Quantification of line-edge roughness of photoresists. II. Scaling and fractal analysis and the best roughness descriptors

V. Constantoudis, a G. P. Patsis, A. Tserpepi, and E. Gogolides
Institute of Microelectronics (IMEL), NCSR ‘‘Demokritos,’’ P. O. Box 60228, Aghia Paraskevi, 153-10 Attiki, Greece

(Received 26 September 2002; accepted 3 March 2003; published 25 April 2003)

A search for the best and most complete description of line-edge roughness (LER) is presented. The root mean square (rms) value of the edge (sigma value) does not provide a complete characterization of LER since it cannot give information about its spatial complexity. In order to get this missing information, we analyze the detected line edges as found from scanning electron microscope (SEM) image analysis [see Paper I: G. P. Patsis et al., J. Vac. Sci. Technol. B 21, 1008 (2003)] using scaling and fractal concepts. It is shown that the majority of analyzed experimental edges exhibit a self-affine character and thus the suggested parameters for the description of their roughness should be: (1) the sigma value, (2) the correlation length \( \xi \), and (3) the roughness exponent \( \alpha \). The dependencies of \( \xi \) and \( \alpha \) on various image recording and analysis parameters (magnification, resolution, threshold value, etc.) are thoroughly examined as well as their implications on the calculation of sigma when it is carried out by averaging over the sigmas of a number of segments of the edge. In particular, \( \xi \) is shown to be connected to the minimum segment size for which the average sigma becomes independent of the segment size, whereas \( \alpha \) seems to be related to the relative contribution of high frequency fluctuations to LER. © 2003 American Vacuum Society.

[DOI: 10.1116/1.1570844]

I. INTRODUCTION

As the dimensions of microelectronic devices enter the sub-100 nm region, the molecular line-edge roughness (LER) of photoresists starts to pose a serious limitation on the fidelity of the transferred patterns on the underlying substrate. To find out the most suitable material properties and process conditions for reducing the LER of resist structures requires a method for quantifying and characterizing it. Since top-down scanning electron microscope (SEM) images of fabricated resist lines are commonly used for the qualitative LER estimation, the measurement method has to be based on their analysis. In the previous article of this series [to be referred hereafter as Part I], an off-line image analysis method for the detection of resist line edges from top-down SEM images was presented and an extensive study of the behavior of their sigma value and its dependencies on various image analysis parameters was performed. Furthermore, a comparison of the sigma results of this off-line analysis with the corresponding on-line results was realized.

In this article, we proceed to the investigation of the spatial aspects of LER using scaling and fractal concepts. The motivation for this analysis is twofold. (1) First, it is a fact that the sigma cannot provide a complete and thorough description of the roughness of a line edge. This can be easily demonstrated by inspecting Fig. 1 where two line edges with the same sigma value are depicted. Obviously, despite the equality of the sigma, these edges have quite different appearances. A closer look at these edges reveals that this difference is mainly due to the different spatial distribution of roughness along the edges, which cannot be described by the sigma value since this requires second order statistics on edge points. Therefore the question that arises is what more LER parameters are needed for the characterization of the spatial complexity of an edge and the quantification of LER.

During the last 20 years, many researchers have suggested that fractal geometry could be applied to the study of the spatial roughness of curves and surfaces and provide through the fractal dimension \( D \) their quantitative description. Consequently, a lot of methods for the reliable calculation of \( D \) have been proposed and comparative studies of their results have been carried out for both theoretical and experimental curves and surfaces. One of the most well known methods, the variation method, has been also applied to the investigation of the fractal nature of lithographically produced surfaces. However, for real irregular curves, such as the resist line edges we are interested in, \( D \) is not a sufficient descriptor since the fractal behavior does not extend to all scales; it has an upper limit (determined by the correlation length \( \xi \)) whose value influences the spatial morphology of the edge. Therefore a complete characterization of the spatial roughness requires the determination of both the fractal dimension \( D \) and the correlation length \( \xi \). These two parameters, which provide the best descriptors of spatial roughness, can be extracted by either the scaling analysis of the curve based on the study of the correlation functions (or equivalently the dependence of sigma on the measurement scale) or the frequency analysis based on the study of the Fourier transforms of the curve. In fact, scaling or frequency analysis provides the roughness exponent \( \alpha \), which, however, is related to the fractal dimension \( D \) in this article, we are going to use the scaling analysis and the

\(^{a}\text{Author to whom correspondence should be addressed; electronic mail: vconstantoudis@netonline.gr}\)
correlation functions for the calculation of the spatial roughness parameters $\alpha$ and $\xi$.

