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An Optimized Parameter Guidance System for Line/Space CD Metrology

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ABSTRACT

In semiconductor industry, as physical sizes of integrated circuit (IC) components continue to shrink, critical dimension (CD) metrology plays an important role in manufacturing process monitor and control. However, when prior knowledge of E-beam tool conditions and statistics of underlying imaging samples are limited or missing, metrology parameters (such as imaging conditions and CD measurement parameters) are often selected empirically and not optimized in terms of measurement accuracy or precision. Common practice involved in fine-tuning some of the parameters may result in a time-consuming trial-and-error cycle.

In this paper, we propose a guidance system to provide an optimized set of metrology parameters given a line/space pattern image or images of scanning electron microscope (SEM). The proposed system models input condition with a comprehensive set of model parameters and then statistical analysis is done based on modeling outputs. A set of metrology guidelines, such as measurement parameters and achievable precisions, can be recommended by the proposed system. The validity of our method has been demonstrated by comparing the recommended parameters with the optimal parameters found by brute-force search on a set of 100 SEM images of line/space patterns.

Keywords: CD metrology setup, line, e-beam, precision, accuracy

1. INTRODUCTION

In manufacturing processes of ICs, finished or unfinished circuit components are inspected to ensure that they are manufactured according to design specification and are free of defects. Inspection systems utilizing optical microscopes or charged particle (e.g., electron) beam microscopes, such as a scanning electron microscope, can be employed. As the physical sizes of IC components keeps shrinking while SEM noise level keeps increasing, accuracy and yield of metrology for defect detection become more and more important. In addition, the CD control plays a critical role in monitoring semiconductor manufacturing processes and reproducibility of features on a wafer[1-6].

During metrology setup, one needs to make multiple selections of parameters to control image acquisition and CD measurement, such as imaging conditions (landing energy, field of view (FOV), pixel size, number of frames averaged, etc.), edge sampling distance and measurement box length, and settings of edge estimation algorithms[1,2]. However, due to lack of ground truth knowledge of tool physical conditions and statistics of underlying imaging samples in practice, some of the aforementioned parameters are determined empirically. Since such choices may not be optimal, it may in turn lead to inaccurate CD measurements and wafer signature, and may also impact system throughput. In addition, there is a wide variety of parameters to choose. A sub-optimal choice of some of the parameters may cause inaccurate measurement results and have a negative impact on the diagnosis of potential problems during the manufacturing processes. Therefore, a practical guideline of parameter tuning is crucial for metrology research and applications.

The most fundamental guideline set is proposed by the International Technology Roadmap for Semiconductors (ITRS) [7-9]. First, to avoid artificially low roughness, the measurement area is recommended to be longer than 2-µm, with 10 nm sampling distance along the line. Second, it was requested to eliminate the contribution of SEM noises to get proper metrology estimation. However, concerning the amount of parameters mentioned above, these two guidelines are quite insufficient[10]. Moreover, studies have shown that even these two guidelines may not be general enough. For example, based on a study for understanding the impact of various SEM parameters on roughness, the optimal sampling distance for several roughness measurements were shown to be larger than the values recommended by the ITRS guideline[11]. Therefore, more guidelines need to be further explored with varied concerns.

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Measurement precision and bias are considered the most significant concerns for metrology setup[1]. The measurement precision is defined as three standard deviation repeatability. It represents the amount of spread in the distribution of values measured on the same sample multiple times. The measurement bias, on the other hand, derives from the fact that the true measurement is mixed with the measurement noise and thus induces loss of accuracy. In the literature, simulation models are widely used to help reducing CD uncertainty (which precision is achievable) and approaching unbiased measurement[12-23]. One significant group of simulation models is based on Monte Carlo models. Its representative is a simulation software named MONSEL, which was developed and maintained by the National Institute of Standards and Technology (NITS) in 1990s[12-14]. The simulated SEM image produced by MONSEL is considered as the most closely resembling reality. Since then, Monte Carlo models have been widely used to study the CD-SEM precision and accuracy, as well as their dependence on varied imaging and measurement conditions[1-5,15,16]. However, due to its limited speed, another group of simulators based on parametrical models were proposed[17-21]. One example is an analytical model of metrology physics, namely ALM[18], with many geometry-dependent parameters. Beyond empirical approaches for localizing edges, ALM-based edge detection algorithm has presented less sensitivity to noise and thus improved accuracy and precision of SEM metrology applications. For example, by adding ALM to a conventional model for Optical Proximity Correction (OPC), it has been shown that OPC model accuracy could be improved by taking systematic noises in CD-SEM metrology into account[22]. In another example, J. Belissard etc. have used the D. Nyysonen[23] model with diffusion for sensitivity analysis of model-based feature estimation on linescan[21]. Consequently, tables of acquisition conditions have been recommended to determine the uncertainty of geometrical measurements in certain noise level.

