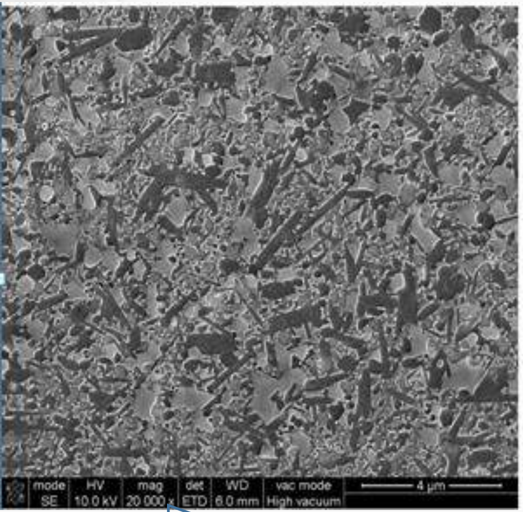
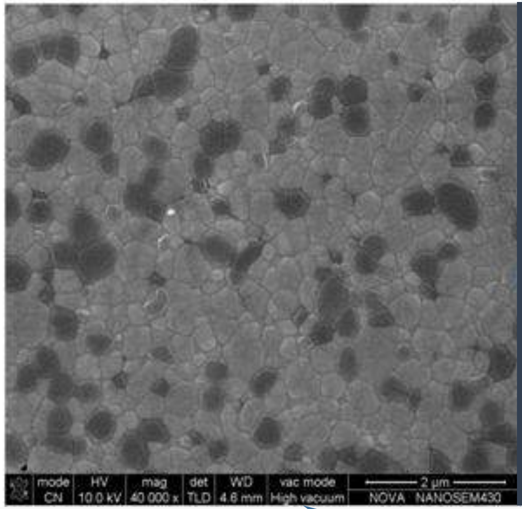
1.General Field of the Research





Introduction

Microstructural analysis is an important part of material science. The accurate analysis of the microstructure image of the new composite ceramic material can effectively optimize the material preparation process and improve the product performance.

At present, the analysis methods for the microstructure image of ceramic materials mainly include manual calculation and enumeration, as well as image analysis methods based on the traditional edge detection based on mathematical morphology.

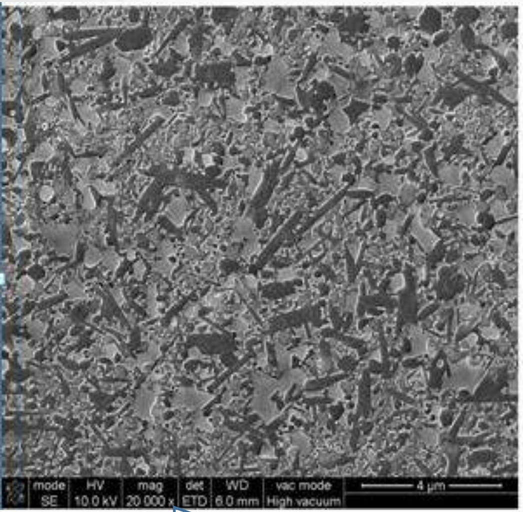
01 Si_3N_4-TiN Multiphase Ceramic

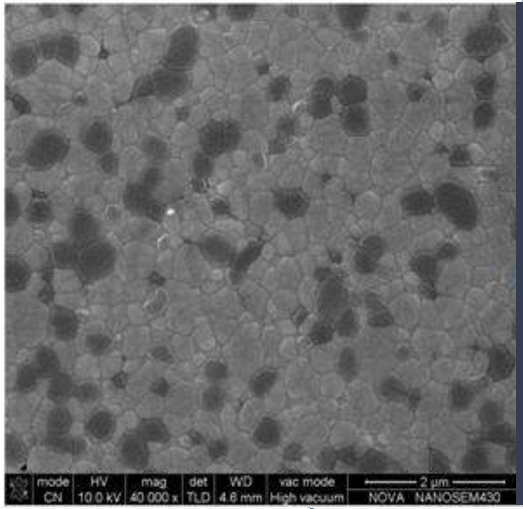
Multiphase ceramics with different aspect ratio

02 Al_2O_3-ZrO_2 Multiphase Ceramic

Multiphase ceramics with different background contrast

1.General Field of the Research





Introduction

However, the existing methods have many problems, such as complicated process, unable to achieve automatic detection and recognition, which restrict the efficiency and accuracy of image analysis.
The domain reason is that the image background is complex, and the boundary between the target grain and the background is difficult to be divided by a unified standard.

