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A New Image Restoration Technique for SEM

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Abstract: This paper proposes a new fast and effective method of image restoration to improve the resolution of SEM images. In our approach, image resolution is improved by deconvolution with the point spread function modeled as the intensity distribution of the electron beam at the specimen's surface. The beam intensity distribution under each imaging condition is estimated by electro-optical simulation to achieve high resolution. We propose an iterative technique for the deconvolution process with a cost function where the restored image at each iteration can be compared with the original image more directly. A wavelet shrinkage denoising algorithm was applied to efficiently suppress noise amplification in noisy images, The empirical results demonstrate the outstanding improvements in both resolution and noise suppression. The proposed iterative method also speeds up deconvolution by about 3 to 50 times more than the conventional Richardson-Lucy method.

1. INTRODUCTION

Scanning electron microscopes (SEM) have been widely used for observing microstructures in many fields, such as in semiconductor manufacturing, medical diagnostics, and bio-technology because of their high resolution of several nanometers (Goldstein *et al.*, 2003). SEM images have especially been utilized to monitor the semiconductor manufacturing process and to inspect defects in semiconductor chips. Improvements to the spatial resolution of SEM are required so that semiconductor devices can continue to shrink in size and increase in density.

A focused electron beam scans across a specimen's surface point by point to form the SEM image, where the number of detected electrons emitted from the specimen is represented by a gray level. As the spatial resolution is mainly determined by the beam spot size at the specimen's surface, a great deal of effort has been made to reduce the spot size. However, further improvements to resolution in electro-optics (*i.e.*, hardware) tend to become too difficult. because of the spot-size limitations imposed by diffraction aberrations.

However, image restoration algorithms can be used to reconstruct observed degraded images to high-resolution images in software approaches. In many image restoration techniques, a restored image can be obtained by deconvolving the observed image with the point spread function (PSF), which represents the degree of blurring (Banham and Katsaggelos, 1997).

The spatial spread of the electron beam at the sample surface is the main cause of SEM image blur. In some image restoration methods, PSF is modeled as the intensity distribution of the electron beam (Goldenshtein *et al.*, 1998). Since the beam intensity distribution varies with imaging conditions, such as accelerated voltage, probe current, and the angle of the beam, it is difficult to estimate the beam intensity distribution under each condition accurately.

Iterative algorithms for image restoration have been widely investigated. Their advantages are that there is no need to calculate the inverse of PSF and that knowledge about the original (blur-free and noise-free) images can be built onto the iterative process. However, iterative algorithms have a serious disadvantage in that they are too time consuming to obtain good results especially in the field of semiconductor manufacturing, where the need to obtain SEM images quickly has increased. Therefore, much faster iterative algorithms are required for them to be feasible in that field.

To efficiently solve these problems, we propose a new iterative method of restoring SEM images. In the proposed method, the beam intensity distribution under each imaging condition estimated by electro-optical simulation is used as PSF. In addition, the proposed method utilizes a cost function to achieve faster processing where the restored image at each iteration can be compared with the original image more directly.

This paper is organized as follows. Section 2 describes conventional iterative image restoration algorithms and Section 3 presents the proposed SEM image restoration technique. We discuss a way of estimating the beam intensity distribution by using an electro-optical simulator, and a way of implementing fast iteration. Section 4 presents the simulation and experimental results. Finally, concluding remarks are given in section 5.

2. IMAGE RESTORATION

2.1 Introduction

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Fig. 1 outlines the SEM image degradation model. The observed SEM image is blurred because the intensity distribution of the electron beam at the specimen's surface has been spread to some extent because of diffraction and lens aberrations. The observed image is also noisy due to fluctuations in the number of detected electrons because the yield of electrons from the specimen is variable. Then, the degradation model is described by

$$y[k,l] = A[k,l] * x^{+}[k,l] + n[k,l], \tag{1}$$

where A, y, x^+, and n respectively represent PSF defined as the beam intensity distribution, the observed image, the original image, and additive noise. Operator "*" represents the spatial convolution. $[k, l]$ represents the position of the image. Another representation in terms of a matrix-vector formulation of Eq. (1) is given by

$$y = Ax^{+} + n, \tag{2}$$

where images y, x^+, and n are lexicographically ordered vectors of length KL (K, L: width and height of images), and PSF A represents a matrix of size $KL \times KL$.

The purpose of image restoration is to estimate the original image x^+ from the observed image y by solving Eq. (2). This estimated image is called the restored image.