Another concern is the standardization that derives comparable results. Given a single reference sample, observation has shown that there exists an unacceptably large spread of metrology results on roughness throughout the industry, resulting in difficulty for comparison of metrology results among various institutions or to specifications. Due to lack of stringent guidelines for the choice of metrology setting parameters, G.F. Lorusso etc. have proposed a standard setting for acquiring the CD-SEM images, namely the IMEC roughness protocol[10]. It attempts to replace the limited set of ITRS recommendations and produce more robust and comparable results of line width roughness across the industry.

Based on the concerns above, we have proposed an optimized parameter guidance system for CD metrology in this paper. Conceptually, the guidance system is presented in *Fig. 1* below. This system is capable of providing optimized parameters for image acquisition and CD measurement, as well as an estimate of the achievable metrology precision and optionally the metrology accuracy. Based on different tasks, the CD here could be line width, line space, line pitch, etc. The edge estimation algorithm behind the measurement could also be any existing ones like maximum derivative, regression to baseline, threshold, threshold, sigmoidal fitting, and model-based library fitting (MBL)[1,2]. In the rest of this paper, we will use line width and the conventional threshold method as the exemplar target CD and edge estimation algorithm for our guidance system. It would be useful for tool-to-tool calibration and cross-institution or cross-algorithm comparison.

In Section 2 we describe our guidance system. Section 3 gives the results and discussion, followed by conclusions in the last section.

2. GUIDANCE SYSTEM FOR OPTIMIZED PARAMETERS

2.1 Overview

We first present an overview of our optimized parameter guidance system in this paragraph and in *Fig. 1*. Followed will be more detailed description of each step. The system inputs are one or several real SEM images and some auxiliary information. Several levels of simulated noises are then added to simulated linescan image and compared with input SEM image(s). A set of level-based model parameters is then estimated for our build-in linescan image simulator. After applying the CD measurement method on a number of images produced by our simulator, the precision and the bias are determined from the measured CD and the benchmark CD, along with some recommended settings for image acquisition and used edge estimation algorithm.

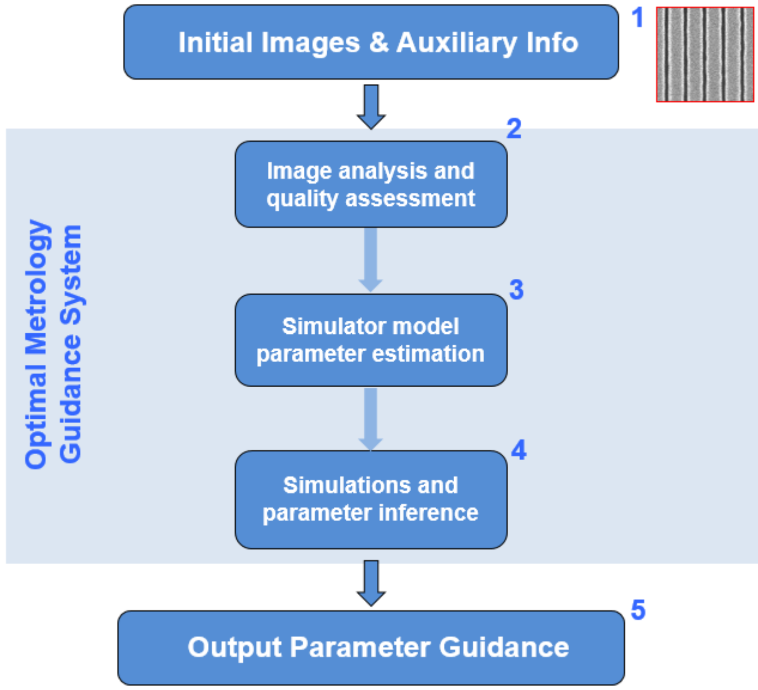

Figure 1. Design diagram of our metrology guidance system.

2.2 System input

As presented in *Fig. 1*, one or several real SEM images of the desired patterns are collected and feed into our guidance system as input. Besides, the user could also import other auxiliary information in nanometer, such as targeted measurement precision, optionally, pattern parameters (i.e.: targeted CD, period, roughness, roughness sample step, edge slope angle), imaging parameters (i.e.: foreground yield, background yield, charging strength, spot size, spot resolution, pixel size, physical size, strength of various noises) and measurement parameters (i.e.: smoothing window size, differential window size, threshold).