(2) The second motivation refers to the studies investigating the influence of the LER on various microelectronic device properties. In these studies, LER is usually represented by an analytical form of its autocorrelation function, which describes its spatial complexity and is connected to electrical and magnetic properties of the fabricated devices. Most times, the used analytical forms include apart from the sigma, the correlation length $\xi$ and recently the roughness exponent $\alpha$. Therefore the examination of the effects of LER on various device properties requires an investigation of the behavior of the correlation length $\xi$ and the roughness exponent $\alpha$.

The article is organized as follows. In Sec. II we review some definitions of the correlation functions and introduce the spatial roughness parameters $\xi$ and $\alpha$. It is stressed that the parameter sigma, $\xi$, consists of the most complete set of LER descriptors in the case of self-affine edges. When some quasiperiodicity is present in edge structure, the selected wavelength has to be added. The self-affine or quasiperiodic character of an edge can be extracted from the form of the correlation functions as will be explained in Sec. II. Section III examines the dependencies of $\xi$ and $\alpha$ on the various image recording and analysis parameters, such as the magnification and the resolution of the SEM image, the Gaussian noise filter parameters, the threshold value, and the type of algorithm used for the detection of the edge. In general, it is shown that $\alpha$ is more systematically sensitive to changes of some of these parameters than $\xi$, which remains impressively independent of their variation. In Sec. IV, our attention is focused on the influence of $\xi$ and $\alpha$ on the calculation of sigma done by averaging over the sigma values of a number of segments of the edge. Examining a lot of experimental edges and in accordance with similar theoretical analysis, we find that the average sigma becomes independent of the length $L$ of the used segments only when $L$ is larger than several ($\sim 6$) times the correlation length $\xi$. Furthermore, in the second part of the same section, we discuss the delicate issue of the high frequency roughness and argue that its best description is provided by the roughness exponent $\alpha$. Finally, the main points of the article are summarized in Sec. V.

II. SPATIAL ROUGHNESS PARAMETERS

The most common way of studying the spatial distribution of roughness of an edge is by examining the correlations between the distances $\delta_i=\delta(y_i)$ of the edge points from the linear fit of the edge at different positions $y_i$, $i=1,...,N$, where $N$ is the total number of equidistant points on axis $y$ along the edge (see Fig. 1). The height-height correlation function $G(r)$ quantifies these correlations and is defined at $r=md$ as

$$G(md) = \left[ \frac{1}{N-m} \sum_{i=1}^{N-m} (\delta_i - \delta_i)^2 \right]^{1/2},$$

(1)

where $d$ is the distance between two neighboring points.

$G(r)$ is associated with the more widely used normalized autocorrelation function $R(md)$:

$$R(md) = 1 - \left[ G^2(md)/2\sigma^2 \right],$$

(2)

where $\sigma$ is the abovementioned sigma value (the rms deviation of the edge points $\delta_i$ from its linear fit).

The form of $G(r)$ is very important for the characterization of the spatial aspects of roughness. Statistically persistent regular oscillations in $G(r)$ reveal the existence of a quasiperiodicity in line edge whose wavelength can be extracted by the position of the first minimum of the oscillations. On the other hand, a power law behavior [$G(r) \sim r^\alpha$] means that the line edge is a self-affine fractal, i.e., it remains statistically invariant when it is stretched ($\alpha$) or contracted ($\alpha$) isotropically in different directions. The exponent of the power law is called roughness (or Hurst) exponent $\alpha$ and it is connected to the fractal dimension $D$ through a relation, which for lines is $\alpha = 2 - D$. In real line edges, the power law behavior lasts up to a specific distance after which the height correlations vanish, $R(r)$ tends to zero, and, according to Eq. (2), $G(r)$ stabilizes at (or oscillates randomly about) the value $\sqrt{2}\sigma$. This distance is connected to the correlation length $\xi$, which is defined as the value of the lag length at which the autocorrelation function drops to $1/e$ of its value at zero lag or equivalently the height-height correlation function increases to the $\sqrt{1-1/e}$ of its maximum value $\sqrt{2}\sigma$, i.e.,

$$G(\xi) = \sqrt{1 - \frac{1}{e}} \sqrt{2}\sigma.$$ 

(3)

