RECOVERY OF NANOWIRE MORPHOLOGY AND DISTRIBUTION BY A
COMPUTER VISION-ASSISTED APPROACH

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Abstract:
Nanomaterial has demonstrated its advantages in a variety of application fields such as biosensors and next-generation computer chips. It is important yet challenging to precisely capture and recover the morphological characteristics of nanomaterial for nanomanufacturing quality control. We propose a computer vision-assisted approach in this paper to recover the structural details of nanowires and their spatial distribution. First, we develop a geometric model for nanowire length measurement and a model calibration method based on statistical fitting to deal with bias. Second, we devise a morphology-based detection algorithm to identify nanowires from Scanning Electron Microscope (SEM) images in the presence of defects, and design a simple yet novel similarity function for correspondence establishment. The identified nanowires are fed into the geometric model to calculate their lengths. The experimental results show that our proposed method can effectively identify nanowires and establish correspondence with high detection accuracy and low false alarms in estimating lengths of a large number of nanowires on a substrate. Our approach can be readily integrated to assist nanomanufacturing and its quality control.

Keywords:
Nanomanufacturing; Morphology characterization; Nanowire detection; Correspondence establishment; Computer vision

1. Introduction

It is important to recover and analyze the morphological characteristics (i.e., length, diameter, etc.) of nanomaterial for quality control in nanomanufacturing [1]. In order to quantitatively measure the nanostructures, multiple Scanning Electron Microscope (SEM) images are taken from different perspectives (or angles) and the structural details can be reconstructed using a geometric model. Nevertheless, traditional methods [1, 2] require manually identifying feature points of nanomaterial in the images and manually establishing correspondence, thus not applicable to performing morphology characterization of a large number (e.g., tens of thousands) of nanowires on a substrate. Furthermore, existing approaches do not consider the bias introduced during the imaging process. To overcome these problems, in this paper we propose a computer vision-assisted approach to recover the details of one-dimensional nanostructures automatically [3]. Our approach is aimed to identify nanowires effectively and estimate their lengths accurately in presence of defects. Compared to the statistics-guided approach proposed by Wang et al. [2], our approach has the following advantages: (1) requiring two instead of three images as input; (2) considering model calibration to deal with bias; (3) using image processing techniques instead of manually to identify nanowires; (4) accurately estimating the lengths of a large number of nanowires instead of using statistical resampling methods.

The immediate goal of this paper is to develop feasible methods for the identification of nanowires and estimation of their lengths from SEM images containing a large number of nanowires. The geometric model for nanowire length measurement requires a pair of images (i.e., top view and projection view images) as input. Since the appearance of a SEM image is very sensitive to angle change, traditional pixel-to-pixel correspondence establishment methods [4] are not feasible for this application. Therefore, we need to first identify the feature points in both images and then establish the correspondence of the feature points between top view and projection view images. We adopt a morphology-based method [5] for nanowire detection in the top view image and a modified Canny edge detector-based method [6] for nanowire detection in the projection view image. We design a similarity function considering the neighborhood pattern of feature points for correspondence establishment and investigate the performance using a correlation-based method and that of a dynamic programming method. The experimental results show that both methods can achieve high accuracy in establishing the
correspondence between the SEM images acquired from different angles. An interesting observation is that although the dynamic programming method can deal with occlusion, its accuracy is lower since the mismatching tends to propagate along the scanning direction.

The rest of the paper is organized as follows. Section 2 describes the geometric model for nanowire length measurement. In Section 3, we design a practical approach for feature point detection in both top view and projection view SEM images, respectively. Section 4 presents a novel similarity function and two matching approaches for correspondence establishment between top view and projection view images. Section 5 provides the geometric model calibration method that considers the bias introduced in the imaging process. Finally, Section 6 concludes the paper with some discussion on future research directions.

2. Geometric model

Our geometric model requires two images (i.e., top view and projection view images) on the same nanowire substrate. We assume that normal nanowires are perpendicular to the substrate plane. Figure 1 illustrates the geometric model. First, a top view image is taken by placing the nanowire substrate parallel to the camera lens (xy-plane in Figure 1(a)). Then, we rotate the substrate around x-axis with α angle and take the projection view image of the nanowires. Figure 1(b) shows a nanowire projected to yz-plane. The solid red line represents the nanowire before rotation and the dash red line represents the rotated nanowire. Assuming that the distance from the bottom-end of the nanowire to x-axis is \( l_1 \) before rotation and \( l_2 \) after rotation, we can obtain the length \( (h) \) of the nanowire by Equation (1) as follows:

\[
h = \frac{l_1 \cos\alpha - l_2}{\sin\alpha}
\]

3. Feature point detection

In this section, we describe an automatic approach to identify nanowire feature points for both top view image and projection view image. The feature point that we aim to identify is the top-end of each nanowire. Specifically, we employ a morphology-based method for feature point detection in top view images and a modified Canny edge detector-based method for feature point detection in projection view images. Figure 2 shows a pair of SEM images of zinc oxide nanowires (with 1,000×1,000 pixels) acquired respectively from top view and projection view.

