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Machine Learning Powered Image Segmentation

Tobias Volkenandt[1], Stefanie Freitag[1] and Michael Rauscher[1]

[1.] Carl Zeiss Microscopy GmbH, Oberkochen, Germany.

Today it is often no longer sufficient to just acquire images of materials. Instead, researchers are interested in gaining real insight into their specimens. In order to turn images into information it is necessary to run automated image analysis or evaluations on the data. However, the evaluation algorithms in most cases need segmented image data as input. Achieving a segmented dataset to enable the subsequent analysis is the new challenge today's microscopists face.

Different techniques and algorithms exist to provide segmentation of microscopic images. The most common ones are probably simple thresholding and watershed, which work well on clean data. Unfortunately, microscopic images are prone to noise and image artefacts. Machine learning based approaches have shown huge potential to overcome these issues. They can be trained to have certain tolerance against variance of the input data. However, these approaches are not easy to use and afford to be an image analysis expert to apply them correctly.

In this contribution, we present a new software module for machine learning powered image segmentation that is robust, fast and easy-to-use. It is seamlessly integrated in the microscope's acquisition and analysis software framework for direct access. Operators of any skill level can be trained to use the software and perform advanced image segmentation within minutes. The solution works with any kind of image data covering 2D and 3D datasets from light-, electron-, ion or x-ray-microscopes and can even deal with 6D datasets by high-end light microscopy. It reads all important file formats, covering tiff, jpg, png, czi and txm.

For creating and training a model, the new software module features an intuitive training user interface. No parameters have to be known and set, except for just one. The user can decide to use a handpicked 33-dimensional feature vector or use a separate deep-trained neural network to determine the feature vector based on the input data. After defining the classes, the user labels them with a simple painting tool directly in the training images. The amount of labeling that has to be done depends on the targeted accuracy of the model. The user can check the segmentation result any time during the training and decide on further refining the model in an iterative manner. In the end, the model is ready and can be used for segmenting the same kind of data repeatedly.

Figure 1 shows an exemplary segmentation use case. The original image on the left is an SEM image of a FIB cross-section of a CIGS solar showing different layers. The layers have been labeled as illustrated in the center image to train the segmentation model. On the right, the result of the segmentation is shown. The different layers have been clearly segmented and can be well distinguished. This data would be ready for further analysis of e.g. the layer thickness or homogeneity. The model did not get confused by the crystallographic contrast visible in the ZnO contact layer nor by the droplets visible in the CIGS layer which are artefacts stemming from the FIB preparation. On the contrary, it did detect that the buffer layer (segmented in red) is not completely homogeneous, as can be quickly verified in the original image. Further analysis would have to show whether this a real effect or an artefact by the FIB preparation.

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A similar segmentation result would have been difficult to achieve via thresholding or watershed techniques, which would have misinterpreted the multifold contrasts and artefacts in this data. While for the machine learning based approach not more than some labeling was necessary to train the model and segment the image. In addition, the created model can be reused and applied to further cross-section images of similar solar cells or even a 3D image stack acquired e.g. by FIB-SEM tomography.

Further application examples of this software module will be shown in the presentation, covering 2D and 3D datasets. The presentation will focus especially on the aspect of ease-of-use, but also provide information about the segmentation speed and quality of the presented solution [1].

References:

[1] Visit www.zeiss.com/zen-intellesis for further information and your free 30-day trial version.

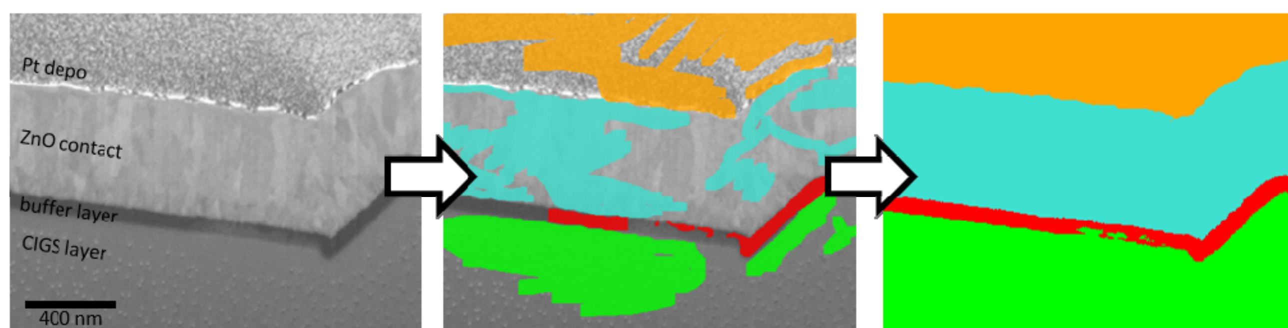

Figure 1. Segmentation workflow illustrated on the example of an SEM image of a FIB cross-section of a CIGS solar cell. The original image (left) has been labeled (center) to train a model for segmentation of the different layers. The result of the segmentation is shown on the right.

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