2.3 Image analysis

Our system applies a comprehensive analysis and assessment on the input SEM images and patterns-of-interest. First, a parametric sigmoid function is fit to the signal profile extracted from one edge in the SEM image. Then the measurement level at 50% of the profile height is chosen to produce the edge location. Following aforementioned ITRS recommendation on measurement box length and sampling distance, a group of pattern parameters could be inferred, including line width, line pitch, line roughness, foreground and background yield, etc. Moreover, a set of developed quality metrics based on local and global noise level[24] are qualified on the input SEM image(s).

2.4 Model-based parameter estimation

Similar to the idea of model-based library matching (MBLM)[1], we build up a library of simulated images with similar patterns but over a range of noise levels. Despite the fact that Montel Carlo models like JMONSEL are considered to produce the most closely resembling reality, they are very slow in real application. Thus instead, the build-in simulator we used is close to the parametrical version of Nyyssonen model[23], in which the imaging process is modeled as a surface integral over line geometry of a probability density function (PDF). For simplicity concern, this PDF is modeled as a Gaussian function in our system. Specifically, a series of physical line patterns are generated based on the pattern parameters estimated in previous step. Integrated then are the roughness noise and the sidewall angle noise generated by a random number generator, whose output follows a zero-mean Gaussian distribution defined by the respective input noise parameter as its standard deviation. A list of imaging noises is also generated by the same random number generator, including spot noise, yield noise, stage noise, detector noise, speckle noise, etc. A single image frame is then generated as a combination of local pattern variance and global imaging noises. After repeating this process *N* times, we could average *k* of the *N* resultant frames to generate a simulated image with noise level *k*. *Fig. 2* visualizes the comparison between real SEM image and simulated image in four noise levels.

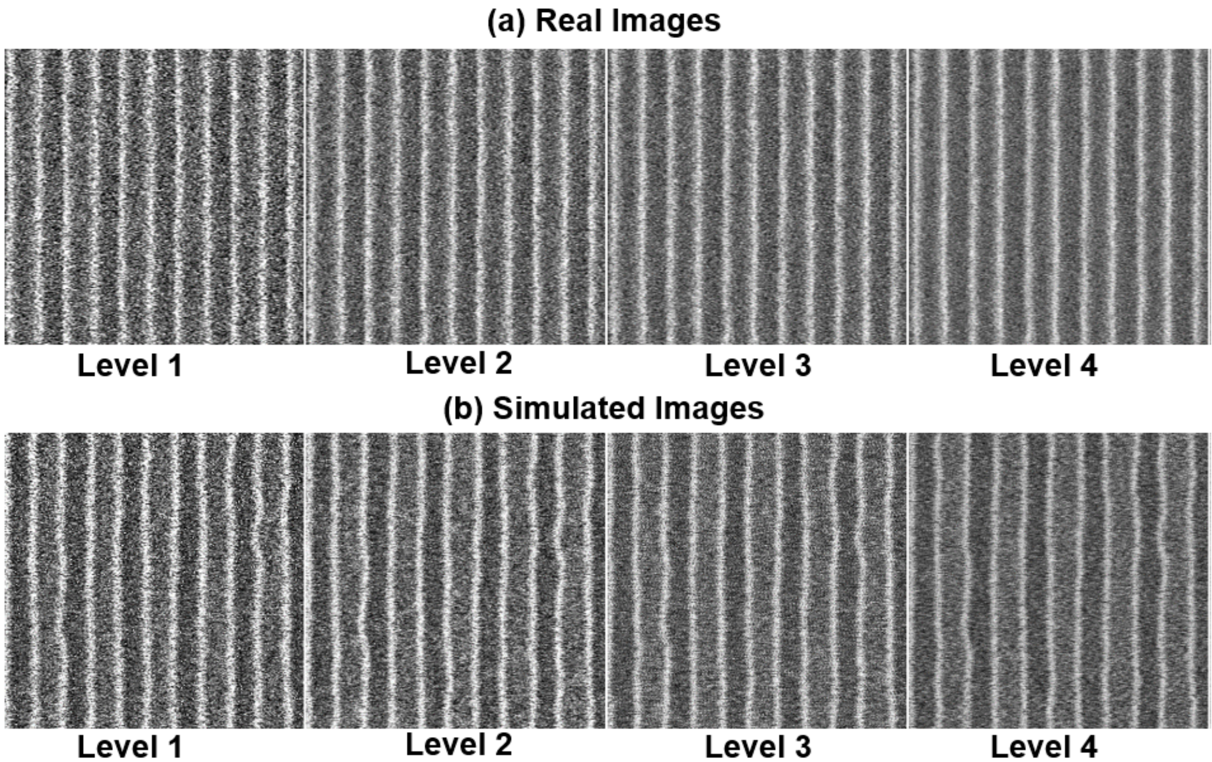

Figure 2. Comparison of (a) real SEM images and (b) simulated images in different noise level. Here level 1 to 4 corresponds to 1F to 4F SEM images.

