ARTIFACT REMOVAL BY LOCAL EXTREMA DETECTION IN IMAGES FROM ELECTRON MICROSCOPY

Pavel Kaspar

Doctoral Degree Programme (1), FEEC BUT

E-mail: xkaspa25@stud.feec.vutbr.cz

Supervised by: Pavel Tománek

E-mail: tomanek@feec.vutbr.cz

Abstract: Processing of images from electron microscopy is important for a succesful analysis of acquired output. As with the majority of digital signals, these are plagued by various types of noise or artifacts. This paper concerns the detection and removal of artifacts created by sample contamination and the following reverse edge detection for displaying image segmentation.

Keywords: LEEM, artifact detection, artifact removal, edge detection,

1. INTRODUCTION

Output images from electron microscopy are usually affected by the presence of noise and artifacts. The greater the magnification of microscopes, the bigger the artifacts are.

Images of polycrystalline copper taken by Low-energy electron microscope (LEEM), which guarantees high contrast and little noise [1], were used as a sample for the processing (Figure 1). Much larger artifacts are present, however, caused by microparticles on the sample or acquisition setup. Improving the signal to noise ratio is very important for the following image analysis of taken images and further information gathering.

Currently there are several interesting ways to approach artifact detection and removal, but they work mostly with quantifiable attributes, like for example physics based method [2]. If we are presented with artifacts, that have no connection to the image, no distortion around them caused by the source of the artifact, or are not caused by a condition affecting the whole image, majority of approaches are not usable. Such artifacts must be detected and targeted individually.

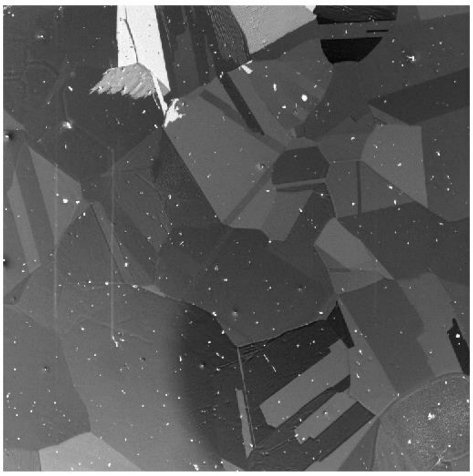

Figure 1: Polycrystalline copper image taken by LEEM, magnification 1.333 x 10^3

2. IMAGE PROCESSING

2.1. ARTIFACT DETECTION

The best method for removal of classic artifacts would be the median filtering. That only works for impulse noise. Here the artifacts are caused by contamination of the sample or acquisition setup [3] and in the current magnification they take up much more space pixel wise, and therefore are resistant to the median filtering. This could be circumvented by a nonlinear filter with training algorithm and iterative optimizer [4], or by modifying data input for another nonlinear, standard median filter. The latter became the general principal for this approach to artifact detection and subsequent removal.

Before the main body of the image processing began, it was important for the detection quality to adjust the brightness scale. Histogram equalization was not used, because that would not only affect the contrast, but also highlight other pixel imperfections, thus distorting the image and the search for artifacts would become very complicated. The adjustment was such, that 1% of the image data were set as the highest and lowest intensity, the rest was spread equally by the ratio to the maximum or minimum from the original image.