2.2 Iterative Method

In many iterative methods, the problem of trying to estimate original image x^+ by using Eq. (2) is formulated as an optimization problem that minimizes a certain cost function, $L(x)$. To minimize cost function $L(x)$, subject to nonnegativity constraints $x_t \geq 0$ for all t, the following algorithm has been proposed (Nagy and Strakos, 2000):

$$x_t^{(j+1)} = x_t^{(j)} - c^{(j)} x_t^{(j)} \left(\frac{\partial L}{\partial x}(x^{(j)}) \right)_t, \tag{3}$$

where $x^{(j)}$ represents the restored image at the j-th iteration. A column vector, $c^{(j)}$, of length KL represents the step size at the j-th iteration.

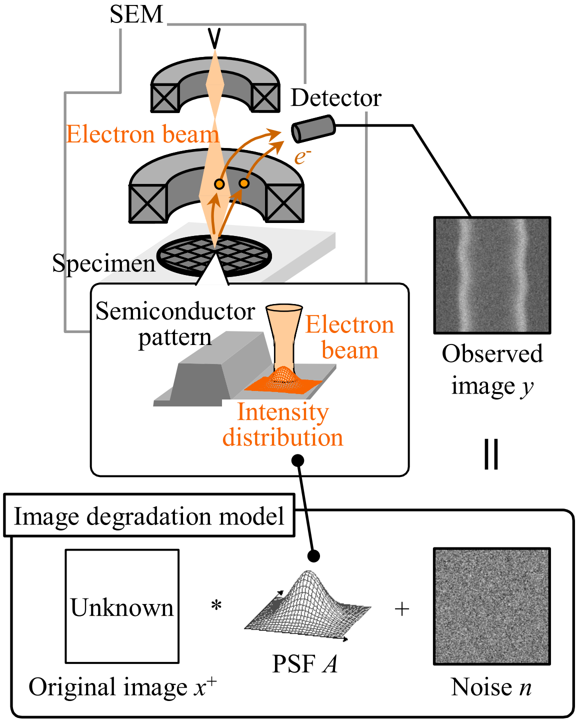


Fig. 1. SEM image degradation model

In the Richardson-Lucy (RL) method, which has been widely implemented in image restoration, the following cost function is used (Lucy, 1974; Kaufman, 1993):

$$L^{(j)}(x) = \frac{1}{2}\left\| D^{(j)}(y - Ax) \right\|_2^2, \tag{4}$$

where $L^{(j)}(x)$ is the cost function at the j-th iteration, which varies with each iteration. $D^{(j)}$ is a diagonal matrix whose i-th diagonal element is $D^{(j)}_{ii} = (Ax^{(j)})_i^{-0.5}$. The gradient of $L^{(j)}(x)$ is

$$\frac{\partial L^{(j)}}{\partial x}(x) = A^T (D^{(j)})^2 (Ax - y). \tag{5}$$

By substituting Eq. (5) into Eq. (3) and by assuming $(c^{(j)})_t = 1$ for all t, the following iteration of the RL method is obtained:

$$\begin{aligned} x_t^{(j+1)} &= x_t^{(j)} - x_t^{(j)} \left(A^T (D^{(j)})^2 (Ax^{(j)} - y) \right)_t \\ &= x_t^{(j)} \left(A^T (D^{(j)})^2 y \right)_t \\ &= x_t^{(j)} \sum_i A_{i,t} \frac{y_i}{\left(Ax^{(j)} \right)_i}. \end{aligned} \tag{6}$$

3. PROPOSED IMAGE RESTORATION ALGORITHM

3.1 Introduction

Fig. 2 outlines the data flow for the proposed image restoration algorithm. The observed image and the corresponding imaging condition are input for the algorithm. The intensity distribution of the electron beam under the given condition is estimated as PSF by using the electro-optical simulator. Our technique first denoises the observed image to suppress noise amplification, and then obtains the restored image, x, by deconvolving the denoised image with the PSF. The wavelet shrinkage algorithm, which provides high performance for many applications, has been applied to image denoising (Mallat, 1998). The wavelet shrinkage algorithm can effectively preserve the detailed structure and reduce noise even for a low signal-to-noise ratio.

3.2 Estimate of Intensity Distribution of Electron Beam

The proposed algorithm uses an electro-optics simulator to precisely estimate the intensity distribution of the electron beam to restore images under each imaging condition.