When a range of noise levels is simulated, these noises and their images form our library. Input SEM images are then compared with this library to find the parameters that produce the best matching noises. However, different from MBLM which considers the image similarity, we consider the noise level similarity instead. That is, the same set of quality metrics in previous step is applied on the library images. The noise level of the library image with the closest quality metrics to the SEM image(s) is assumed to represent the noise of the SEM image(s) well. Respectively, the set of simulation model parameters for this library image is determined for the next step in order to ensure close simulation of input conditions. The closest noise level could be replaced by noise level interpolation for better performance.

2.5 Simulations and parameter inference

In this step, aforementioned build-in simulator utilizes the estimated model parameters to generate a set of simulated images for CD measurement tests. The edge positions are then determined by the target edge estimation algorithm. The linewidth is thus the distance between left and right edge positions. By repeating the noise loop a number of times, we could simulate CDs measured on linewidth multiple times. *Fig. 3* illustrates this step in detail.

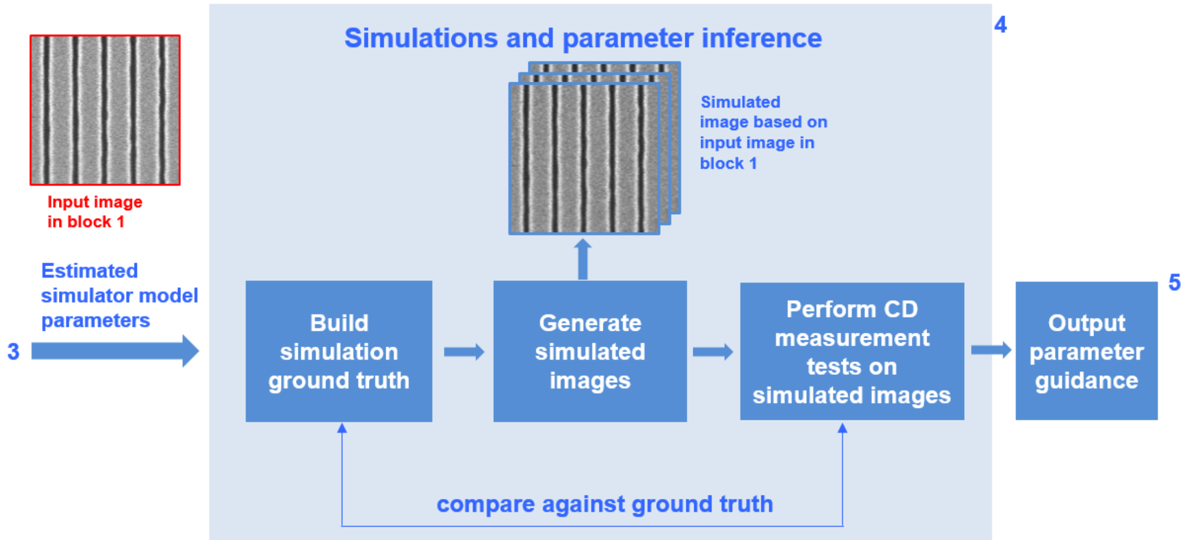

Figure 3. Detailed description of step 4.

2.6 System output guidance

The three standard deviation of the CD distribution produced from step 4 is the precision estimation, whereas the difference between its mean and the ground truth CD (pattern parameters in step 2) reflects the bias estimation. Thus our system could output the estimation of measurement precision and accuracy for given parameters. By applying brute force search of all possible combinations of imaging and/or measurement parameter values, the guidance system will output the best precision and accuracy, as well as its respective parameter recommendations for imaging conditions and CD measurement, such as FOV, spot size, pixel size, number of frames, number of sampling edges per image, sampling distance and height, search range, and threshold of conventional threshold method.

3. RESULTS AND DISCUSSION

3.1 Evaluation of noise level estimation

Given an IMEC wafer, we collected the real images using ASML-HMI's EP5 E-Beam tool under different SEM conditions on the same positions in the same dies. While we fixed other SEM conditions like pixel size (to be 1nm/pixel), we vary the frame average (1 to 4 frame averages) when collecting the images. As we could see from the left two images in *Fig. 4*, different frame average result in SEM images with various noise levels. We then feed one real image for each frame average condition as the input into our simulation tool. As we could see from the right two images in *Fig. 4*, our simulation tool correctly estimates the frame average number and generates simulated images that are highly resemble to the input real images.