A typical form of $G(r)$ of a real self-affine edge is shown in Fig. 2. A power law behavior for small distances is followed by saturation at the value $\sqrt{2}\sigma$ for large distances ($r \gg \xi$). As we can easily deduce, the whole form of $G(r)$ is in fact determined by the values of three parameters: the roughness exponent $\alpha$ (or the fractal dimension $D$), the correlation length $\xi$, and the sigma value. Therefore we can support that
this triad of parameters provides the most complete description of the roughness of a self-affine line edge and the study of their behavior reveals different aspects of LER. The sigma value has to do, by definition, with the vertical dimension of roughness and gives no information about its spatial complexity. In most line edges the height distribution function is Gaussian and the sigma value is in fact its standard deviation. The correlation length $\xi$ defines a representative lateral dimension of a rough line edge. If the distance between two edge points is within $\xi$, the heights at these two points can be considered correlated. However, if the separation of two edge points is much larger than $\xi$, then we can say that the heights at these two points are independent of one another. The behavior of the height correlations for $r<\xi$ is described by the roughness exponent $\alpha$, which in fact gives the rate at which these correlations decrease and tend to zero as the distance $r$ increases. Since height correlations for small $r$ amount to high frequency fluctuations, $\alpha$ gives a measure of the contribution of high frequency fluctuations to roughness relative to the low frequency ones. This relation of $\alpha$ with the high frequency fluctuations can be more clearly shown in Fig. 3 where the amplitude $F(\omega)$ of the Fourier transform of a self-affine line edge is depicted. Here the self-affinity is associated with a power law behavior for high spatial frequencies $\omega$ and its exponent is connected to the roughness exponent $\alpha$. Therefore it is clear that the smaller the value of $\alpha$, the more important the relative contribution of high frequency roughness becomes. We are going to discuss this point more thoroughly in Sec. IV. Moreover, it has to be stressed that the Fourier transform can also give the sigma value and the correlation length $\xi$. The first through the Parceval’s theorem while the second is the inverse of the frequency at which the Fourier transform starts to decrease [the “knee” of the $F(\omega)$, see Fig. 3]. In fact, the scaling analysis is the equivalent of the Fourier analysis in spatial domain. However, we have observed that for the majority of edges known at a limited number of points, the presence of

![Fig. 2. Typical example of the height-height correlation function $G(r)$ of an experimental resist line edge. Note the power law behavior which corresponds to a self-affine structure and the saturation of $G(r)$ for $r \gg \xi$ at the value $\sqrt{2}\sigma$. In addition, the definitions of $\alpha$ and $\xi$ are shown.](image1)

![Fig. 3. Typical example of the Fourier transform of an experimental resist line edge. Note the power law behavior for high frequencies which corresponds to a self-affine behavior and the relation between its exponent (the slope of the curve in the log-log plot) and the roughness exponent $\alpha$. Smaller values of $\alpha$ signify larger relative contribution of high frequency fluctuations to roughness.](image2)

III. DEPENDENCE OF SPATIAL ROUGHNESS MEASURES ON SEM IMAGE PARAMETERS

This section considers the spatial roughness of resist line edges, which have been detected from SEM images by means of the off-line image analysis method presented in Part I. The MATLAB code developed there has been completed by the calculation of the height-height correlation function $G(r)$, which, according to the previous section, gives the necessary information about the spatial complexity of LER. Hence, after selecting on the SEM image the edge we want to study, the MATLAB code outputs its $G(r)$ function. The first result we obtain by examining a lot of line edges is that the majority of them can be characterized as self-affine. Therefore the description of their spatial roughness requires the calculation of $\alpha$ and $\xi$. These can be extracted from the form of the $G(r)$ function. The roughness exponent $\alpha$ equals the slope of the linear part of $G(r)$ for small $r$ when it is plotted in a log-log plot and the correlation length $\xi$ can be calculated by using relation (3). However, the morphology of the detected line edge and consequently the form of $G(r)$ and the values of $\alpha$ and $\xi$ depend on a number of parameters, which influence the final form of the edge. These parameters can be separated into the image analysis and image recording parameters. The first are involved in the image analysis algorithm developed in Part I and include the Gaussian filter noise parameters used for smoothing the image, the threshold value for the edge detection, as well as the applied algorithm, which can be based on either the direct signal or its derivative. The second control the recording of the image and include the magnification and the pixel size chosen in taking and saving the image. The meaningful and reliable calculation and use of $\alpha$ and $\xi$ requires a sufficient control of their dependencies on both categories of the pa-
rameters. For this reason, we have examined the line edges of two resists (called F and G) from SEM images varying systematically the above parameters.