By shifting the x-axis to the top-end of one nanowire, we can calculate its relative length with other nanowires using Equation (1). Here, \( l_1 \) and \( l_2 \) can be obtained by identifying the top-end of each nanowire in top view and projection view images, respectively (see Section 3 for more details). Since the nanowire is not unique, the correspondence has to be established between \( l_1 \)'s in the top view image and \( l_2 \)'s in the projection view image. That is to say, each nanowire should have a pair of \( l_1 \) and \( l_2 \) (we will discuss more about this in Section 4). The angle \( \alpha \) is known when the images are taken (we choose \( \alpha = 5^\circ \) in this paper). Note that in this model we assume that there is no rotation around y-axis or z-axis for simplicity. In practice, however, the bias introduced by the rotation around y-axis and z-axis is unavoidable. In Section 5, we will detect and estimate this rotation by a statistical fitting approach, and then calibrate the geometric model to improve the measurement accuracy.

3.1. Detecting feature points in top view images

Recognizing that in the top view image, the top-end of a nanowire has high intensity compared with the background (see Figure 2-a). We can convert the gray-level image into a binary (back-white) image and use a region-based segmentation technique [7] to identify the feature point. To improve the performance of such a method, we first apply the morphological top-hat filtering [5] on the gray-level image to enhance its contrast considering the disk-shape of the nanowire's top-end point in the top view image. Figures 3-a, 3-b, and 3-c show the results of applying this method. From the figures, we can see that this method can effectively identify the nanowire top-end. The defect (bundle) can almost be completely removed by applying top-hat filtering. However, the region-based detection method is likely to identify multiple nanowires as one when they are close to each other. Another problem is that it is sensitive to noise. To reduce such effect, we propose and devise a feature detection method based on watershed segmentation [8] as follows:

1. Apply top-hat filtering on the top view image (Figure 3-a).
2. Threshold the result of top-hat filtering into a binary (black-white) image (Figure 3-b).
3. Compute the distance transformation of the black-white image (Figure 3-d).
4. Smooth the distance transformation with a Gaussian filter to avoid over-segmentation.
5. Apply watershed segmentation onto the result of Step (4) and then calculate the center point of each segment.

Figure 3-f shows the result after applying the watershed segmentation method. One can observe that this method can (1) successfully split multiple nanowires close to each other; (2) avoid over-segmentation by using a Gaussian filter to smooth the distance transformation; but (3) miss some low intensity nanowires (short and thin) due to the smoothing operation.

3.2. Detecting feature points in projection view images

We first try the similar detection method (as designed for top view images) on projection view images. Figure 4-a shows the result of watershed segmentation-based feature detection on the projection view image. One can see that each nanowire is identified as multiple feature points. The reason is that in the projection view image each nanowire is a bar with intensity decreasing from top to bottom instead of a disk-shape in top view image. Although one may adopt more sophisticated morphological operations to extract feature points, we turn our attention to the edge feature of nanowires in projection view images. Isotropic edge features may be useless since we only need to know the top-end of each nanowire. Figure 4-b shows the result of...
Canny edge detection [6] and Figure 4-c shows the corresponding feature points by applying a region-based segmentation. Again, we can see that the result is oversegmented since the edge detected for a single nanowire is not well connected.

After observing that the top-end of a nanowire in the projection view image shows a horizontal edge, while the body of the nanowire shows vertical edges (the bottom of a nanowire does not show any edge because of the gradual intensity change from top to bottom), we focus on the horizontal edge only. Here, we still adopt Canny's principles [6] because it can yield connected and thin edges. The difference is that, in Canny edge detection one calculates the magnitude of gradient by considering the gradient in both (horizontal and vertical) directions, while in our method we only consider the gradient in the vertical direction, hence only detect horizontal edges and ignore vertical edges. Figure 4-d shows the result of 'horizontal' Canny edge detection. The result demonstrates that this method can effectively detect the horizontal edges on nanowire's top-end and ignore the vertical edges. However, the edges shown in Figure 4-d are still not well connected.

