Automated Pore Segmentation in Powders for Additive Manufacturing Based on Convolutional Neural Network

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Abstract: The pores in metal powders have a great impact on the mechanical properties of 3D printed parts. Thus, it is very important to realize automated pore segmentation. However, the tiny size and unclear boundaries limit this task. Considering this, we propose an Efficient-UNet network with the deep-supervised method for pore segmentation. On the one hand, more representative features are extracted by EfficientNet and fused with features in the decoder. On the other hand, deep supervision branches are connected with the decoder to prevent gradient disappearance. Benefiting from the above aspects, our proposed network model can segment small-sized pores with ambiguous boundaries. Experiments on our metal powder dataset demonstrate that our method achieves more precise results with clear advantages than other semantic segmentation methods.

Keywords: pore segmentation; micro-CT; convolutional neural network

1 Introduction

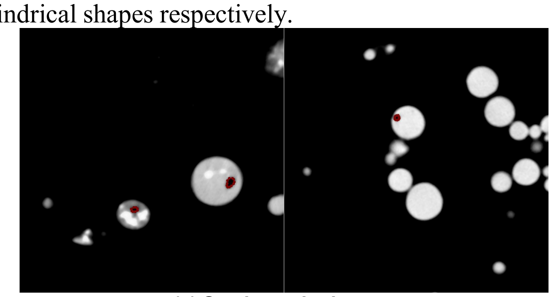
Selective-laser melting (SLM) is a representative technology for additive manufacturing (AM), which employs a high-energy laser beam to melt and solidify the pre-coated alloy powder layer by layer in a short time [1]. Its raw material is generally a single-component metal powder, mainly including stainless steel, nickel-based alloys, titanium alloys, etc.

The current processing technologies for metal powder mainly include the gas-atomization process and the plasma rotating electrode process. Both methods will inevitably produce pores during the manufacturing process, leading to the formation of hollow powder [2]. Cunningham [3] studied that powders influence the porosity rate and mechanical properties of 3D printed parts, and found that pores in the powders would be passed on to the completed components.

To improve the mechanical properties of 3D printed parts, metal powder for SLM requires a lower hollow powder rate. The testing methods of hollow powder mainly include the metallographic method and micro-CT method. Through the metallographic method, a 2D cross-section image of metal powder can be obtained by optical microscope. However, because this method cannot achieve 3D characterization of the powders, it has significant randomness and low measurement efficiency [4]. To overcome its shortcomings, the micro-CT testing technology for metal powder has attracted extensive attention. Plessis [5] provided information on powder internal porosity through high-resolution micro-CT scans and a detailed analysis of Ti6Al4V metal powders. The above research has established the foundation to further study automated pore segmentation in metal powders based on micro-CT. However, due to the unclear boundary of the pore caused by the small scale, it is quite difficult to test and represent the pores for traditional image processing algorithms. Above all, an Efficient-UNet network with a deep-supervised method is proposed to recognize and segment the pores accurately.

2 Experimental procedure

As shown in Figure 1,the powder materials we selected are steel and TC4. To solve the problem of poor dispersion, the metal powders were embedded in the resin. Before using CT scanning, the two samples were sanded into regular cylindrical shapes respectively.



(a) Steel powder image;
(b) TC4 powder image
Figure 1 Metal Powder Image with annotations

Data collection

The equipment for data collection is nan-Voxel 3000 micro-CT produced by Sanying Precision Instruments Co., Ltd. It is equipped with a micro-level focus and transmission radiation source. So the flat panel detector can reach a spatial resolution of 500nm, which can meet the requirements of metal powder defects on high resolution. The sample is placed on a high-precision rotary table and then CT scanning is performed on it. The projection data obtained by scanning is reconstructed using the Feldkamp (FDK) method to obtain a 3D volume data model, so as to obtain 2D tomographic image data.

Detection

We employ sensitivity (sen), specificity (spe), intersection over union (IoU), Dice coefficient to measure the accuracy of the network model in our task.

$$sen=\frac{TP}{TP+FN} \quad (1)$$

$$spe=\frac{TN}{TN+FP} \quad (2)$$

$$IoU=\frac{TP}{TP+FP+FN} \quad (3)$$

$$Dice=\frac{2TP}{2TP+FP+FN} \quad (4)$$

3 Result and discussion

Comparation with state-of-the-art methods

The quantitative results in Table 2 have proved it. We achieve 0.6691 IoU and 0.7717 Dice by our network. Compared with UNet, UNet++, and Deeplabv3plus, it has higher sensitivity of detection for positive results. But for specificity, the quantitative results of the four networks were almost the same, proving that their ability to judge negative results was almost identical.

Tabel 1 Comparisons with state-of-the-arts on dataset

Method	SEN	SPE	IoU	Dice
UNet	0.8720	0.9996	0.6547	0.7566
UNet++	0.8599	0.9996	0.6552	0.7549
Deeplabv3plus	0.8469	0.9994	0.6242	0.7300
Ours	0.9057	0.9995	0.6691	0.7717

The influence of deep supervised loss

No matter where the deep supervision loss is, it will lead to a better performance than without deep supervised loss. Phase 1+ Phase 3 performs best in Dice score. Adding Phase 2 fails to produce significant improvement. Therefore, Phase 1 is necessary for our task to boost performance.

Table 2 Ablation Studies for deep supervised loss.

Method	SEN	SPE	IoU	Dice
No deep supervised loss	0.8718	0.9996	0.6491	0.7524
Phase 1 + Phase 2 + Phase 3	0.8989	0.9990	0.6696	0.7692
Phase 2 + Phase 3	0.8700	0.9997	0.6581	0.7579
Phase 1 + Phase 3	0.9057	0.9995	0.6691	0.7717

4 Conclusion

In this paper, a pore segmentation method is proposed to achieve automatic testing for powders in SLM. Specifically, the EfficientNet is utilized as our backbone network for multi-level feature extraction. The decoder module with a deep supervision branch fuses the multi-level features and restores them to high resolution. Through them, our method can obtain the pore edge even if the boundary is not clear in an end-to-end manner. Experiments demonstrate that the proposed method achieves 0.6691 IoU and 0.7717 Dice score, which has obvious advantages over other semantic segmentation methods.

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