A. Effect of image analysis parameters

As explained in Part I, the resist line edges can be obtained by using either the algorithm which is based on the analysis of the signal of the image or the algorithm based on the derivative of the signal. In order to get a better agreement with the on-line measurements of the sigma value, the signal algorithm is preferred, since the derivative based algorithm for the same smoothing gives line edges with sigma values larger than those of the signal algorithm. What are the effects of the algorithm choice on the other two roughness parameters, \( \alpha \) and \( \xi \)? The MATLAB code we use outputs for each resist line two height-height correlation functions \( G(r) \): one for the line edge of the direct-signal algorithm and the other for the line edge of the derivative based algorithm. The comparison between these two \( G(r) \)’s reveals that for all resist lines and independently of the choice of the other image analysis and recording parameters, the roughness exponent \( \alpha \) of the edge obtained by the derivative algorithm is clearly smaller than that of the edge of the signal algorithm. The difference is always larger than 0.1. Smaller \( \alpha \) means that the derivative based algorithm gives edges with more important high frequency fluctuations, which is probably the reason for the larger sigma values found in Part I. We have to stress, however, that since the derivative algorithm is more sensitive to noise, these high frequency fluctuations may come from the SEM instrument itself and not from the edge morphology.

In contrast to the behavior of \( \alpha \), the correlation length \( \xi \) is not influenced noticeably by the type of algorithm used for the edge detection. In the following, since the effect of the type of algorithm employed on LER descriptors is well determined, we can resist our study to lines edges obtained by using the direct signal based algorithm.

In Part I, a Gaussian noise-smoothing filter has been applied to the initial image before the use of the algorithm for edge detection. The Gaussian noise-smoothing filter is determined by three parameters. The first gives the number of pixel rows at which the smoothing filter will be applied, and in our calculations was always chosen equal to 1. This means that a one-dimensional smoothing filter was applied to the images. The second parameter is the total number of pixels involved in the Gaussian smoothing process, whereas the third equals the standard deviation of the applied Gaussian smoothing function. In this section, we examine the dependence of \( \alpha \) and \( \xi \) on the last two parameters. We vary these parameters keeping their ratio almost unchanged so that the relative contribution of different pixels to the smoothing process remains the same. In particular, the set of Gaussian noise-smoothing filter parameters we study are: \((1,5,1), (1,11,3), (1,21,7), \) and \((1,39,13)\). Also we examine the case where no smoothing filter has been applied to the image (standard deviation of the filter \( = 0 \)). The results for the dependence of both \( \alpha \) and \( \xi \) are shown in Fig. 4. In the image we examined, the pixel size equals 1 nm and therefore the standard deviation of the filter function is measured in nm. As expected, \( \alpha \) is somewhat sensitive to the smoothing process and increases as the Gaussian filter function widens, but stabilizes after standard deviation of the filter \( \approx 5 \) nm. In other words, the line edge becomes less irregular in small scales when the smoothing function includes more points along a pixel row. The correlation length \( \xi \) remains constant for all sets of smoothing parameters. Only for the case of no smoothing, it takes a smaller value.

The third parameter of the image analysis category is the threshold value of the signal required for the edge detection. Figure 5 shows the effect of this threshold on \( \alpha \) and \( \xi \) values. We note that although \( \alpha \) is more sensitive to the variation of the threshold value than \( \xi \), both quantities remain almost unchanged for a wide range of threshold values. Therefore the choice of the threshold value is not crucial for the calculation of \( \alpha \) and \( \xi \), provided that it is chosen to be larger than 30% of the maximum value of the intensity of the signal.

---

**Fig. 4.** Dependence of \( \alpha \) (closed boxes) and \( \xi \) (open boxes) on the Gaussian noise-smoothing function parameters. On the horizontal axis we note the values of the standard deviation of the used Gaussian functions in nm (we keep the ratio of width over standard deviation equal to 3). The estimation of \( \alpha \) and \( \xi \) was carried out for the sets of filter parameters shown in the text. Note the constancy of \( \xi \) and the reasonable dependence of \( \alpha \) on the smoothing process. Results are for F resist and a threshold value of 60% for the signal threshold algorithm. Similar results are obtained for the G resist.