01 Si_3N_4-TiN Multiphase Ceramic

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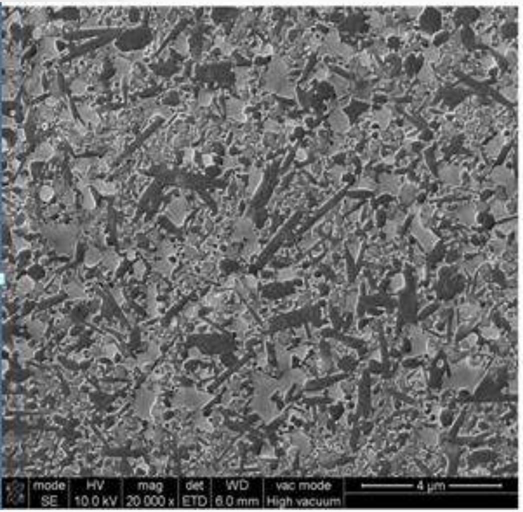
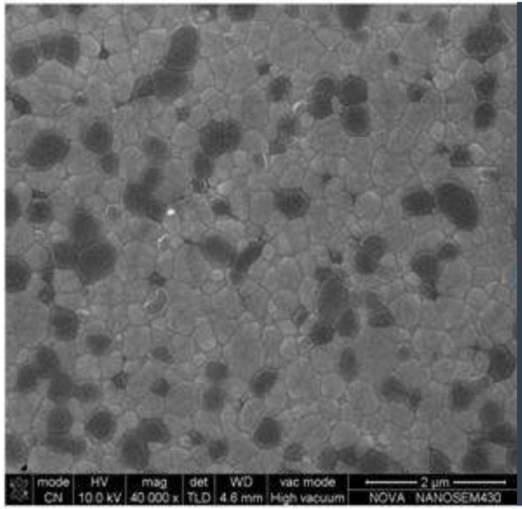
2.Research Aim



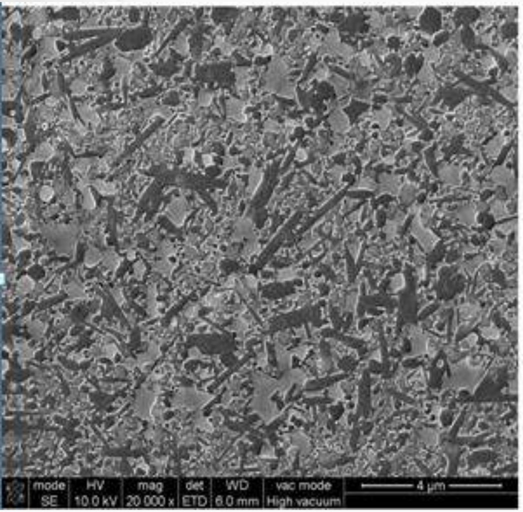


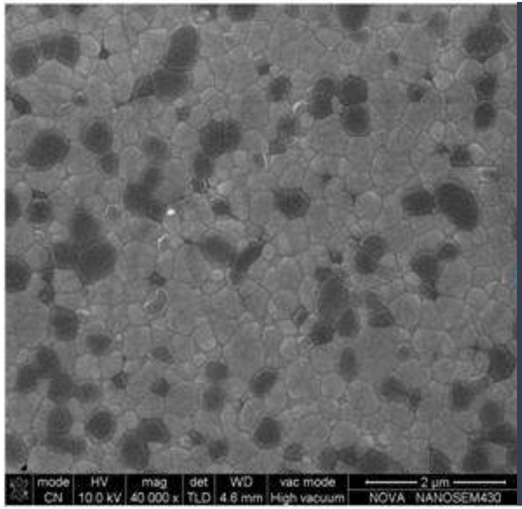
Research Aim

To solve above difficulties, this research aims at designing a Multi-model Fusion Instance Segmentation Method for Microstructure Analysis of Multiphase Ceramic Materials.

