thermoscientific

Metrology of Semiconductor Devices using Machine Learning and Active Shapes

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ABSTRACT

We Introduce a new automated method for metrology critical dimension extraction from (S)TEM images. The image is first processed through a trained fully convolutional neural network to extract coarse contours of the device under measurement. Next these contours are extracted using snakes, also known as active contours. The final critical dimensions can be reported either using descriptive statics or using key-points, generated by the neural network, that define the beginning and ends points of critical dimensions. This workflow combines classical computer vision and metrology techniques with neural network techniques to fully automate the metrology workflow.

INTRODUCTION

Metrology of semiconductor device architecture is challenging due to structural complexity, atomic-scale engineering, low signal to noise and contrast to noise ratio in the electron micrographs. Efficient, automated tools that can measure critical dimensions of the devices in electron micrographs can be a part of solution for process monitoring, uniformity control and structural modelling through OCD, CD-SEM, e-beam tech., etc.

In this paper we demonstrate a machine learning based computer vision method for fully automated metrology of semiconductor devices such as fins and nano-wires using (S)TEM images. A coarse segmentation of devices in the image is obtained using a deep convolutional neural network followed by a generalized active shapes algorithm that accepts the coarse segmentation as the initial model and deforms the shape of the segmented object to more precisely fit the boundary of the devices.

MATERIALS AND METHODS

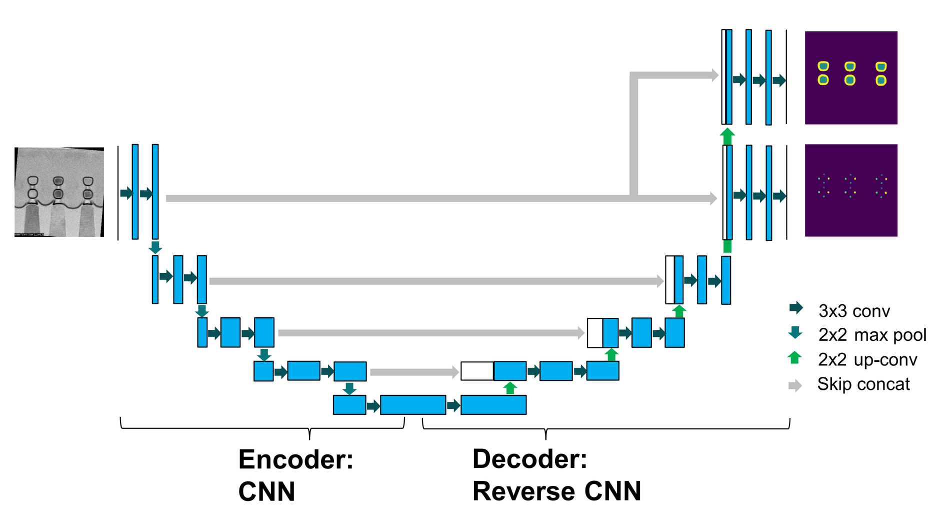
To implement the image segmentation network, we created a variant of the popular U-net architecture [1]. A deep convolutional neural network consists of layered convolution kernels where the kernel elements are learned from training data. For image segmentation, the layered convolutional kernels with interwoven activation functions and pooled down sampling act as a sophisticated convolutional object detector. When this detector sweeps across the image, it yields a strong response when an object of interest is found. Given the large stride and effective kernel size, the feature map created by this kernel is coarse, so the resulting feature map must be up sampled using a series of learned deconvolution kernels. This results in a segmented image of same dimensions as the input image where the pixel values correspond to the class label of the pixels. In addition to predicting the segmented image, we also predict key-points representing salient features in the image, which can be used to guide measurement of important critical dimensions of the structure of interest.

Although segmentation of the regions by convolutional neural network is generally accurate, the accuracy and precision requirements for process monitoring and quality control requirements are very high. Often this requires subpixel boundary detection accuracy. We have found the segmentation by deep-learning to be accurate to perhaps a few pixels. Thus, a post-processing step such as active shape optimization, to refine the segmentation and improve the accuracy is necessary. An active contour is a restricted active contour that deforms within a predefined space seeking the peaks of intensity gradient magnitude while keeping the overall shape features intact[2]. The boundary of the segmented regions obtained by deep-learning defines the initial shape model as well as restricted space for shape-deformation. The control points of the shape model deform and move seeking device boundary in the image by energy minimization process using the intensity gradient vector field of the underlying image data.