**Fig. 5.** Effect of the threshold value for the signal based algorithm on \( \alpha \) (closed boxes) and \( \xi \) (open boxes). Both parameters remain unchanged for threshold values greater than 0.3 (30%). Results are for F resist and for Gaussian filter parameters (1, 21 nm, 7 nm). Similar results are obtained for the F resist.
Taking into account the above results, we choose for the following calculations the Gaussian filter noise parameters equal to (1.21 nm, 7 nm) and the threshold value equal to 60% of the maximum intensity value. According to Figs. 4 and 5 these values belong to the ranges of the image analysis parameters where both $\xi$ and $\alpha$ remain constant. Statistics over many line edges was not needed in this section since the effect of the image analysis parameters on $\alpha$ and $\xi$ is similar for all edges and no deviations have been found. However, the influence of the image recording parameters is subtler and in order to obtain a clear result statistics over many line edges is necessary. Therefore the results of the following section will in fact be average values calculated over many line edges of the same structure.

B. Effect of image recording parameters

The top-down SEM images of the resist lines we analyze in the following were taken using two magnifications (75 000 and 150 000) and were stored (saved) using three resolutions. Furthermore, for each magnification and resolution three images were taken at different fields of view of the resist structures. Actually, the magnification used determines the dimension of the image: 1920 × 1920 nm$^2$ for 75 000 magnification and 960 × 960 nm$^2$ for 150 000. The recording resolution of the image, on the other hand, refers to the number of image pixels used to represent the image: 480 × 480 pixels or 960 × 960 pixels or 1920 × 1920 pixels. Thus the pixel size for each image can be calculated by dividing its dimension by the number of the pixels. As a result, for the 75 000 magnification the pixel sizes of the images we analyzed are 4, 2, and 1 nm, where for the 150 000 magnification becomes 2, 1, and 0.5 nm, respectively (see Table I of Part I).

The dependence of the correlation length $\xi$ on the pixel size for the two magnifications and for both resists is shown in Fig. 6. Each value of $\xi$ is in fact an average over the values of $\xi$ of the left edges of all resist lines of all images which have the specific magnification and pixel size. The error bars shown in the figure correspond to the standard deviations of these values from their average value and in most cases do not exceed 20% of the average value. As one can see, all the values of $\xi$ lie between 20 and 25 nm except for the values corresponding to the pixel size 0.5 nm which are a bit larger. Therefore we can conclude that the correlation length $\xi$ is statistically independent on both the magnification and the pixel size of the image, at least up to pixel size equal to 4 nm.

Let us examine now the influence of the magnification and pixel size on the roughness exponent $\alpha$. Figure 7 shows the results for the average values of $\alpha$ and their standard deviations for both resists, both magnifications, and for all image pixel sizes. Two conclusions can be drawn from this figure. The first is the slight decrease of $\alpha$ as the pixel size increases. This behavior holds for both resists and magnifications, and it means that the relative contribution of high frequency fluctuations to roughness becomes more important when the pixel size increases. The second conclusion is that the magnification of the image does not seem to have a systematic effect on the value of the roughness exponent $\alpha$. For the same pixel size, the two magnifications give values of $\alpha$ which lie within the error bars of each other.

Summarizing the findings of this section, we can conclude that the two spatial roughness parameters $\alpha$ and $\xi$ exhibit different behavior as regards to their dependence on the image parameters that contribute to the detection of the final line edge. On one hand, the correlation length $\xi$ was found to be almost independent over all the image parameters we studied. On the contrary, the roughness exponent $\alpha$ seems to be more sensitive to the variations of the same image parameters. Moreover, this sensitivity differs from one parameter to another. Obviously, it is more systematic and controllable for the image analysis parameters, whereas it is subtler and needs good statistics to be fixed for the image pixel size. For this reason, reliable and meaningful spatial LER analysis requires the use of images with the same pixel size, i.e., the same magnification in taking the image and the same resolution in saving it. Furthermore, statistics over the edges of the same image or different fields of view of the same edge are necessary in order to reduce random effects and get reliable average values.