This type of method is more robust, with the combination of 3 different models(U-Net, U-Net++ and Mask R-CNN), and it can achieve automatic detection as well as output the information of each detected grains.

2.Research Aim





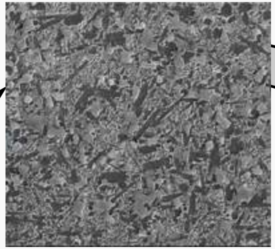
Research Aim

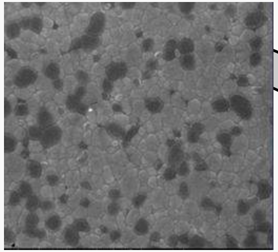
Given these characteristics, this research intends to realize extracting information of the microstructure image of the new composite ceramic material in a more robust and efficient way than before.

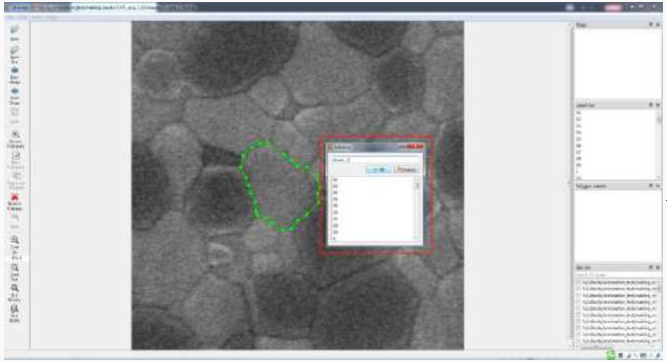
3.Research Approach

START

SEM







Annotation

NEXT

01 Image Collection and Data Annotation

The first step is to collect and annotate microstructure images of 2 kinds of composite ceramic material (**Si_3N_4-TiN & Al_2O_3-ZrO_2**).

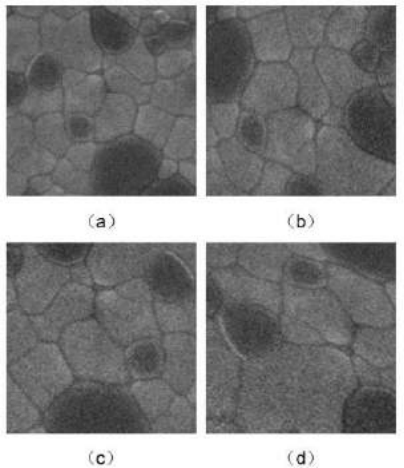
Microstructure images are collected by SEM(Scanning Electron Microscope), with 1024×943 pixels.