To avoid the over-segmentation problem and reduce the effect of defects (bundles), we increase each edge point by 1-pixel in this study. Figure 4-e shows the result of 1-pixel region growth based on Figure 4-d, and Figure 4-f shows the result of corresponding detected feature points. One can see that our method has high accuracy even for nanowires close to each other and at the same time, low false alarms for nanowire detection.

By comparing the results of our method with the manually obtained results (using a semi-automatic tool developed based on our method), we can calculate the detection accuracy and false positive rate of our feature point detection method for both top view image and projective view image. Table 1 shows the results on a pair of images with 2,000x2,000 pixels.

<table>
<thead>
<tr>
<th>Image View</th>
<th># of Detected Nanowires</th>
<th>Accuracy</th>
<th>False Positive Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top View</td>
<td>1,664</td>
<td>98.48%</td>
<td>0.42%</td>
</tr>
<tr>
<td>Projection View</td>
<td>1,656</td>
<td>98.61%</td>
<td>1.03%</td>
</tr>
</tbody>
</table>

4. Correspondence establishment

Recall that in our geometric model, in order to calculate the length of a nanowire, its feature point identified in the top view image has to match its corresponding feature point in the projection view image. In this section, we first consider a correlation-based method for correspondence establishment by considering the neighborhood pattern of each feature point. Then, we use a dynamic programming-based method for correspondence establishment by applying the ordering constraint, and compare the performances between the two approaches to show the feasibility of the approaches.

We first introduce a novel similarity function that we use to calculate the matching score by considering the neighborhood pattern of a feature point. This function is used in both correlation-based method and dynamic programming method in this study.

4.1. Similarity function for correspondence establishment

Figure 5 illustrates how we calculate the similarity by considering the neighborhood patterns. The red dot in the center represents the aligned feature points, respectively, in the top view image and the projection view image. We consider a neighborhood area of $n \times n$ pixels in both images ($n = 11$ in Figure 5). Black dots and circles are the identified feature points in the top view image and the projection view image respectively.

(1) For each feature point $(x, y)$ in the neighborhood of a top view image, we search for the feature points in the range of $(x \pm \Delta x, y \pm \Delta y)$ in the projection view image ($\Delta x = \Delta y = 1$ as shown in Figure 5).

(2) Similarly, for each feature point $(x', y')$ in neighborhood of the projection view image, we search for the feature points in the range of $(x' \pm \Delta x, y' \pm \Delta y)$ in the top view image.

(3) Count the numbers of feature points in top view and projection view images as $S_T$ and $S_P$ respectively, and the sum of isolated feature points in both images as
4.3. Applying ordering constraint for correspondence establishment

The second method introduces the ordering constraint and employs a dynamic programming method for correspondence establishment [9]. Since the feature points are not exactly aligned along y-axis, we select a scanning area along y-axis with width equal to $2\Delta x$ in x-axis direction, and then shift the scanning area by $\Delta x$ each time. Similarly, we select the corresponding point with the highest similarity value and discard the corresponding points with similarity value less than a threshold $t_{th}$. Figure 7 shows the result of dynamic programming approach for correspondence establishment.

5. Geometric model calibration

Lastly, we observe that the obtained nanowire length decreases along x-axis direction (see Figures 6-c, 6-f, 7-c, and 7-f for the linear regression on spatial distribution of nanowire length). This motivates us to relax our geometric model by considering the rotation around y-axis ($\beta$) and the rotation around z-axis ($\gamma$). We calibrate the model by performing statistical fitting on the x-direction shift from the top view image to the projection view image as a
6. Conclusion

In this paper, we have proposed a geometric model for nanowire length measurement and devised a computer vision-assisted approach leveraging SEM images to recover nanowire length and its spatial distribution. Specifically, we have developed a morphology-based method and a horizontal edge detection-based method to identify nanowires in top view image and projection view image, respectively. A novel similarity function is then designed for correspondence establishment between the SEM images. The experimental results have demonstrated that our method can not only identify nanowires with high accuracy and low false alarms in presence of defects, but it can also establish correspondence between SEM images effectively. Finally, considering the bias introduced during the SEM imaging process, we have proposed and developed a method for geometric model calibration based on the statistical fitting approach to further improve measurement accuracy. In the future, we will consider more sophisticated approaches (such as cooperative approaches) for improved correspondence establishment and investigate reconstruction from SEM images of three-dimensional (3-D) models [10] for a complete morphological characterization of nanowires.

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References