IV. THE IMPORTANCE OF $\alpha$ AND $\xi$ IN QUANTIFYING LER AND THE DEPENDENCE OF SIGMA ON EDGE LENGTH

Up to now, when we were referring to sigma value, we meant the sigma calculated over the whole line edge. How-
ever, sometimes it is easier or necessary to calculate sigma by averaging over the sigma values of a number of nonoverlapping segments of the edge included in boxes with the same length $L$, as shown in Fig. 8.

This is the case for the on-line measurements of sigma as explained in Part I and in Ref. 28. In general, this average sigma value ($\sigma_{ave}$) depends on both the number of boxes and their length $L$. The dependence on the number of boxes was examined in Part I, and here we investigate the dependence on their length when their number is kept fixed (equal to 5). If we want to characterize reliably the roughness of a line edge using this average sigma, this value has to be independent on the box length $L$. Thus the question that arises is to determine the minimum length $L_{con}$ after which the average sigma remains almost constant and independent on the box length $L$. In the following, we will show by examining experimental line edges that this minimum box length $L_{con}$ necessary for reliable results is related to the value of the correlation length $\xi$.

Let us show in Fig. 9 the curves $\sigma_{ave}$ versus $L$ for various line edges averaging over five boxes for each $L$. All the edges shown in the figure have $\xi=25$ nm. We see that for small $L$ $\sigma_{ave}$ depends strongly on $L$, whereas after a value of $L$ approximately equal to $6\xi$ the $\sigma_{ave}$ seems to stabilize to a value slightly smaller than the sigma of the whole edge, i.e., $L_{con}=6\xi$. Therefore in order to get a $\sigma_{ave}$ independent of the box length $L$, the box length has to be more or less larger than $6\xi$. Similar analysis of a lot of experimental edges detected using the off-line method of Part I confirm this result. Furthermore, theoretical analysis for the stabilization of the square $\sigma_{ave}$ using specific analytical forms for the autocorrelation function leads to similar results. These results stress the practical importance of the knowledge of $\xi$, since in fact it determines the crucial box length $L_{con}$ for reliable calculation of the $\sigma_{ave}$. Needless to say, that the determination of $\xi$ requires the knowledge of the whole line edge and therefore the application of the off-line analysis for the edge detection. Thus for comparison among resists and processes one has to be careful and work with box lengths larger than $L_{con}$ or more safely use always the same length of the measurement box. This is probably why in the new ITRS roadmap this length is specified as being four times the Technology node.29

Let us come back to the behavior of $\sigma_{ave}(L)$ for small $L$, and discuss the delicate issue of the high frequency LER. On-line measurement methods use the value of $\sigma_{ave}$ for a specific small $L$ (16 or 32 nm) as an indicator of the contribution of high frequency fluctuations to LER. In Fig. 10, we will show by inspecting an example that sometimes this method can lead to an unclear conclusion. The diagram in this figure depicts the curves $\sigma_{ave}(L)$ for two experimental line edges (1 and 2) in log-log scales. As we can easily see $\sigma_{ave,1}(L=32 \text{ nm})<\sigma_{ave,2}(L=32 \text{ nm})$ and therefore, according to the above argument, the high frequency component of the LER of the line edge 2 is more important than that of the line edge 1. Nevertheless, if we select $L=16$ nm for a representative length for high frequency roughness the

Fig. 7. Dependence of the roughness exponent $\alpha$ on the pixel size and the magnification of the image for both F (a) and G resist (b). Note the slight decrease of $\alpha$ as the pixel size increases, i.e., edges show slightly more important high frequency roughness as resolution becomes coarser and image file size is reduced.

Fig. 8. Schematic of the calculation of average sigma as a function of the edge length $L$. The five boxes of the same length $L$ are shown, which include the segments of the edge used in the calculation of the $\sigma_{ave}(L)$.

Fig. 9. Average sigma vs the segment length $L$ for various experimental line edges. Note that $\sigma_{ave}$ strongly depends on $L$, and becomes independent of $L$ for $L>6\xi$.

Fig. 10. Magnification of the image for both $F$ and $G$ resist.
conclusion is the opposite since \( \sigma_{\text{ave,1}}(L=16 \text{ nm}) > \sigma_{\text{ave,2}}(L=16 \text{ nm}) \). This ambiguity is not rare since many times the curves \( \sigma_{\text{ave,1}}(L) \) of different line edges intersect each other.