Finally key-points, defined by the neural network, can be used to extract specific critical dimensions. These key-points can define the beginning and end of some measurement like device height and width. Additional descriptive statistics can also provide valuable metrology data.

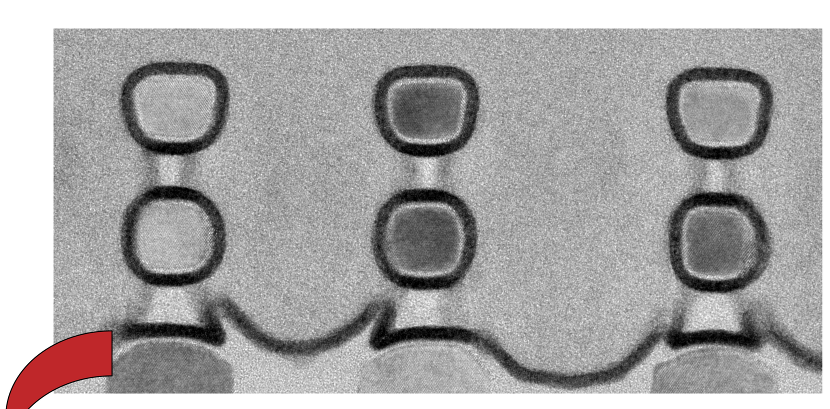
RESULTS

Figure 1. MNET architecture

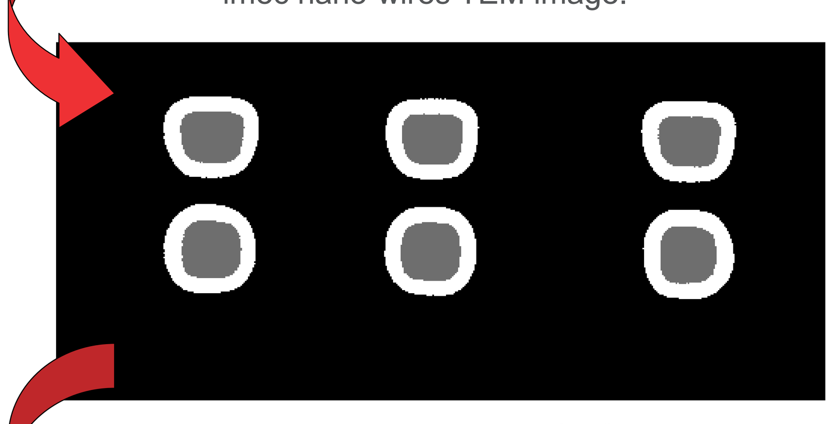


The MNET is a variant of the popular U-NET architecture. The image is fed through the encoder, which extracts coarse semantic information and feeds the decoder stage, which extracts fine details. The key-points are created by branching the decoder. In this figure the key-points are branched at the last decoder transposed convolution step, but in some embodiments, the branching occurs earlier.

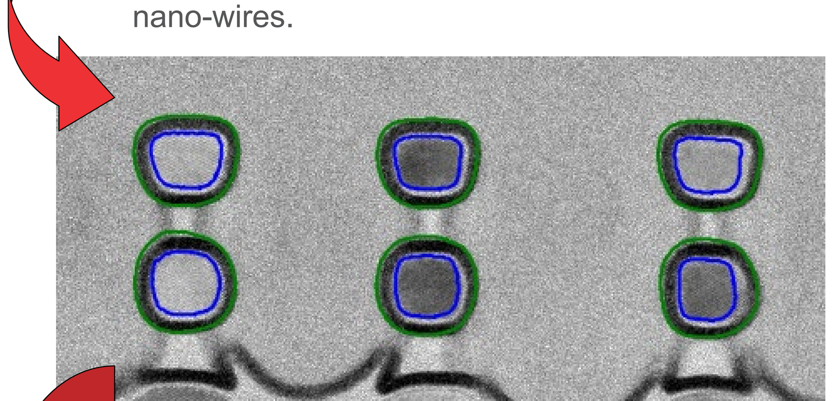
Figure 2. Data flow: From (S)TEM image to metrology