Fig. 3 shows the method of estimating the beam intensity distribution. It involves three steps: calculation of the

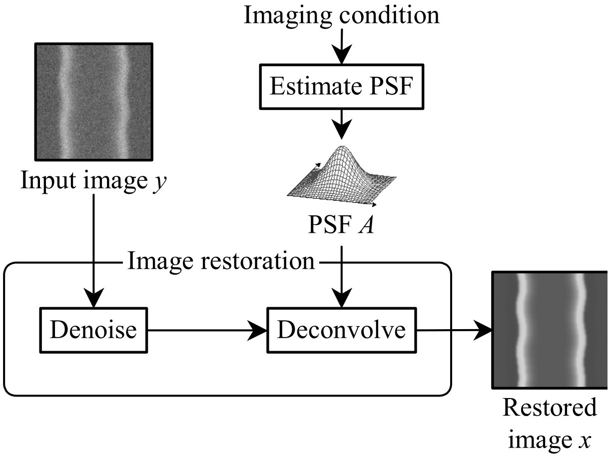


Fig. 2. Data flow for proposed algorithm

electromagnetic field in the SEM column (step 1), calculation of the parameters of the electromagnetic lenses (step 2), and estimation of the beam intensity distribution (step 3). In step 1, the electromagnetic field distribution in the SEM column is calculated by using imaging conditions such as the acceleration voltage and excitation current for the electron lenses. In step 2, parameters, such as the magnification of lenses and aberration coefficients, are calculated by simulating the electron trajectory. In step 3, the intensity distribution of the electron beam is estimated based on electron diffraction theory by using the imaging conditions and the lens parameters (Sato, 1997). In this method, the beam intensity distribution can be estimated by taking the main factors responsible for resolution degradation in SEM images into consideration, *i.e.*, diffraction aberration, chromatic aberration, spherical aberration, and the size of the demagnified electron source. We assumed that the beam intensity distribution was not spatially variable, and out-of-focus blur was negligible.

3.3 Iterative Method

The cost function, $L(x)$, in Eq. (4) represents the comparison between Ax and $y = Ax^+ + n$, where the restored image, x, is compared with the original image, x^+, indirectly. In this method, however, the difference in the high-frequency components between images Ax and Ax^+ is small and is difficult to utilize to generate restored image x, since operating PSF A attenuates the high-frequency components of these images. Therefore, we propose a method of comparing restored image x with original image x^+ more directly. The basic idea underlying the proposed method is that cost function $L(x)$ does not need to be able to be computed, but the iteration formula, such as Eq. (6), must exist to calculate the restored image.

In the proposed method, we have considered the following cost function instead of Eq. (4):

$$L_k^{(j)}(x) = \frac{1}{2}\left\| D^{(j)}(A^k x^+ - A^k x) \right\|_2^2 . \qquad (7)$$

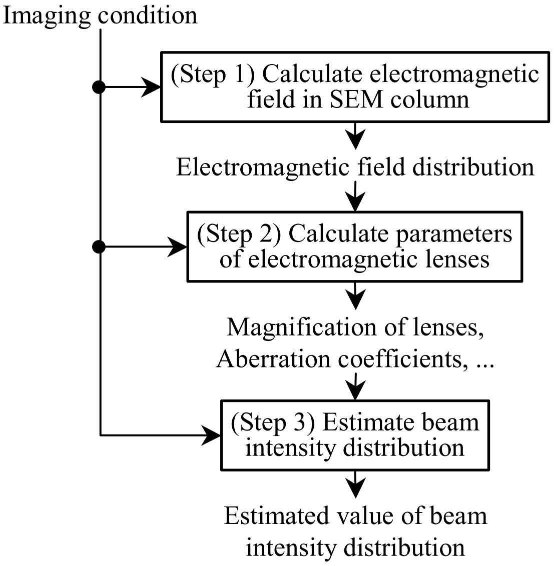


Fig. 3. Method of estimating beam intensity distribution

The function, $L_k^{(j)}(x)$, compares $A^k x^+$ with $A^k x$, where k is a real constant, ($k < 1$).

In Eq. (7), restored image x is compared with original image x^+ more directly than in Eq. (4) because of $k < 1$. We assumed that matrix A was diagonalizable. Actually, in many cases $A[-k, -l] = A[k, l]$ in Eq.(1), so matrix A is symmetric, which is diagonalizable. In that case, A^k can be defined as

$$A^k = Q(Q^T AQ)^k Q^T , \qquad (8)$$

where Q is the orthogonal matrix for diagonalizing A, and Q^T is the transpose of matrix Q. Q^TAQ becomes a diagonal matrix, and $(Q^TAQ)^k$ is a diagonal matrix whose i-th diagonal element is the i-th diagonal element of Q^TAQ to the k-th power, *i.e.*, $(Q^TAQ)_i^k$.