Is there any alternative way of characterizing high frequency LER without such problems? According to the relevant literature on the characterization of surface roughness and Sec. II of this article the answer is yes and this measure is the roughness exponent \( \alpha \). It has to be emphasized that this alternative way cannot confront the difficulties mentioned above because \( \alpha \) does not provide an absolute measure of the high frequency LER, which in fact cannot be clearly defined, but a relative measure of the contribution of high frequency fluctuations to roughness in comparison with the contribution of low frequency fluctuations. This can be more easily grasped if we mention that for small \( L \) \( \sigma_{\text{ave,1}}(L) \) obeys a power law with exponent equal to \( \alpha \), i.e., \( \sigma_{\text{ave,1}}(L) \sim L^\alpha \). This behavior is exhibited by the \( \sigma_{\text{ave,1}}(L) \) curves of Fig. 9 and clearly \( \alpha_1 < \alpha_2 \). Therefore as regards the high frequency LER of the edges 1 and 2, the undoubted conclusion is that the relative contribution of high frequency fluctuations to the roughness of edge 1 is more important than that of edge 2.

In general, \( \sigma_{\text{ave}}(L) \) curves are very useful since one can compare the resist and process giving the smallest sigma for a specific \( L \). Furthermore, the importance of these curves (and the values of \( \alpha \) and \( \xi \) that determine their forms) becomes more evident as the technology node decreases, since, according to the ITRS 2002 Roadmap,\(^{29}\) a decrease in technology node leads to reduction of the edge length \( L \) of the measurement box and therefore to movement down the \( \sigma_{\text{ave}}(L) \) curve towards smaller \( L \) values and smaller sigma values. Obviously, the higher the values of \( \alpha \) and \( \xi \) of a specific line edge are, the more significant the reduction of the sigma value is expected as the technology node decreases.

V. SUMMARY AND FUTURE PERSPECTIVES

Let us summarize the main points of the article with some hints for future work. We started by illustrating through an example the incompleteness of the sigma value to provide a description of LER since by definition it ignores the spatial aspects of roughness. These aspects can be investigated by means of the height-height correlation function \( G(r) \), whose behavior for the experimental edges of the resists F and G studied up to now revealed their self-affine character. Certainly, the verification of the generic character of this finding requires the examination of the line edges of a large number of resists and now we are working towards this direction.

Furthermore, an interesting open question is the influence of the plasma etching process on LER. Does self-affinity survive after a plasma etching process has been applied? The investigation of this question is also one of the aims of our research in the near future. Self-affine lines and surfaces require for their complete description apart from the sigma the correlation length \( \xi \) and the roughness exponent \( \alpha \) (related to the fractal dimension), and hence the best choice of LER descriptors should be the set of parameters (sigma, \( \xi \), \( \alpha \)). Sigma represents the vertical dimension of roughness, \( \xi \) shows the range of correlations on the edges, and \( \alpha \) gives a measure of the relative contribution of the high frequency fluctuations to LER. Then we examined the dependence of \( \xi \) and \( \alpha \) on the image recording and analysis parameters (magnification, pixel size, threshold value, filter parameters, and type of algorithm). This is a crucial issue because it has to do with the reliability of the calculated values, and the conditions under which we can trust the comparison between resists and processes as regards their LER. It has been found that for reasonable ranges of image parameters both \( \xi \) and \( \alpha \) are sufficiently independent of these parameters, with the exception of the slight dependence of \( \alpha \) on the pixel size the image was recorded with and the type of algorithm used. After the determination of the complete set of LER descriptors, a protocol for reliable LER measurements and hence resist comparison can be constructed.

Finally, two more implications of \( \xi \) and \( \alpha \) on LER behavior were examined. First, the \( \xi \), in accordance with theoretical arguments, was shown to be connected to the minimum box size for which the average sigma (calculated over the sigmas of all boxes) becomes independent of the box size. Thus the knowledge of \( \xi \) is very important for a reliable calculation of the average sigma. Second, the advantages of \( \alpha \) for the characterization of the relative contribution of high frequency roughness to LER in comparison with on-line measurements were exhibited through a typical example.

ACKNOWLEDGMENTS

This work was funded by the European ISST project 30143 “157 nm CRISPIES” for 157 nm lithography.

27 The fluctuations in the Fourier transform can also be reduced by using the integrated Fourier (or power) spectrum (see Refs. 7 and 19).