In fact, the correct frame average number means that we have a correct and comprehensive similarity score / evaluation metric about the SEM noise. The high visual consistency indicates that we also have a good estimation of line yield and line roughness estimation from the initial input.

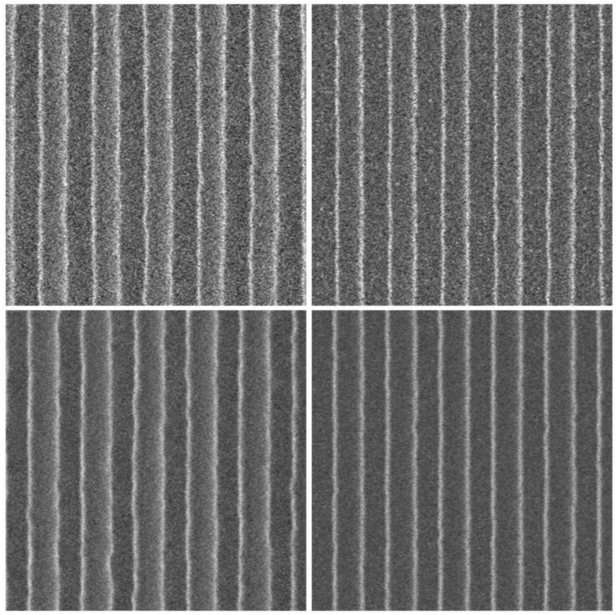

Figure 4: Comparison of real and estimated simulation result. Top left: real 1-frame image; Top right: simulated 1-frame image; Bottom left: real 4-frame image; Bottom right: simulated 4-frame image.

3.2 Estimation of number of independent measurement points needed for single image convergence

Among the settings for line CD measurement, users need to make a decision on how many measurement points are needed. In most cases, one would expect sub-sampling of measurement points may lose useful information in the FOV. On the other hand, over-sampling or redundant placement of measurement points is not only more costly to compute, but sometimes provides little or no additional improvement for the averaged CDs.

In *Fig. 5*, we show experiments with different sampling numbers of measurement points (marked as red H-bars), whereas the averaging length of each measurement point is fixed. With different sampling numbers, we record measurement values over 1000 simulated images generated by the same set of image parameters. For each sampling number, we then have the distributions of the averaged CDs and could further construct confidence intervals of.

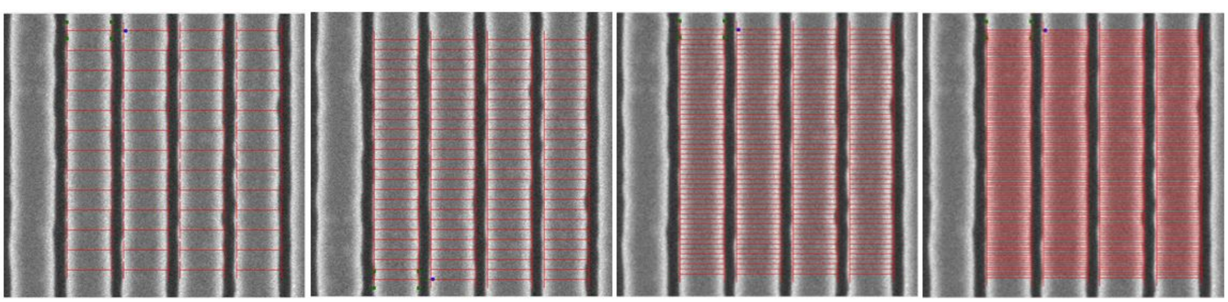

Figure 5. Setup for the study of measurement point number. Each measurement area box consists of a number of sampling measurement points along the same line. Despite the similar measurement area box, different numbers of sampling measurement points (H-bars in red) are applied for investigation. The H-bar height is fixed so that the gray-level average along the line for each measurement is consistent.

From *Fig. 6*, we could see no improvement of the confidence interval after the measurement point become “saturate” in the image. In other words, dependent measurement points / overlapping H-bars covering the same area of the image would not improve the measurement precision. Therefore, as a guideline for determine the appropriate number of measurement points, we should have independent measurement points / non-overlapping H-bars that cover as much as the effective area of the FOV (usually in the center part of the image to avoid boundary issues).