When matrix A is singular (A has at least one zero eigenvalue), the gradient of $L_k^{(j)}(x)$ can be computed if and only if $k \geq 0.5$. Especially, in the case of $k = 0.5$, Eq. (3) can be rewritten as

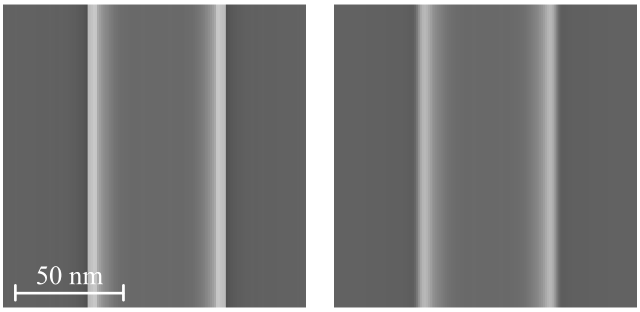
$$x_t^{(j+1)} = x_t^{(j)} \frac{y_t}{\left(Ax^{(j)}\right)_t} , \qquad (10)$$

and then the restored image, $x^{(j)}$, can be calculated.

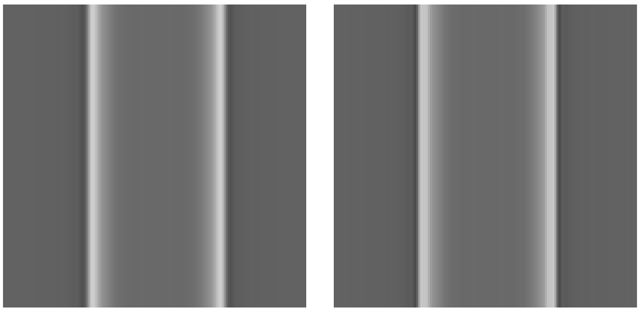
4. PERFORMANCE EVALUATION

4.1 Simulation

Our simulation was done using SEM secondary electron images obtained from an SEM image generating simulator that used Monte Carlo simulations. Fig. 4 shows (a) the original image, (b) the blurred image, which has degraded spatial resolution due to convolution with the beam intensity distribution calculated by the electro-optical simulator, (c) the restored image using conventional RL image restoration , and



(a) Original image (b) Blurred image



(c) Restored image (Conventional RL, $J = 10$) (d) Restored image (Proposed, $J = 10$)

Fig. 4. Simulated SEM images (Noise free)

(d) the restored image using our proposed image restoration method. In these methods, the same beam intensity distribution that was utilized to generate the obtained image (Fig. 4(b)) was used as PSF, and the number of iterations J was 10. Restoration with the conventional method (Fig. 4(c)) a produced certain degree of improved resolution, but resulted in insufficient restoration at the edges by comparison with the original image. The results revealed that the image restored with the proposed method (Fig. 4(d)) had more enhanced edges than that restored with the conventional method.

Fig.5 compares the convergence speed of images restored with the conventional RL and proposed methods, where the original image in Fig. 4(a) was used. The horizontal axis represents the number of iterations. The vertical axis is the mean squared error (MSE) between the original and restored images. This means that the proposed method produced substantially lower MSE than the conventional method at the same number of iterations. The new approach reduced the number of iterations by a factor of approximately 3 to 50 to have almost the same MSE.

4.2 Experiment

Fig. 6(a) shows two observed SEM secondary electron images. The images restored by the conventional RL method is shown in Fig. 6(b) and that restored by the proposed method is shown in Fig. 6(c). In this experiment, the beam intensity distributions estimated by the electro-optical simulator (Fig. 3) under corresponding imaging conditions were used as PSFs. The number of iterations J was 10. The images restored by the conventional method (Fig. 6(b)) show greater improvements in edge sharpness than the observed images. In contrast, the images restored with the proposed method (Fig. 6(c)) achieved additional improvements in sharpness, and have excellent resolution.

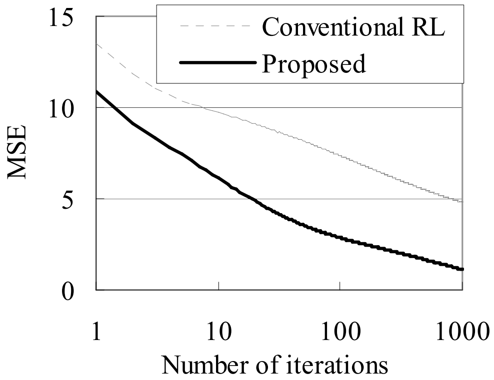


Fig. 5. MSE between original and restored images

Note that as the angle of the specimen was tilted at increased, the number of detected electrons increased. This phenomenon, called the edge effect, produced bright spots on the observed image. The proposed method clearly demonstrated the edge effect, which was difficult to recognize in the observed images.