The obtained images are annotated via *Labelme.*

3.Research Approach

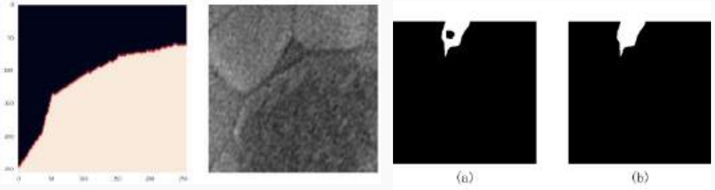
01

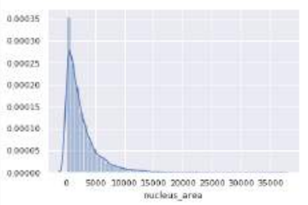
Data Augmentation

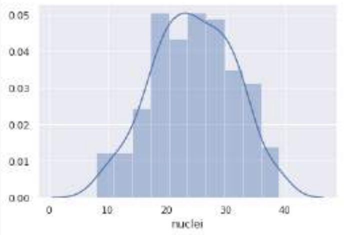


02 Data Augmentation and EDA

The second step is data augmentation and EDA.
Data augmentation:
Through reading the mask in batch and performing the transformation such as turning, translation, rotation and random cutting (or combination of the above) with the original image at the same time.
EDA(Exploratory Data Analysis):
The data set is explored and visualized , in order to prevent using the low quality data which may cause a negative influence on the segmentation performance of the models.







EDA

NEXT

3.Research Approach

01

02

Model Training

03 Model training and Evaluation

The third step is training models and evaluating their performance, including tuning different parameters(pre-trained weights, optimizer, learning rate, loss, etc.) and setting evaluation standard.

In the process of model training, a total of four different network frameworks and backbones (Mask R-CNN & Resnet-50, Mask R-CNN & Resnet-101, U-Net & Efficientnet-b4, U-Net + + & Efficientnet-b4) are used, and additional cell image data training weights are used as the pre-trained weights in order to boost training.

表1 模型性能评估结果（Al_2O_3-ZrO_2复相材料）

模型框架 &Backbone	AP_{50}/%	预测掩膜平均耗时/s
Mask R-CNN & Resnet-50	74.0	2.88
Mask R-CNN & Resnet-101	76.5	2.91
U-Net & Efficientnet-b4	75.4	2.76
U-Net++ & Efficientnet-b4	76.8	3.09

表2 模型性能评估结果（Si_3N_4-TiN复相材料）

模型框架 &Backbone	AP_{50}/%	预测掩膜平均耗时/s
Mask R-CNN & Resnet-50	39.9	4.08
Mask R-CNN & Resnet-101	46.6	4.57
U-Net & Efficientnet-b4	47.7	3.86
U-Net++ & Efficientnet-b4	48.5	4.21

Evaluation

NEXT

3.Research Approach

01

02

Model Training

03 Model training and Evaluation

The third step is training models and evaluating their performance, including tuning different parameters(pre-trained weights, optimizer, learning rate, loss, etc.) and setting evaluation standard.

In the process of model evaluation, two indexes are used to evaluate it: AP50 and the average time of prediction.

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Evaluation

NEXT

3.Research Approach

01

02

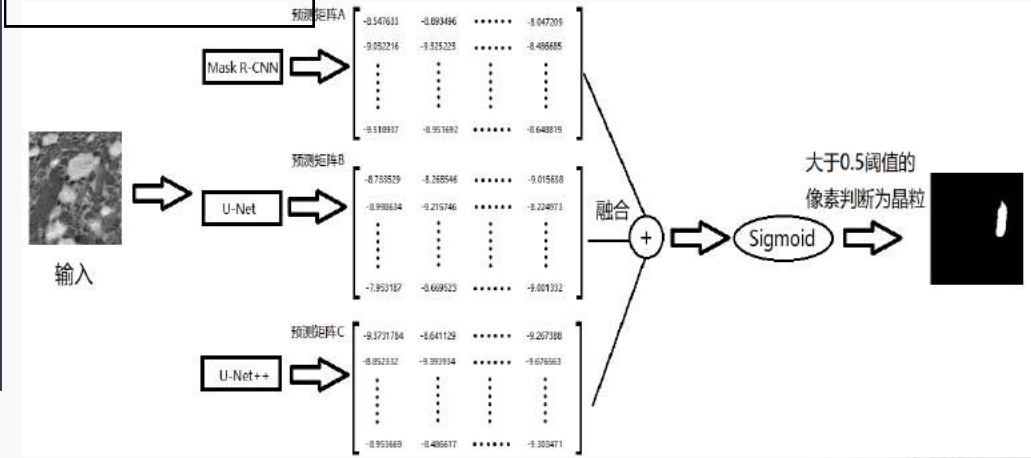
03

04 Model Fusion

The fourth step is model fusion, the prediction matrix from 3 models (Mask R-CNN & Resnet-101, U-Net & Efficientnet-b4, U-Net + + & Efficientnet-b4) are selected.