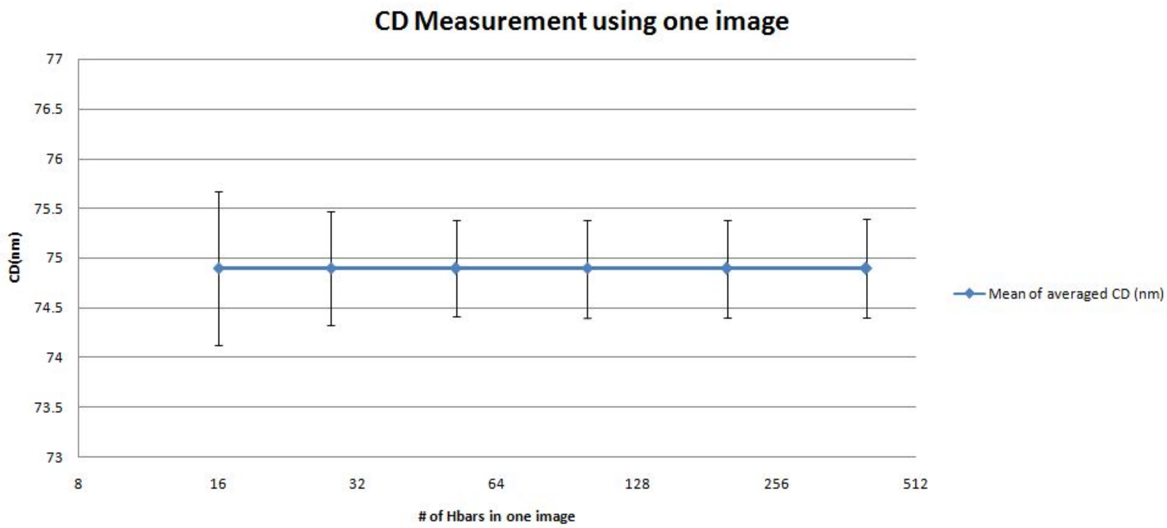

Figure 6. Three-sigma confidence interval plot for different measurement point numbers. No further improvement of the confidence interval after number of measurement points reached to around 50 H-bars. Here the ground truth CD is 75 nm.

While we could repeat similar experiments on measurement values on real SEM images, there are certain reasons why our simulation tool provides some convenience. Without the ground truth, measurement parameters are chosen in an arbitrary way as long as they give reasonable values, because we are not sure how far our measured mean is to the ground truth CD. Knowing the ground truth CD, we could be able to automatically set those parameters so that the absolute error (bias) is within a very small error tolerance.

3.3 Precision estimation

One important aspect of measurement method is the precision, which is about how well we could repeat the metrology algorithm. Even for 1D line/space patterns, with so many measurement parameters to tune, it is usually difficult for engineers to determine which set of parameters would yield to a CD measure result that is best repeatable. In many cases, engineers do not even have a good estimate of what the range of precision could be under different SEM conditions.

To validate whether our simulation is a good estimator on such metrology tasks, we pick ten dies near the center of the wafer, visualized in *Fig. 7*. We scan one image for one die and repeat for ten runs and calculate precision under industry conventions.

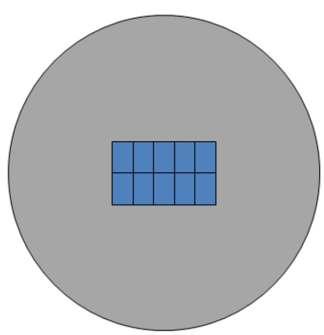

Figure 7: Visualization of ten dies picked near the center of the IMEC wafer.

For this set of data, we vary two measurement parameters: smooth window size and threshold. First, to set up some ground truth using this data, we loop through the two parameters within the predefined search range, measure all 100 images, and calculate precisions for each parameter set. Then we take one randomly picked image from the 100 real images as the input image to our simulation tool. The tool outputs simulation images and estimate precisions based on measuring those simulation images. *Fig. 8* shows the real image and one simulated image, as well as their respective local gray-level and gradient profiles.