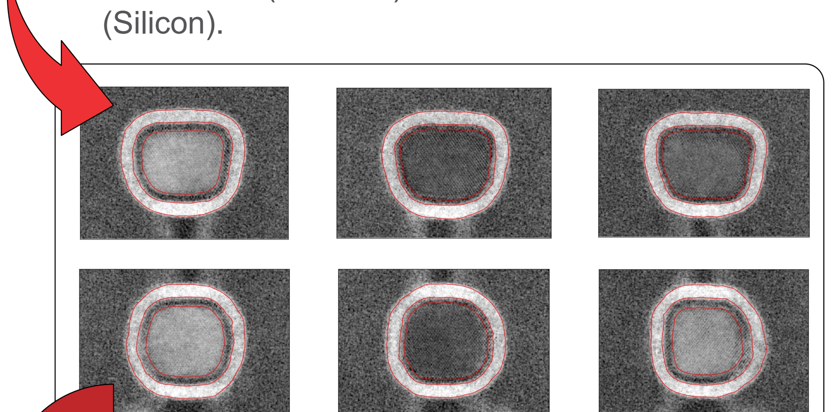
imec nano-wires TEM image.



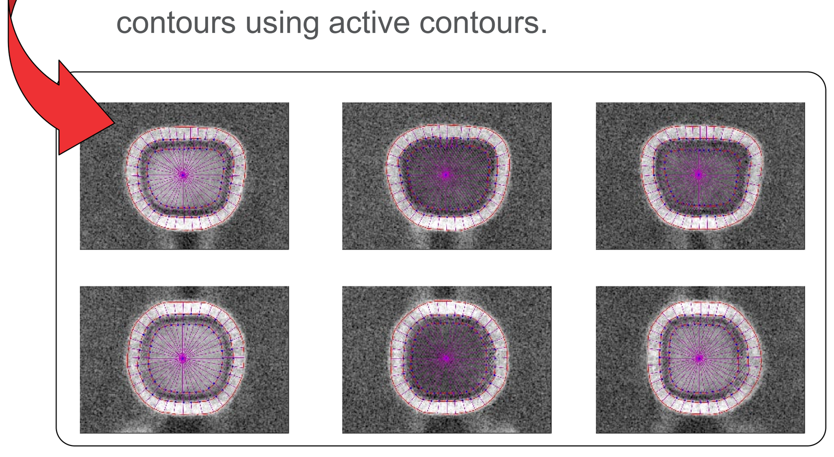
Raw MNET segmentation result of imec nano-wires.



imec nano-wires overlaid with contours extracted from segmentation results. Green shows the outer wires (Hafnium). Blue shows the inner wires (Silicon).

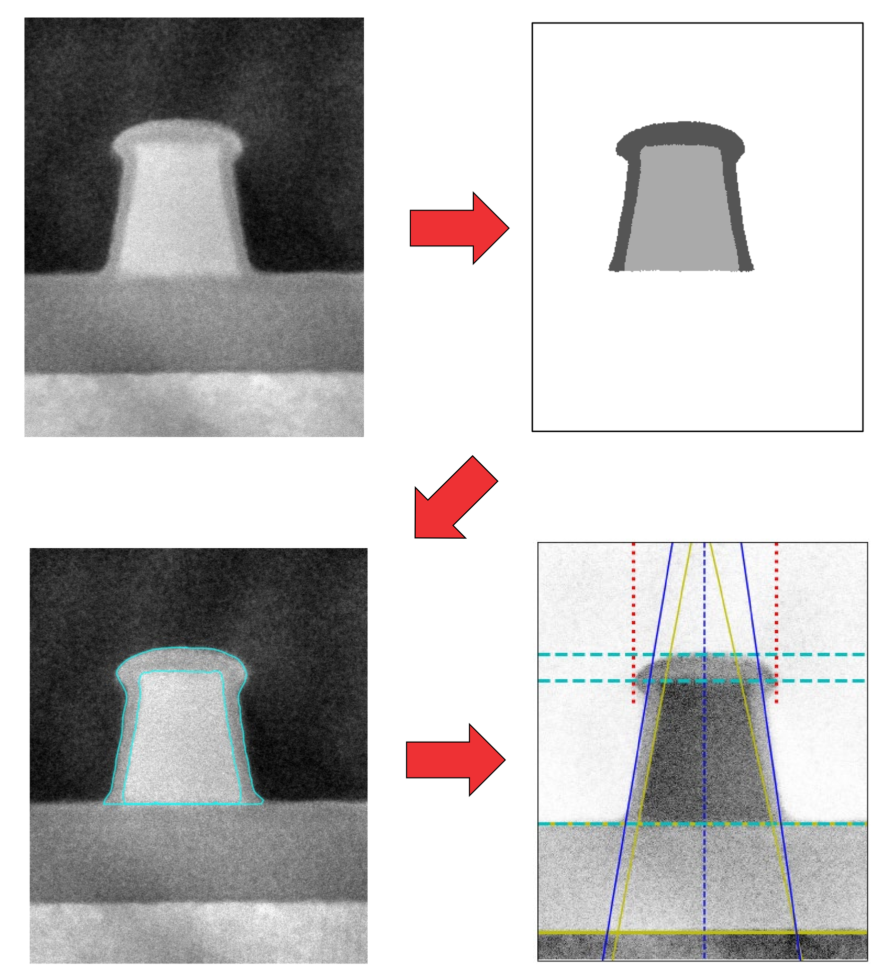


Active contour refinement of MNET extracted contours using active contours.