5. CONCLUSION

We proposed a new method of restoring SEM images that improves their resolution. The intensity distribution of the electron beam was estimated by electro-optical simulation to appropriately restore images under the corresponing imaging condition. We also proposed an iterative deconvolution technique with a cost function where the restored image at each iteration could be compared with the original image more directly.

Our simulation results revealed that the proposed method sped up deconvolution by about 3 to 50 times to achieve almost the same improvement in resolution as that with the conventional Richardson-Lucy method. The experimental results also demonstrated the outstanding improvements both in resolution and noise suppression.

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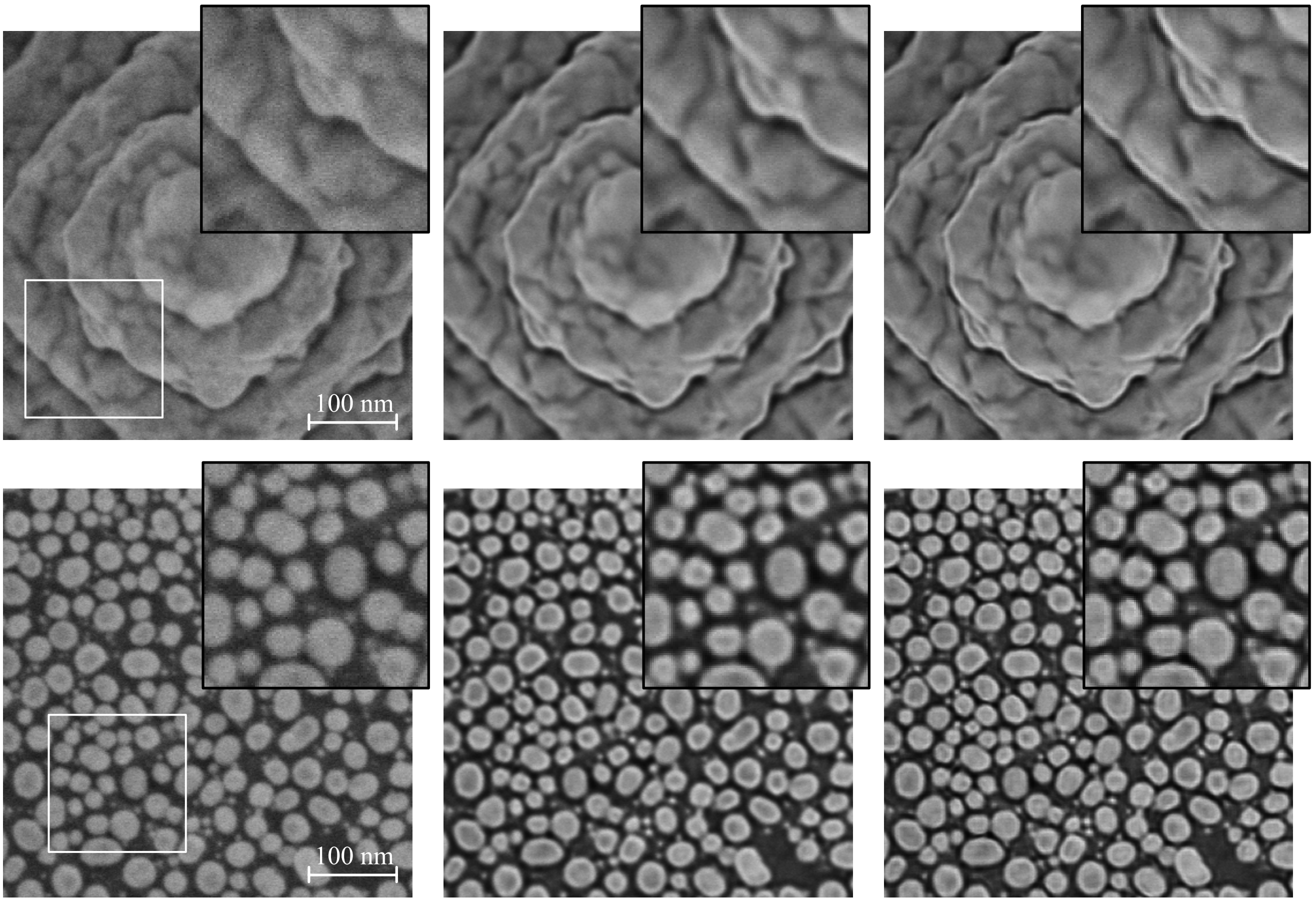

(a) Observed images

(b) Restored images
(Conventional RL, $J = 10$)

(c) Restored images
(Proposed, $J = 10$)

Fig. 6. Observed and restored SEM images

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