In the process of model fusion, the input image is predicted by three models, and then the prediction matrix corresponding to each pixel in the input image is obtained. The larger the corresponding values are, the higher the possibility that the model thinks that the pixel is a grain.

Model Fusion



NEXT

3.Research Approach

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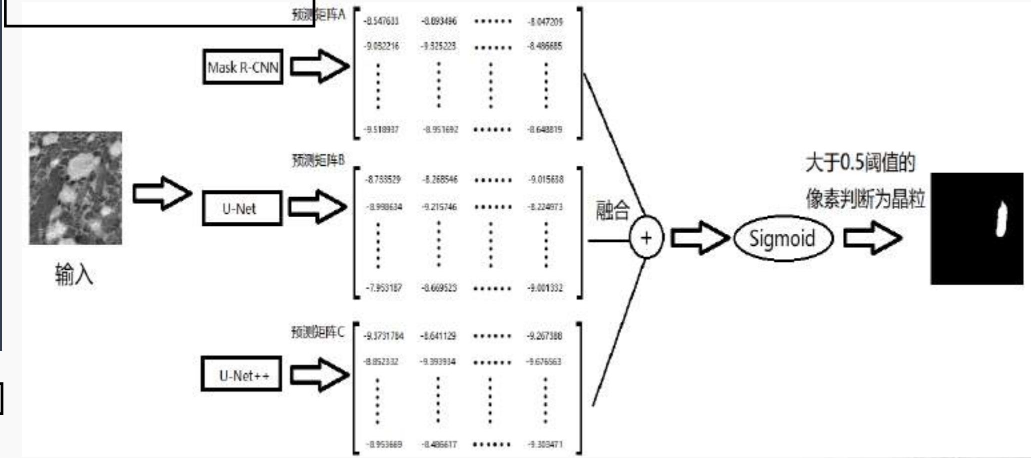
02

03

04 Model Fusion

After that, the fusion matrix is obtained by weighted addition of the three prediction matrix, and then the values in the fusion matrix are normalized to the range of [0,1] by sigmoid function. The threshold value is set to 0.5 and the following judgment is performed, that is, the pixels larger than the threshold value in the fusion matrix are judged to be grains, otherwise it is judged to be background.

Model Fusion

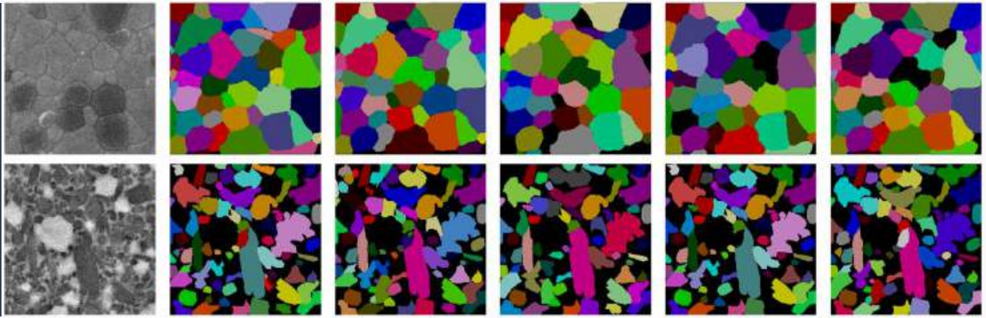


NEXT

3.Research Approach

04 Model Fusion

After comparison, it can be found that for Al_2O_3-ZrO_2, the performance of AP50 after fusion is 2.1% higher than that of single model AP50 with the best performance, while Si_3N_4-TiN is 3.8% higher.



