Style transfer based data augmentation in material microscopic image processing

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Abstract

Recently progress in material microscopic image semantic segmentation has been driven by high-capacity models trained on large datasets. However, collecting microscopic images with pixel-level labels has been extremely costly due to the amount of human effort required. In this paper, we present an approach to rapidly creating microscopic images with pixel-level labels from material 3d simulated models. Usually images extracted directly from those 3d simulated models are not realistic enough. It is easy to get semantic labels, though. We introduce style transfer technique to make simulated image data more similar to real microscopic data. We validate the presented approach by using real image data from experiment and simulated image data from Monte Carlo Potts Models, which simulate the growth of polycrystal. Experiments show that using the acquired simulated image data and style transfer technique to supplement real images of polycrystalline iron significantly improves the mean precision of image processing. Besides, models trained with simulated image data and just \( \frac{1}{3} \) of the real data outperform models trained on the complete real image data. In the study of such polycrystalline materials, this approach can reduce pressure of getting and labeling images from microscopes. Also, it can be applied to numbers of other material images.
Introduction

The quantitative analysis of microstructures is essential in the control the properties and performances of metals or alloys [1-2]. An important step in this process is microscopic image processing [3] which is used to extract significant information in a microstructure [4]. Compared to image classification task [5], semantic segmentation [6], which output the pixel-wise label of original image, is commonly used in microscopic image processing and material structure characterization. Recently progress in material microscopic semantic segmentation [7-9] has been driven by high-capacity models trained on large datasets. Unfortunately, the generalization performance of these models are hindered by time-consuming labeling of material microscopic images. Therefore, such big available datasets with pixel-wise label for semantic segmentation are lacking in material fields.

We are therefore interested in creating very large image datasets with pixel-accurate semantic labels for different kinds of materials. This dataset may substantially increase the accuracy of semantic segmentation models, which at present appear to be limited by data. Creating large datasets with pixel-wise semantic labels is known to be very challenging due to the amount of human effort required to trace accurate object boundaries. In addition, the more detailed the semantic labeling, the smaller the dataset [10].

In this work, we explore to use 3d simulated models to create large-scale pixel-accurate ground truth data for training semantic segmentation systems. Such 3d simulated methods can build rich visualization representation models. For example, see figure 1, the Monte Carlo Potts models can represent polycrystalline structure of materials, in which the grain size and distribution are similar to the real grain structure [11-12]. By using computer techniques, it is easy to get simulated image data with pixel-level label from 3d models. However, those acquired contents in simulated image data are too simple to look like realistic. Hence, there is a challenge to apply simulated image data to real microscopic image processing system. In order to make the simulated image more realistic, we propose to transfer the style from real microscopic image to the simulated image while still retaining the original content [13-14].

![Figure 1: (a) the Monte Carlo Potts model. (b) a slice image from the model. (c) a microscopic image of polycrystalline iron. And we only add the scale bar in this image. All microscopic images share the same scale bar in this paper.](image-url)

This image-to-image conversion can be simply described as the input of one high-resolution
image, and the output of another high-resolution one after processing. We are more interested in the fact that the output and input no longer look the same, but the underlying global structure remains unchanged. And, it’s shown that conditional Generative Adversarial Networks (condition GANs) do a good job on the task of Style Transfer [15-18].

By using our presented approach, we have created pixel-level semantic segmentation ground truth for 28800 images extracted from Monte Carlo Potts models. The collecting of simulated image dataset is no longer limited by the speed of human’s labeling. On the experiment of semantic segmentation of material polycrystalline image datasets, we show that using our simulated image dataset increases the mean precision of real microscopic image processing. In addition, models trained with simulated image data and just $\frac{1}{3}$ of the real image data outperform models trained on the complete real image data, which reduces pressure of getting and labeling images from microscopes. In total, this approach can apply data augmentation to numbers of other materials.

**Material**

**Polycrystalline Iron**

The images were collected by an optical microscope, and the samples were taken from a hot-rolled iron plate and forged into a round bar with a diameter of 30 mm. Then the iron bar was fully recrystallized by annealing at 880°C for 3 hours. The samples were polished for a fixed time and etched using 4vol% nital solution, with an average section thickness of 1.8μm.

**Method**

**Extracting information from 3d models**

In the study of computer simulation of grain growth, Monte Carlo Potts model has been able to generate lots of structure close to actual grain [11-12]. But the existing work lacks a comprehensive quantitative characterization of such a polycrystalline structure model. As shown in figure 1, we used Monte Carlo Potts method to establish a large-size 3d digital model of the polycrystalline materials. Then, the section images were obtained from three dimensions, called simulated image data. We also calculated the ground truth mapping grain boundaries. The 28800 simulation images we acquired are two orders of magnitude more than the existing real microscopic images of polycrystalline iron grain dataset. However, the simulated image data is simple and pure, containing only grain boundary information with no texture information. Therefore, simulated image data can’t be directly used in machine learning based algorithm.
Style Transfer

We use style transfer algorithm to make simulated image data to acquire the texture of real image data. Specifically, we use conditional GANs to carry out transformation, the so called pix2pix [15]. Conditional GANs convert image $x$ to image $y$. The given image $x$ is called the condition, as the input of the generator $G$. During training, the generator $G$ forges the output $G(x)$. While, the discriminator $D$ distinguish $G(x)$ from $y$. Both modules are optimized by adversarial training to make “fake” $G(x)$ be closer to “true” $y$. More importantly, the output $G(x)$ must retain the underlying structural similarity to the condition $x$.