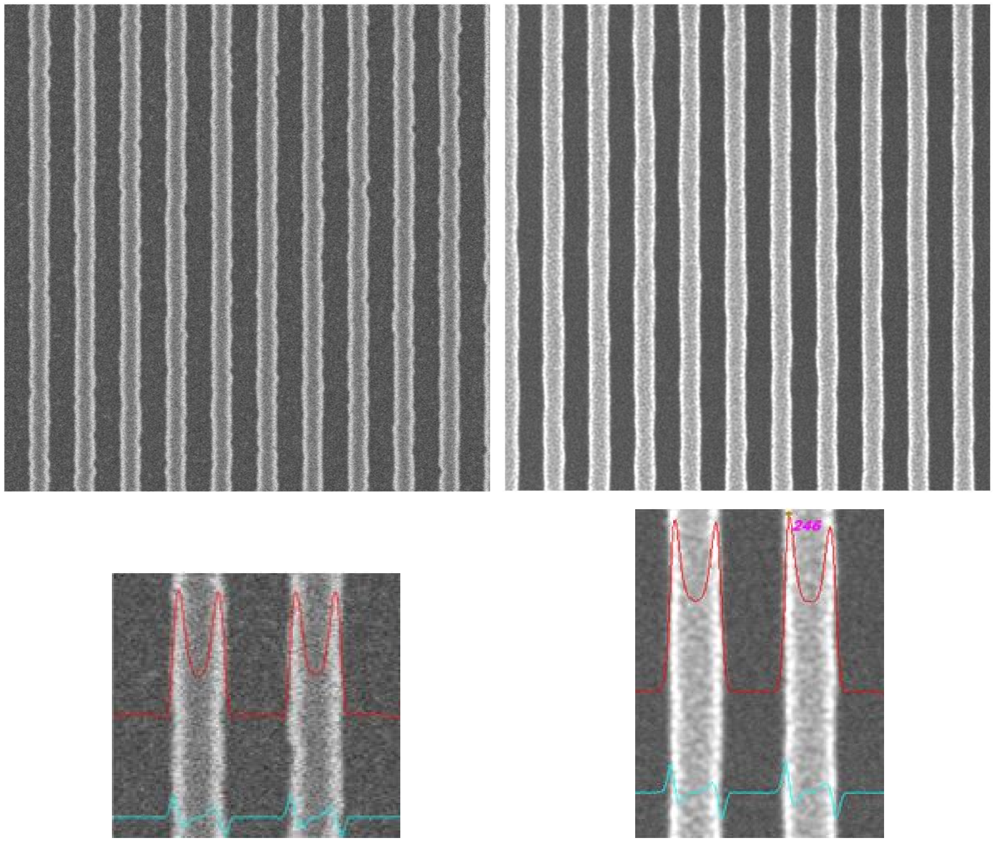

Figure 8: Top: Simulated images vs. real images; Bottom: Gray-level (in red) and gradient (in blue) profile comparison

One might argue that for this data set, the two profiles may not look exactly identical. But for our edge estimation algorithm for line edges, as long as the gray level profile is identical or similar near the line edges (up to a linear transform), the edge point determined by the edge detection algorithm, and thus the conclusions on line CD measurement, would remain relatively the same.

The comparison result of precision estimation is shown in *Fig. 9* and *Fig. 10*. We see that using all 100 real images, with various combinations of measurement parameters (threshold and smoothing window size) within a predefined search range, the best precision (~0.05nm) is achieved with smoothing window size = 5 or 7 and threshold somewhere between 60 and 70. We see our simulation tool outputs a good estimation of the precision range for different parameters. The estimated best precision value (~0.06nm) is very close to the actual one, and the parameters that achieve the best precision are also very close to the actual parameters used. Furthermore, the estimate is stable even we use different input image from the 100 real images pool. This shows that our simulation images are good indicators for the precision estimation, and they also provide accurate guidance for the setup of the key CD measure parameters.

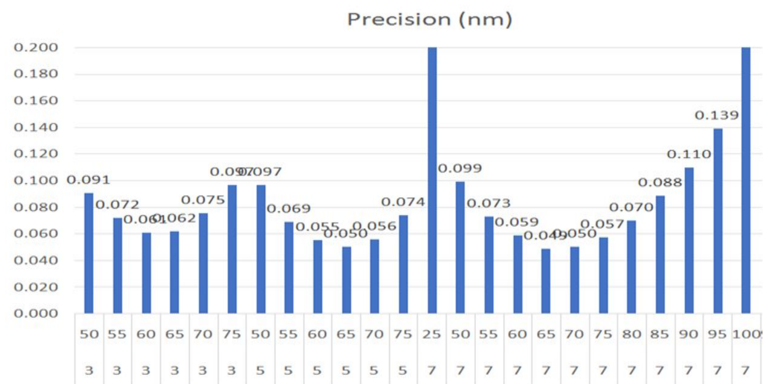

Figure 9: Precision result based on all 100 real images, with various combinations of measurement parameters within a predefined search range for conventional threshold method. In the horizontal axes, the first row is the threshold and the second the respective smoothing window size. The vertical axis is the precision in nm. The best precision (~0.05nm) is achieved with smoothing window size = 5 or 7 and threshold somewhere between 60 and 70.

