

A Machine Vision Fuzzy-Based Technique for Detection of Defected Pores in AFM Images

Amjed Al-Mousa
 Computer Engineering Department
 Princess Sumaya University for Technology
 Amman, Jordan
 a.almousa@psut.edu.jo

Oday Al-Dweik
 Computer Engineering Department
 Princess Sumaya University for Technology
 Amman, Jordan
 oday1997dweik@gmail.com

Abstract—This paper presents an expanded technique to automatically characterize pores in Atomic Force Microscopy (AFM) images and consequently detect defects. The technique deploys a statistical approach to identify the base surface of the AFM image. Then utilize an existing fuzzy-based engine to characterize both pores and surface structures. It treats the above-surface and below-surface parts of the image as two separate images, and then it combines the characterization results from these two images. The technique was tested on porous AFM images and was able to characterize pores successfully and identify defects in the AFM images.

Keywords—Fuzzy logic; image processing; machine vision; characterization; Atomic Force Microscopy (AFM); porous surface.

I. INTRODUCTION

With the rise of nanotechnology and its applications, the need for Atomic Force Microscopy (AFM) images that characterize nanostructure and porous surfaces is becoming extremely essential. However, making sense of these AFM images is a task that requires a lot of expertise in addition to manual effort of inspecting large numbers of sample images for defects. Thus the need to create an automated way to characterize these surfaces was essential.

The work presented in [1, 2] was successful in characterizing surface nanostructures and crystals, but it was not able to handle porous surfaces. The work here expands it to be able to characterize pores in a surface as well, in addition it allows for detection of defected samples based on the pore size as compared to the expected range.

One of the main challenges in characterizing such surfaces is finding the actual height of the base surface; that is the height on top of which nanostructures were grown or etched, and underneath pores exist.

The approach presented in this paper attempts to use statistical methods to identify the base surface. Once the surface is detected it splits the image into two; above surface and below surface images. These images are then processed separately by a Fuzzy Logic engine to detect the structures and pores. And finally, the results are combined from both of these images.

Section II of the paper presents a review of related work, then Section III introduces details of the proposed technique. The results of sample images are then presented in section IV. Finally, a conclusion is outlined in section V.

II. RELATED WORK

In the field of image characterization, a variety of techniques have been used. In [3, 4] statistical approaches have been used where a single quantity is used to describe the entire surface such as; surface roughness, Root Mean Square (RMS), arithmetic average... etc. The issue with this approach is that it lacks the individual information about each pore or structure.

Another technique that is used for surface characterization is the watershed technique, presented in [5, 6]. The technique emulates filling the basins between surface structures with a water in an attempt to find the boundaries between surface structures. However, in cases where the surfaces are very crowded, this results in an over segmentation side effect.

In addition, a variety of images processing technique like; edge detection [7, 8] and blob detection [9] could be used to characterize the AFM images. While these techniques are capable of producing good results for certain images, selecting the specific implementation of the technique and tuning its parameters would require manual intervention.

Finally, a thresholding technique can be used to identify the surface and then identify the structures above that threshold or pores below it [10]. However, the threshold could significantly vary from one sample to another, and this requires manual intervention to examine each sample.

III. ALGORITHM DESCRIPTION

In order for the technique to successfully work with surface structures as well as pores, the system need to automatically determine the base height of the surface. The details of the statistical approach of determining the surface height are presented in Section III.A. Next, a review of the fuzzy engine used for characterization is explained in section B. Finally, the details over the overall system are explained in section C.

A. Base Surface height.

AFM samples usually contain structures (above the base surface) or pores (below the base surface), but not both of them at the same time. Here we are attempting to develop a technique that is able to characterize surfaces that contain both simultaneously. Figure 1 represents a sample cross section in an AFM image that shows a surface structure and a pore. The process of automatically characterizing the image is dependent on finding the approximate height of the base surface.