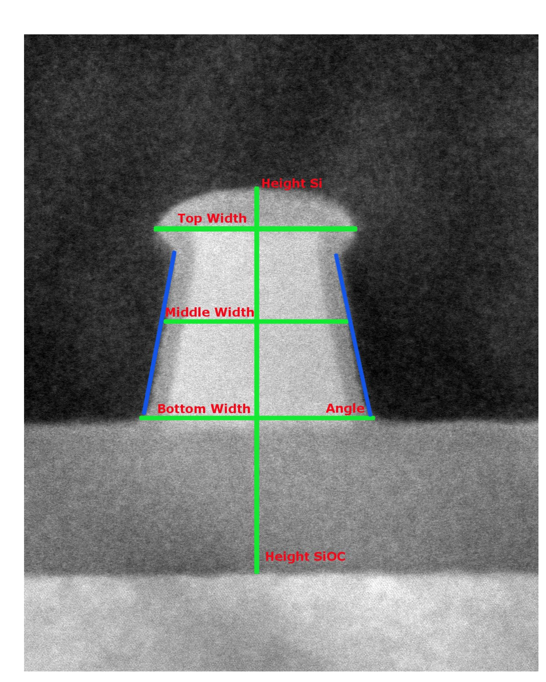
Digitized metrology based on the refined active contours. A cornucopia of measurements is extracted rather than simple height and width. Key-points can be used to extract specific measurements like height and width.