Before

After

表1 模型性能评估结果（Al_2O_3-ZrO_2复相材料）

模型框架 &Backbone	AP_{50}/%	预测掩膜平均耗时/s
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表2 模型性能评估结果（Si_3N_4-TiN复相材料）

模型框架 &Backbone	AP_{50}/%	预测掩膜平均耗时/s
Mask R-CNN & Resnet-50	39.9	4.08
Mask R-CNN & Resnet-101	46.6	4.57
U-Net & Efficientnet-b4	47.7	3.86
U-Net++ & Efficientnet-b4	48.5	4.21

表3 融合模型性能评估结果

材料	AP_{50}/%	预测掩膜平均耗时/s
Al_2O_3-ZrO_2复相材料	78.9	12.08
Si_3N_4-TiN 复相材料	52.3	15.24

3.Research Approach

05 Post Processing，Shape Fitting & Output Information

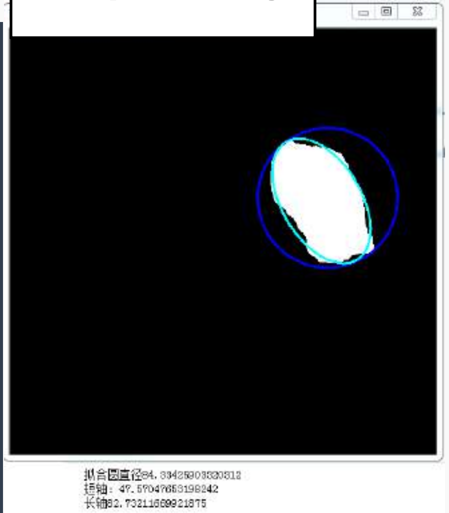
The fifth step includes post processing，shape fitting & output information.

Post Processing:
The area and number of connected regions in the mask are obtained by *OpenCV*, and each connected region is traversed. If its area is less than 150 pixels, it is considered as an invalid region, which is deleted from the predicted mask.

Shape Fitting:
Using *findcontours* in *OpenCV* library to find the outline of masks, and then using *fitellipse* and *minenclosing* function to fit the grain shape.

Output Information:
Finally, the mask is transformed into microstructure image information by integrating them into excel file.

Shape Fitting



Output Information

	A	B	C	D	E
1	晶粒名称	圆直径	椭圆短轴	椭圆长轴	
2					
3	mask_0.pr	168.6685	95.14095	165.4642	
4					
5	mask_1.pr	156.3434	98.85229	153.9702	
6					
7	mask_10.p	70.21416	51.35477	63.12065	
8					
9	mask_11.p	81.9392	51.67942	76.28656	
10					
11	mask_12.p	61.45425	48.3978	59.95788	
12					
13	mask_13.p	104.2355	61.03203	99.67042	
14					
15	mask_14.p	89.4988	63.62942	84.02386	
16					
17	mask_15.p	106.9081	75.66516	101.0789	
18					
19	mask_16.p	57.14256	28.8945	56.81305	
20					
21	mask_17.p	70.0359	49.04614	64.865	
22					
23	mask_18.p	52.95301	34.30774	50.4225	
24					
25	mask_19.p	51.59603	43.52356	47.88248	
26					
27	mask_2.pr	81.3021	62.32051	80.44469	
28					
29	mask_20.p	114.8652	52.59404	112.6888	
30					
31	mask_21.p	67.67689	43.02518	66.04923	
32					
33	mask_22.p	68.8188	29.13232	69.393	
34					
35	mask_23.p	122.3317	33.89413	129.4478	
36					
37	mask_24.p	38.21014	9.781484	40.73866	
38					
39	mask_25.p	101.2425	66.99308	99.59996	
40					
41	mask_26.p	60.20817	33.40079	60.43233	

4. Research Achievements

Patent:
Image Recognition Method and Device of Crystal Material (CN:2019108208000)
Current status: Substantive Examination Procedure

Paper:
Instance Segmentation Method Based on Multi-model Fusion for Microstructure Analysis of Multiphase Ceramic Materials
Current status: Under Review