The detection method uses local maximum detection as the main piece of its algorithm. The window size was set on 20×20 pixels after numerous simulations as the ideal size. Greater window size would mean larger parts of the image used in detection process, therefore causing larger artifact fields to enter the computations and that would in turn cause lower sensitivity. On the other hand, too small detection window would work only with very limited operational sample. The result would be more pixels marked as artifacts then there actually are, thus lowering specificity. Only the maximum in the window was detected and the percent threshold was applied to the value of the window's local extreme. The window then continued to move through the whole image and created a matrix of local extreme positions, detecting extremes one pixel after another in relation to the area of detection window. That itself provided us with the result with high sensitivity, but the specificity was still raher low, because large fields of certain crystallographic orientations were thought of as artifacts as well. For the removal of this problem two other thresholds were introduced – group threshold and final threshold. The group threshold detects, whether the detected pixels are artifacts, or belong to the image. Its format must be in the number of pixels from 0 to the size of the window. In every step it evaluates the number of pixels detected as artifacts, and if the count is higher than the set threshold, the pixels are removed from the artifact selection. This can prevent branding of the large fields in the image as not belonging to the image. Every pixel in the artifact matrix has a number associated with it. The number represents how many times it was deemed an artifact. It is clear, that the pixels on the top and bottom will be searched only once, and the the ones closer to the edge will have less searches than the ones in the center. That is a downside of this method, but in the vast majority the objects in the center are the most important, and the edges are often distorted, and therefore is this method acceptable. The final threshold then dictates how many times must a pixel be detected as an artifact to be selected as one. Output of this proces is a binary matrix representation of artifact positions.

2.2. ARTIFACT REMOVAL

After the succesful artifact detection, it is important to replace them with valid pixels. Because there are multiple deposits unevenly spread across the image with little to none connection to the image itself, image implant method was selected as the best and least complicated for calculation.

In itself the method is basically very simple replacement of data in one picture with the ones from other. The processed image was duplicated, one named as a "donor" image and the other as an "acceptor".

The donor image was subjected to 2D FFT and than adjusted by decreasing the intensity of phase spectrum to 70% of its original value, and then processed by several median filters of different size to deepen the distortion and blurring. That created an image useless for visual analysis.

Thanks to this, the pixels were a very dilluted mean of their surroundings. Pixels were than taken from the distorted donor image, according to the positions of detected artifacts, and put on their corresponding places in the acceptor image. That effectively created a local median filtering of the scene, which would be very complicated otherwise. The whole transplantation process was finished up with a simple 3×3 median filtering on the whole image to simulate healing in of the implants (Figure 2). Greater size of the filter would smooth out details important to the image, while 3×3 filter only affects one-pixel sized discrepancies that may occur when inserting implants.

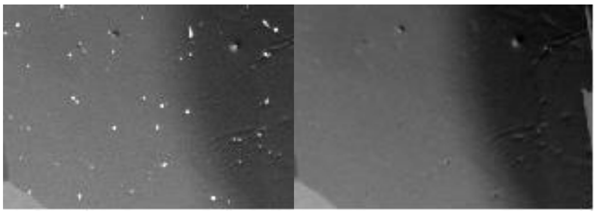

Figure 2: Comparison of the same area of an image before (left) and after (right) artifact removal

Flowchart (Figure 3) shows the computational process of artifact detection and removal in a manner easier to visualise and understand.