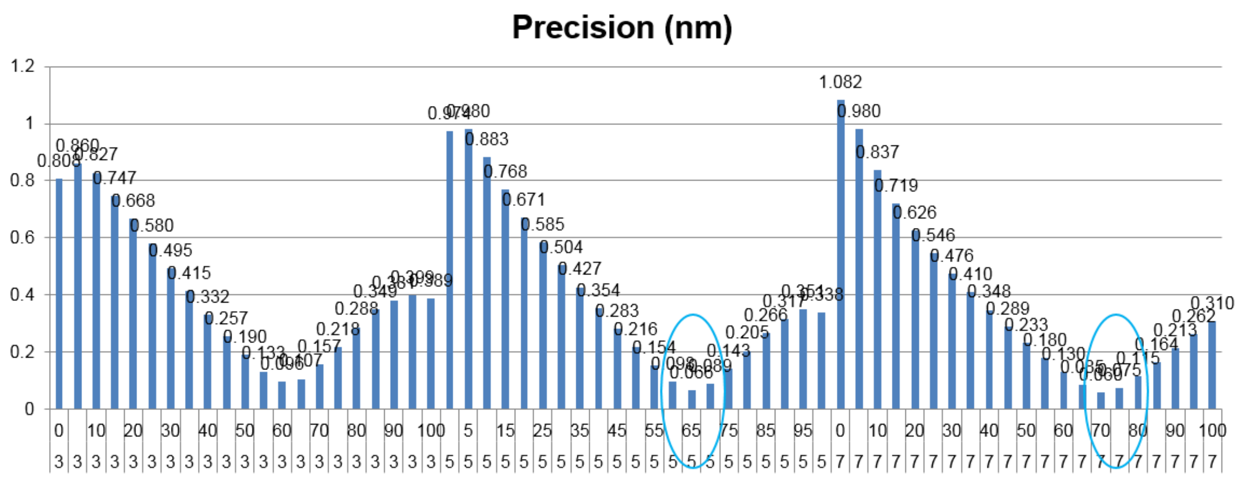

Figure 10: Precision result on our guidance system, using only 1 real image, with various combinations of measurement parameters (threshold and smoothing window size). The axis definitions are consistent with *Fig. 9*. We have significantly good estimations on the best precision (~0.06 nm) and when it could be achieved (smoothing window size = 5 or 7 and threshold somewhere between 60 and 70). Note also that since our simulator takes full control of the measurement parameters, we even have the estimations of precision outside of predefined range (i.e.: thresholds smaller than 50) at very little cost.

4. CONCLUSION

In this paper, we propose a guidance system to provide an optimized set of metrology parameters for a given line pattern SEM image or images. The proposed system removes the guesswork for users during the CD metrology setup stage, and calculates an achievable best precision under current imaging conditions. A built-in Line Pattern Simulator analyzes input images, and models the input line pattern with parameters charactering different aspects of CD metrology, including pattern geometry (line space/pitch, line roughness, edge slopes), material conditions (line yield, gap yield, edge yield, charging parameters), imaging parameters (size of field of view, and beam spot geometry) and associated noise sources (shot noise, material roughness and yield noise, stage movement noise, detector noise, speckle noise etc.). The simulator's goal is to generate simulated images that are highly representative of the input SEM patterns, and its effectiveness is judged by a combination of image quality metrics and feature scores. During the process of simulation, a set of parameters (such as line width, line pitch, and line roughness) are established, based on which a sufficient number of simulated images are generated with the same ground truth. The CD metrology parameters for the original input SEM patterns are then derived from the statistical analysis. This set of metrology parameters is optimal in the sense of achieving the best CD accuracy and precision with respect to the ground truth.

The simulation result has shown that the proposed system can effectively capture the key features from the input and quantitatively parameterize those features into our models. Based on those parameterized models, our simulated images bear remarkable resemblance, from the visual perspective, common metrics of image quality, and the physics of imaging conditions (e.g., number of frame averages), to the input sample image. It thus could be a powerful tool for metrology study, such as power spectral density for roughness[25]. The optimality of the recommended CD metrology parameters is also tested. To this end, a second set of parameters that result in the best precision score are deducted by searching the parameter space in a brute-force manner. The recommended parameters from the proposed system are highly consistent with the second optimized parameters for the test data set. Furthermore, the measurement precision from the brute-force search falls within the precision range that is estimated by the proposed system. Our proposed system not only guides the user through the process of metrology parameter setup stage, but also provides useful statistical information such as achievable precision under current imaging conditions, without excessive acquisition of images or manual tuning of parameters.

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