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Optimization of optical lens-controlled scanning electron microscopic resolution using generalized regression neural network and genetic algorithm

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ABSTRACT

A scanning electron microscope (SEM) is a sophisticated equipment employed for fine imaging of a variety of surfaces. In this study, prediction models of SEM were constructed by using a generalized regression neural network (GRNN) and genetic algorithm (GA). The SEM components examined include condenser lens 1 and 2 and objective lens (coarse and fine) referred to as CL1, CL2, OL-Coarse, and OL-Fine. For a systematic modeling of SEM resolution (*R*), a face-centered Box–Wilson experiment was conducted. Two sets of data were collected with or without the adjustment of magnification. Root-mean-squared prediction error of optimized GRNN models are GA 0.481 and 1.96×10^{-12} for non-adjusted and adjusted data, respectively. The optimized models demonstrated a much improved prediction over statistical regression models. The optimized models were used to optimize parameters particularly under best tuned SEM environment. For the variations in CL2 and OL-Coarse, the highest *R* could be achieved at all conditions except a larger CL2 either at smaller or larger OL-Coarse. For the variations in CL1 and CL2, the highest *R* was obtained at all conditions but larger CL2 and smaller CL1.

1. Introduction

With the development of nanotechnology, sophisticated equipment is demanded to examine in detail fine patterns of processed films. In the context of integrated circuit fabrication, a scanning electron microscope (SEM) is typically used to take images of deposited films or etched patterns. The SEM consisted of many complex components. Depending on their various combinations, the SEM resolution varies considerably. There have been many studies for manufacturing of SEM (Lee, 1993; Mook & Kruit, 1999; Reimer, 1998) Manufacturing SEM requires control and optimization of SEM components such as condenser (or objective) lens or electron guns. Due to complexities involved in each component as well as in a series of connected components, however, optimizing the resolution (*R*) of SEM has been an extremely difficult task. Of SEM components, 4 types of condenser and objective lens play a critical role in determining the *R*. The *R* is expected to vary considerably with their configuration. No analytical models that can accurately predict *R* with all lens configurations have been reported. This mainly stems from a lack of physics, which relates a variety of lens configurations to *R*. An effective alternative to overcome this difficulty is to use a neural network. The neural network approach has promisingly been used to model machine process (Ezugwu, Fadare, Bonney, Da Silva, & Sales, 2005) or materials processes (Chen, Tai, Wang, Deng, & Chen, 2008; Kim, Bae, & Lee, 2006; Kim, Park, Lee, & Han, 2006; Lee et al., 2008; Liau & Huang, 2008). In this study, a prediction model of SEM is constructed by using a generalized regression neural network (GRNN) (Specht, 1991) and an evolutionary genetic algorithm (GA) (Goldberg, 1989). To our best knowledge, this is the first intelligent model for predicting SEM characteristics. This is true at least in the context of control of SEM lens. A statistical experiment was utilized to systematically prepare experimental data. Two sets of data were collected with and without the control of magnification. The GA was employed to improve the prediction performance of GRNN. The constructed model is then compared with statistical regression models. Various 3D plots generated from an optimized model are used to assess lens effects on *R*.

2. Experimental details

The experimental data were collected from SEM equipment. Schematic SEM equipment is shown in Fig. 1. As shown in Fig. 1, the SEM consists of many components, including an electron gun, an anode allignment coil, a condenser lens 1, a sleeve & aperture, a condenser lens 2, a coarse objective lens, a fine objective lens, a scanning deflection coils, a stigmator, and a detector. Among them, those examined in this study include the condenser lens 1 and 2 referred to as CL1 and CL2 respectively, and the fine and coarse

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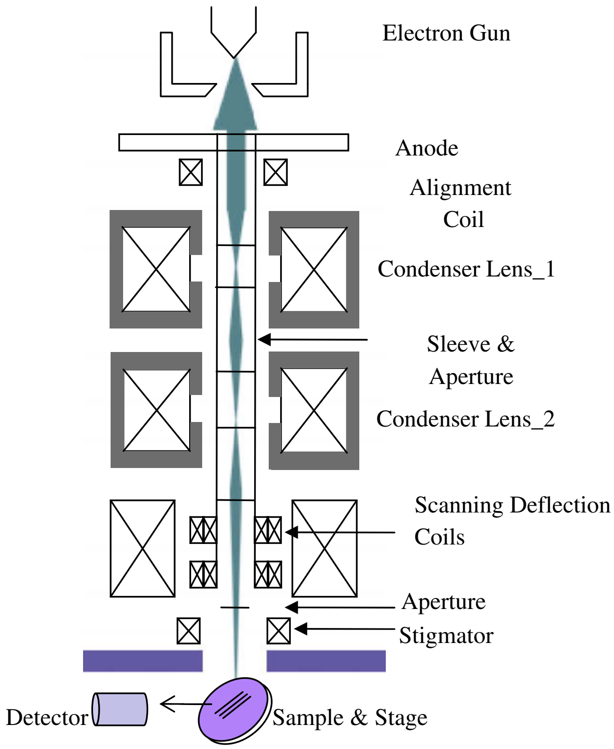

Fig. 1. Schematic of SEM equipment.

objective lens named OL-Fine, OL-Coarse, respectively. The CL1 primarily takes a role to focusing the electron beam from the electronic gun. It reduces the diameter of electron beam. The CL2 reduces the diameter more by concentrating again the electron beam passing the first condenser lens. The OLs are used to adjust the focus more intensively in consideration of the distance between the focus and specimen. A high voltage and a working distance were set to 15 Kv and 10 mm, respectively.

