exceeds 0.7 (Table 1). In the case of IMs, which have the best contrast and unique shape, IoU even exceeds 0.8. Despite the fact that Al<sub>2</sub>O<sub>3</sub> fibers, SiC particles and some IMs could only be differentiated by their morphology, the U-Net was able to correctly assign the class to most of the elements.

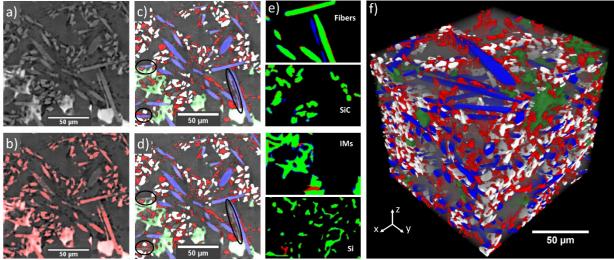
Table 1. Quantitative analysis of the U-Net segmentation result

Phase Metric	Al <sub>2</sub> O <sub>3</sub> fibers	SiC particles	Intermetallics	Eutectic + primary Si	Mean
IoU	0.77	0.72	0.83	0.73	0.76

Further analysis of the segmented phases leads to the following conclusions: as shown by a 3D rendering of reinforcing phases (Figure 1f), the eutectic Si builds bonds between SiC particles and Al<sub>2</sub>O<sub>3</sub> fibers, creating additional 3D interconnectivity. This leads to significant improvement of the material's strength. The SiC particles are partially agglomerated in small clusters, which are nevertheless distributed homogeneously and randomly oriented within the aluminum matrix.

#### References

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**Figure 1:** (a) Reconstructed slice of multiphase composite; (b) The result of a standard threshold method (Otsu); (c) Manually annotated phases:  $Al_2O_3$  fibers in blue, SiC particle in white, Si in red and IMs in green; (d) U-Net Segmentation result; encircled areas highlight differences to the manual segmentation (e) Qualitative example of U-Net segmentation performance (From top:  $Al_2O_3$  fibers, SiC particles, IMs, Si). Green: true positive, Blue: false negative, Red: false positive; (f) 3D rendering of segmented phases (For color coding see figure (c)).