Figure 3. Critical dimension measurements were performed on imec fins

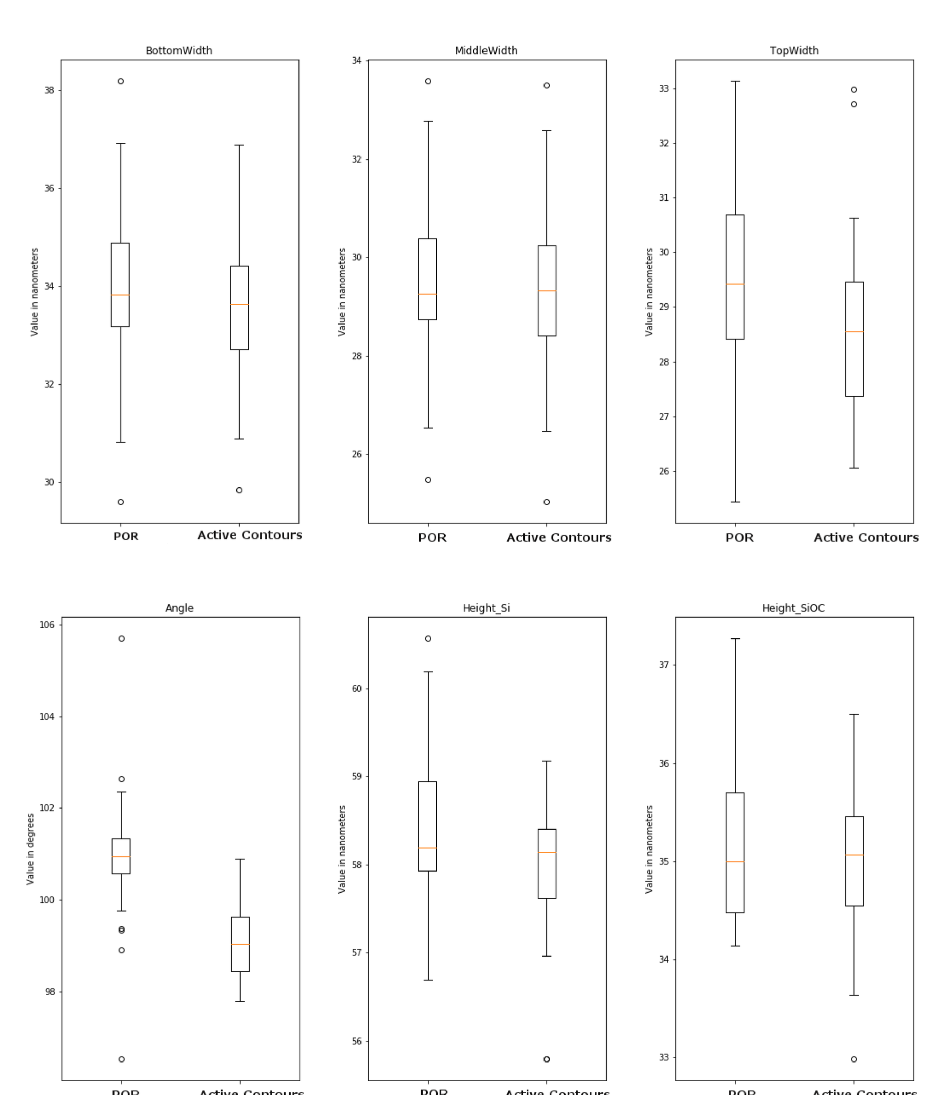


Critical dimension measurements were performed on imec fins using a workflow as in Figure 2: The raw image (top left) is segmented using the MNET (top right). Next, contours are extracted and refined using active contours (bottom left). Finally, using the refined contours, critical dimensions are extracted (bottom right) either by key-points or other methods, like line fitting.

Figure 4. Critical dimension measurements are compared to measurements made using Metrios Edge Finder based metrology[3] (Process of Record)

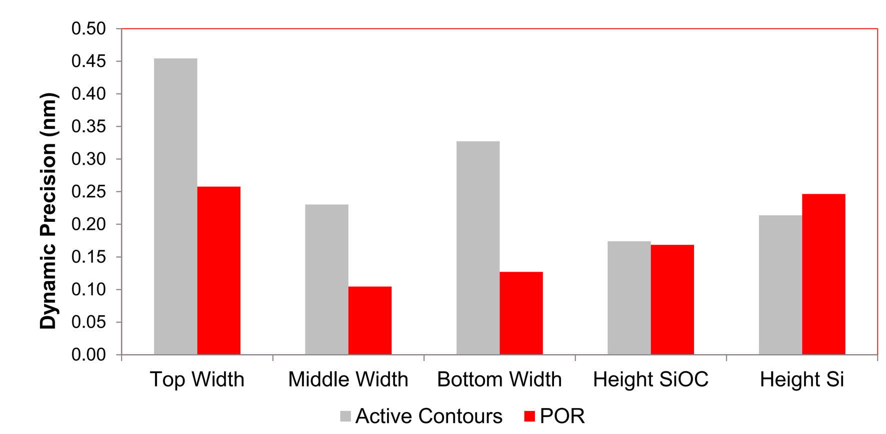


Critical dimension metrology



Box plots, above, show critical dimensions for 200 imec fins comparing Process of Record (POR), which is Metrios Edge Finder based metrology[3], to this work. The median values are comparable except for the angle. Orange lines represent the median values, boxes are the upper and lower quartiles, and the error bars represent the maximum and minimum values. The circles represent outliers, defined as being outside 1.5x the interquartile range.

Figure 5. Dynamic precision of active contours is better than $3\sigma = 0.3$nm for all but one critical dimension



Dynamic precision of Active Contours and POR is under $3\sigma = 0.3$nm for all of POR critical dimensions and all but one for Active Contours. While the dynamic precision for Active Contours is worse than POR, the POR is a semi-manual Metiros[3] recipe, where edge location is hand tuned. The Active Contours are fully automatic.

CONCLUSIONS

We have introduced a new method for extracting metrology critical dimensions automatically from images using machine learning (deep neural networks) and active contours. The workflow performs well on the imec structures we tested on: nano-wires and fins. We showed the results are comparable to POR, albeit with worse dynamic precision, but the results are promising given the early stage of development for this approach. The recipe creation process is automated, rather than semi-automated with hand tuning, and increased descriptiveness of the object under consideration is gained.

REFERENCES

1. O. Ronneberger, P. Fischer, T. Brox *U-Net: Convolutional Networks for Biomedical Image Segmentation*. In: Navab N., Hornegger J., Wells W., Frangi A. (eds) *Medical Image Computing and Computer-Assisted Intervention* – MICCAI 2015. MICCAI 2015. *Lecture Notes in Computer Science*, **9351**. Springer, Cham (2015).
2. T.F. Cootes, C.J. Taylor, D.H. Cooper, J. Graham, *Active shape models-their training and application*, Computer vision and image understanding, **61,** 38-59 (1995).
3. https://www.fei.com/products/tem/metrios/

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