The objective of a conditional GAN can be expressed as:

$$L_{cGAN}(G,D) = E_{x,y}[\log D(x,y)] + E_{x}[\log(1 - D(x,G(x)))]$$

Where $G$ tries to minimize this objective, while $D$ tries to maximize it.

$$G^* = \arg \min_G \max_D L_{cGAN}(G,D)$$

The article [13] explored that generator need to not only fool the discriminator but also be near the ground truth output in an L1 sense, using L1 distance to mix the objective. The L1 loss is described as bellow

$$L_1(G) = E_{x,y}[\|y - G(x)\|_1]$$

The final objective is

$$G^* = \arg \min_G \max_D L_{cGAN}(G,D) + \lambda L_1(G)$$

In order to realize conversion from simulation images to microscopic images, our generator uses the encoding-decoding network U-net [19]. And the encoding-decoding network structure enables the input and output to be shared on the bottleneck layer, which helps to retain underlying structural similarity. The discriminator calculates the loss of local patches between output and ground truth to represent the consistency of high-level details. The structure of style transfer system is shown in figure 2.

Figure 2: The structure of style transfer system, called pix2pix [15]. The discriminator $D$ learns to distinguish $G(x)$ from $y$, the generator $G$ learns to fool the $D$, which is an encoder-decoder network with skip connections between corresponding layers in the encoder and decoder, called U-net [19].
Experiments

Experimental Data

- **Real image data**
  The polycrystalline iron dataset includes total 136 serial section images, having a resolution of 2800 × 1600 pixels, of which the ground truth has 2 semantic classes. It is split into 100 training and 36 test images. The original images were preprocessed into local patches with the size of 400 × 400 pixels, considering the computer capacity and speed. The training images were randomly cut from the training set, while the test set consists of 1000 patches with 400 × 400 size cut from the other 36 original images directly.

- **Simulated image data**
  We train our style transfer system using real image data. As shown in the Figure 3, there are 3 columns of simulated image data on the left side of Figure, while real image data on the right side. Because the conditional characteristics in the network, the boundary of grains in the simulated images is much more prominent than that in the real image data. We found there is no effect on the final result. By using style transfer system, we have acquired 28000 polycrystal simulated images (400 × 400) with pixel-level labels and realistic style.

![Simulated image data](image1.png)  ![Real image data](image2.png)

Figure 3: Simulated image data with realistic style and real image data.
Evaluation models and metrics

We use U-net [19], an encoder-decoder network, to carry out microscopic image semantic segmentation. In encoder-decoder networks, the input goes through a series of convolution-pooling-normalization group layers until the bottleneck layer, where the underlying information is shared with the output. U-net joins the layer-skip connection to transfer the features extracted from the down-sampling layer directly to the upper sampling layer. It makes the pixel location of the network more accurate.

We explored the using of these simulated image data as the data augmentation of the microscopic image dataset. During the training stage, we jointly train on real and simulated data using batch gradient descent with mini-batches of 8 images, including 4 real and 4 simulated. It takes 14K iterations to converge. Finally, the quality of data augmentation is evaluated by the mean precision on the test set.

Our implementation of this algorithm was derived from the publicly available Python [20], Pytorch framework [21], and OpenCV toolbox [22]. The style transfer system and u-net’s training and testing were performed on a system using 4 NVIDIA 1080ti GPU with 44GB memory.

Table 1 provides the results that using the simulated image data during training increases the mean precision by 1.7 percentage point. Besides, the table shows that training on 30% of the polycrystalline iron dataset with our simulated data keeps up with the whole polycrystalline iron dataset on precision. This suggests that our method can generate simulated data which reduces the amount of microscopic images obtained and labeled manually in study of polycrystalline iron image processing.

Table 1 Controlled experiments on Polycrystalline Iron dataset. Training with the full Polycrystalline Iron training set augmented by the simulation images increases the mean precision by 1.7 percentage points. Simulation images also reduce the amount of manually labeled training data by a factor of 3.

| Real image data | 100% | - | 20% | 30% | 50% | 100% |
|-----------------|------|---|-----|-----|-----|------|
| Simulated image data |      | 100% |     | √   |     | √    |
| mAP             | 80.3 | 75.3 | 77.4| 80.3| 81.6| **82**|

Conclusion

In this paper, we propose an approach of data augmentation for material microscopic image processing, which can generate pixel-accurate simulation images with semantic labels. We demonstrate this method by extracting 28800 images from 3d models of Monte Carlo Potts method for polycrystalline iron and adding the style of real microscopic images. Experiments show that the data we generated can improve the performance of semantic segmentation model of real images and reduce the overhead of manual labeling.

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