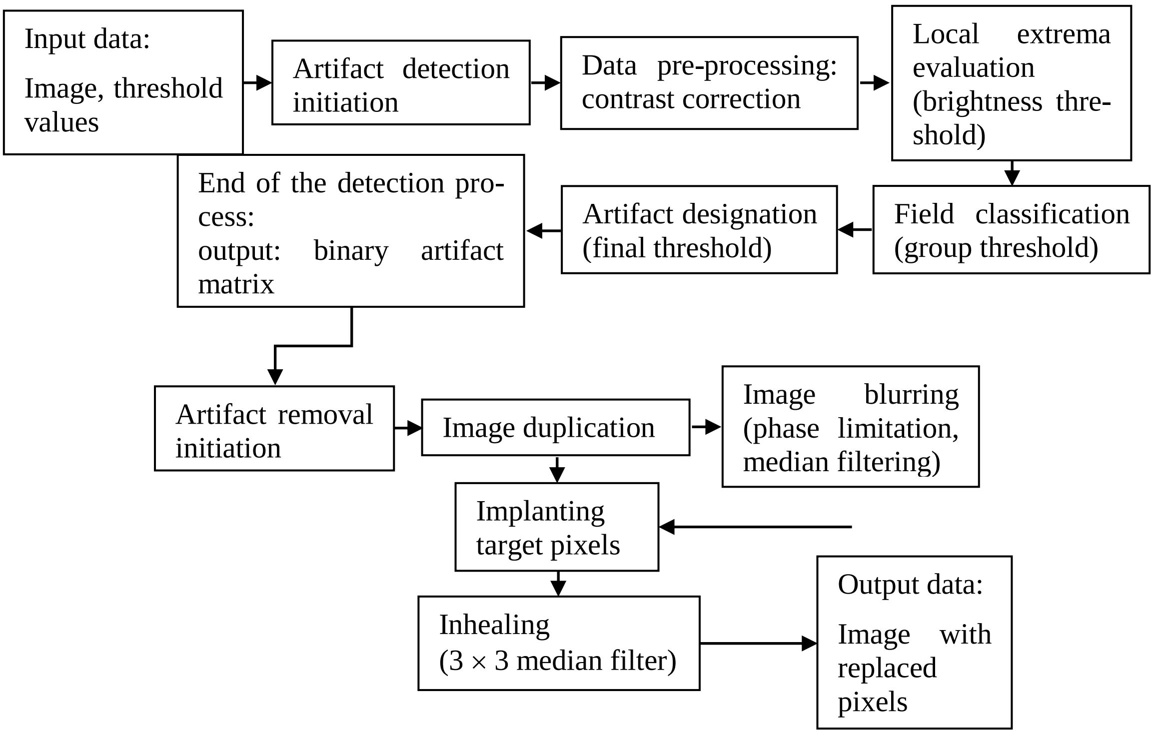

Figure 3: Flowchart of artifact detection and removal process

2.3. EDGE DETECTION

Edge detection is especially important for the segmentation of an image on the basis of different crystalographic orientations, or other attributes affecting the parameters of the image. There is a method, which after an image acquisiton evaporates the sample and with spectrometry it detects parameters and from them it creates an edge representation. For the case of reverse analysis it is necessary to create the representation only from the data on the image. It will not be as exact as the spectrometrical analysis is, but it will provide us with a general idea.

Firstly, it must be said that the edges are detected on the already processed images with removed artifacts. For the representation itself a Canny detector is used [5]. On its own it detects parts of the image, that are not grain edges, but for example cracks in the material, or because of the selected bias it does not detect certain edges at all. To reach a better result a histrogram equalisation is performed. That results in a heavily noise-affected image, useless in itself. Even though Canny detector has a noise removal step in it’s own algorithm, median filtering was needed. Resulting distortion of the image is acceptable because of the aim to only detect edges. These three steps (equalization, filtering and Canny detector) have yielded enough edges, but they were not able to remove the false positive ones, like cracks in the material or unfinished lines in the image.

Because of the inability to remove the false edges, one more operation has been added. For the cleaning purposes a 3×3 matrix was formed with a zero in the middle and ones all around. That basically gives us a pixel surroundings. By convolution of the binary edge matrix with this matrix we get an information about the number of edge pixels surrounding concerned pixels. As the last step all edges, that are not surrounded by enough of edge pixels (given by a set threshold) are removed from the edge representation. A side effect of this procedure is enlargement of edges by one pixel on each side. This effect serves as an improvement of edge visibility in the greyscale image (Figure 4.)

Figure 4: Image without artifacts and with edges

3. CONCLUSION

The method presented for detection of artifacts is very effective for images with artifacts greater then impulse noise. It is quite stable even in images with varying topography, because it uses local extremes adjusted for the size of a scanning window. Artifact removal method is effective only on images with simple topography. The edge detection method is useful for reverse segmentation of the image on areas with different attributes. Because of its algorithm, false edges caused by unsmoothness of the surface may appear.

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