Label-free SEM Content Recognition with Cycle-consistent Generative Adversarial Networks

(Computer Vision)

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1. Problem Description & Proposed Approach

Scanning Electron Microscopy (SEM) has become a powerful tool in nanoscience. Its images provide valuable morphology information and extracting contours from the images is useful for labs or semiconductor companies to evaluate their patterning capabilities. However, there is a lack of suitable tool to efficiently identify the contour of nanostructures. Previous approaches mainly applied edge detection and filtering algorithm and results are highly dependent on the quality of the images.

SEM images are usually noisy and under-resolved, though it is distinguishable to human, the contour of nanostructures extracted by the conventional numerical method are usually inaccurate and biased**. (Figure 1b)** Also, creating labels for given SEM images can be time-consuming and labor-intensive.

Here, we want to launch a **label-free SEM image recognition** project based on the **Cycle-consistent Generative Adversarial Networks' (Cycle GAN) network**. Inspired by its ability to process unpaired training data, we will use lithography design to train the discriminator instead of using labeled data generated manually.

We propose to solve this problem with both supervised learning and unsupervised learning methods:
For the supervised learning method, we will train a CNN with labeled data (paired SEM images and labeled generated from ilastik tool) and use this network as the benchmark of our project. For the unsupervised learning method, we will train a CycleGAN [1] with unpaired training data (SEM images and contours generated from the PhiDL packages) and compare the results with the first method. The authors of CycleGAN provide the implementation in PyTorch. The application was can be also applied to our problem the contour image can be considered as a different "style" of the polygon. We plan to first modify the data pipeline to train the network with our data, then tune the hyper-parameters and introduce new functional modules as the project proceeds.

a

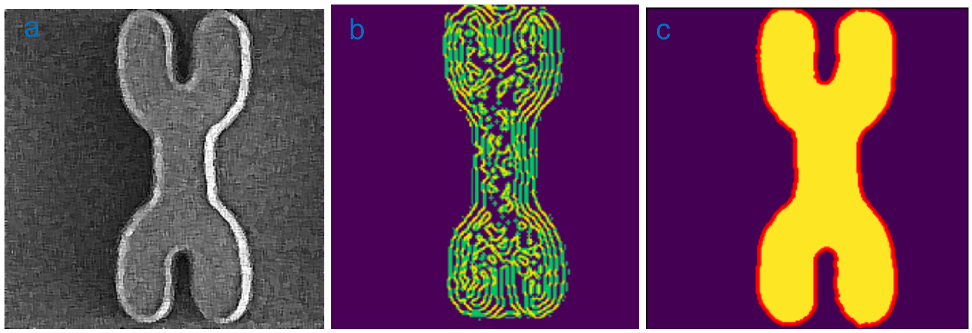

Figure 1: **a**. A given SEM image for nanostructures. **b**. An SEM image applied canny edge detection method. **c**. Label created by the Ilastik tool.

2. Dataset

We will start with a dataset that contains hundreds of SEM images characterizing nanostructures with various shapes, including circles, Vs, Us, and Bones(~90 images Ching-Ting has taken for his project). The nanostructures (polygons) in the images would be labeled using Ilastik as ground truth for CNN network (Figure 1c). A artificial SEM generation tool (http://artimagen.sourceforge.net/) can also be applied to expand the training set if necessary. For lithography design, we will use a PhiDL (https://github.com/amccaugh/phidl) to train the discriminator in the CycleGAN based algorithm.

3. Evaluation

Our goal is to predict accurate contour images for the input polygons, and we plan to evaluate the performance of our model in two metrics. The first metric will be the Per-pixel accuracy as applied in the paper [1], and the second metric will be the edge placement error (EPE) which is widely used in the industry.

4. References

[1] Jun-Yan Zhu*, Taesung Park*, Phillip Isola, and Alexei A. Efros. "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks", in IEEE International Conference on Computer Vision (ICCV), 2017.

[2] Stephan Ihle, Andreas M. Reichmuth, Sophie Girardin, Hana Han, Flurin Stauffer, Anne Bonnin, Marco Stampanoni, Janos Voros, Csaba Forro. “UDCT: Unsupervised data to content transformation with histogram-matching cycle-consistent generative adversarial networks” *Nature Machine Learning*, 1, 461-470 (2019)