Experimental data were collected according to a Box–Wilson experiment (Montgomery, 1992). This design was composed of 2^4 full factorial experiment and eight face-centered center points. The process parameters and experimental ranges adopted in the design are shown in Table 1. Apart from these, one experiment corresponding to the center design point was included. Therefore, a total of 25 experiments were conducted. In each experiment, the *R* first measured without control of magnification. Then, the other *R* was measured by controlling the magnification until an image was best seen. These two *R*s are referred to as "non-adjusted *R*" and "adjusted *R*", respectively. It should be noted that the experiments were conduced by adjusting from the center design point. Here, the center point corresponds to the medium values of each parameter shown in Table 1. The measured *R* was then quantified into three categories numerically corresponding to "0", "0.5", and "1". The highest *R* was set to "1". The collected data are shown in Table 2 and these were divided into two groups of training and testing data. As shown in Table 2, the training data consisted of 17 experiments coming from the full factorial experiment and one center point. The testing data differentiated with the asteroid mark were composed of the remaining eight experiments.

Table 1
Experimental SEM parameters and ranges.

Parameters	Ranges	Units
CL1	0–340	°
CL2	360–1800	°
OL-Coarse	360–1800	°
OL-Fine	360–1800	°

Table 2
Experimental data collected by a Box–Wilson statistical design.

#	CL1 (°)	CL2 (°)	OL-Coarse (°)	OL-Fine (°)	*R* (non-adjusted)	*R* (adjusted)
1	340	1800	3600	3600	0	1.0
2	340	1800	3600	360	0	0.5
3	340	1800	360	3600	0	0.5
4	340	1800	360	360	0	0.5
5	340	360	3600	3600	0	0.5
6	340	360	3600	360	0	0.5
7	340	360	360	3600	0	1.0
8	340	360	360	360	0	0.5
C	170	1800	1800	1800	0	1
9	0	1800	3600	3600	0	0.5
10	0	1800	3600	360	0	0.5
11	0	1800	360	3600	0	0.5
12	0	1800	360	360	0	0.5
13	0	360	3600	3600	0	0.5
14	0	360	3600	360	0	0.5
15	0	360	360	3600	0	0.5
16	0	360	360	360	0	0.5
1	0	1080	1800	1800	0.5	1
2*	340	1080	1800	1800	0.5	1
3*	170	360	1800	1800	0.5	1
4*	170	1800	1800	1800	0.5	1
5*	170	1080	360	1800	0	1
6*	170	1080	3600	1800	0	1
7*	170	1080	1800	360	1.0	1
8*	170	1080	1800	3600	0.5	1

3. Generalization regression neural network

A GRNN was used to construct a prediction model of *R*. A schematic of GRNN is shown in Fig. 2. As shown in Fig. 2, the GRNN consists of four layers, including the input layer, pattern layer, summation layer, and output layer. Each input unit in the first layer corresponds to individual equipment parameter. The first layer is fully connected to the second, pattern layer, where each unit represents a training pattern and its output is a measure of the distance of the input from the stored patterns. Each pattern layer unit is connected to the two neurons in the summation layer: S-summation neuron and D-summation neuron. The S-summation

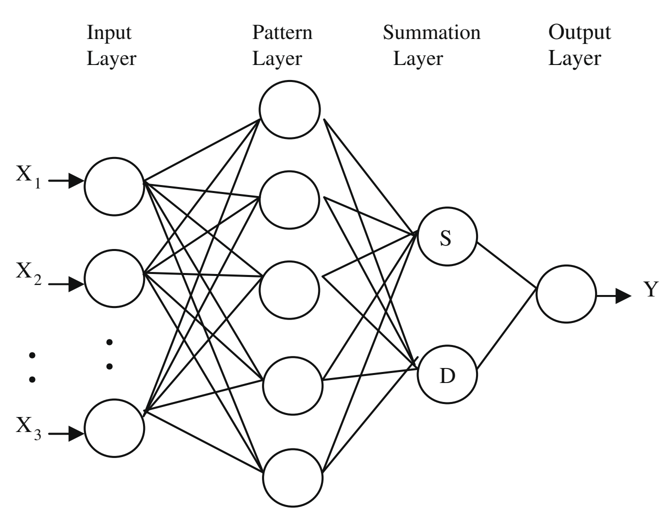

Fig. 2. Schematic of generalized regression neural network.