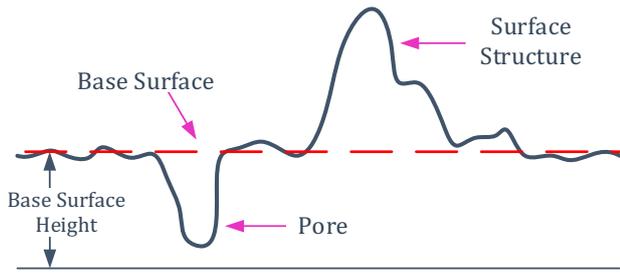


Figure 1: Cross section of an AFM image with a surface structure and a pore

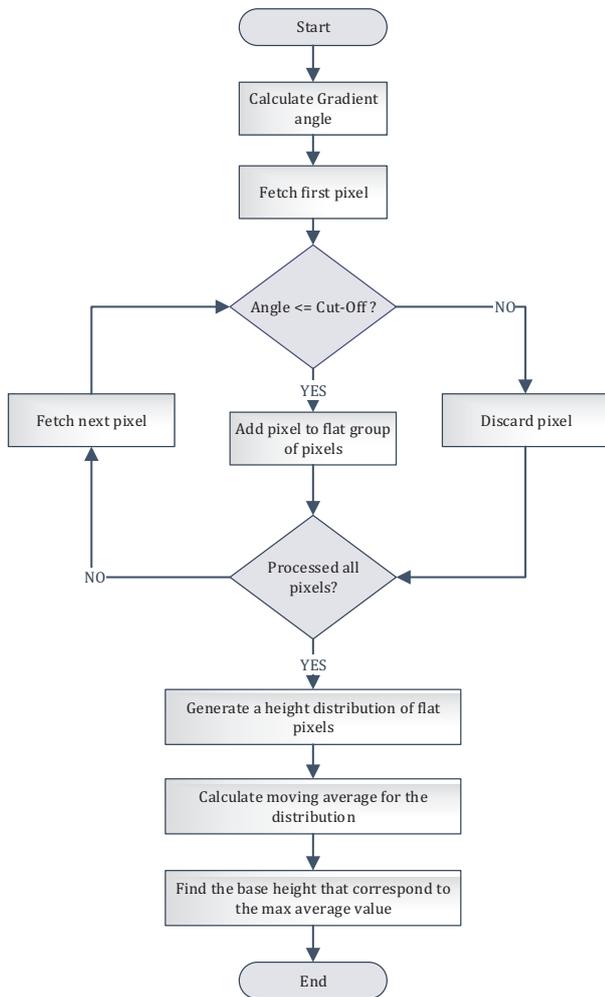


Figure 2: Statistical approach to determine base surface height

The statistical approach deployed is shown in Figure 2. First, the gradient is calculated for the entire surface. Then the algorithm sweeps all pixels discarding any pixel where the gradient exceeds a pre-defined cut-off limit. The aim here is to focus the investigation on the flat areas in the image, which could be either the base surface, the top of surface structure, or even the bottom part of a pore.

Next, a height distribution is generated for the selected “flat” pixels, and a moving average of the distribution values is computed. This actually allows for capturing the height that has the highest count of pixels; which is most likely to correspond to the base surface. In the height distribution, the entry that has the maximum count would identify the height of the base surface.

B. Fuzzy Characterization Engine

The Fuzzy characterization engine which was developed in [1, 2] consists of four stages, shown in Figure 3:

- **Surface Type Detection:** This stage detects whether the surface is crowded or sparse. Each type of surfaces has difference fuzzy rules that fit the surface type.
- **Points Classification:** This is the core of the Fuzzy algorithm, the engine here utilizes the height and gradient information and classifies the pixels into three categories: Tops, inclines, and Bottoms. This stage consists of the three typical fuzzy steps; fuzzification of inputs, application of fuzzy rules, and the defuzzification of outputs.
- **Top Clustering:** This stage groups neighboring pixels that have been identified tops together to form the core of a structure/pore.
- **Point Association:** this stage associates the inclined pixel with the appropriate structure/pore that they belong to.

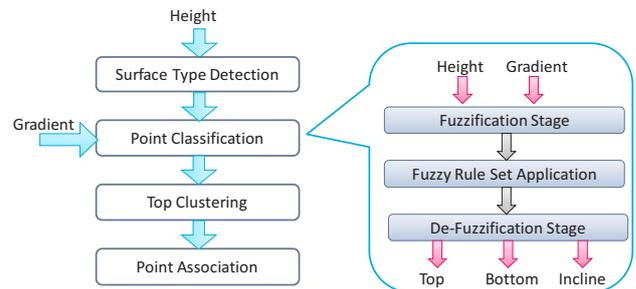


Figure 3: Characterization using Fuzzy Engine

C. Overall System Architecture

Once the base surface height is found as described in the previous sub-section. This value is subtracted from the entire image; this leaves structures with positive heights, the base surface at zero and pores with negative height. Next, as shown in Figure 4, the image is actually split into two images, one for the pores and one for the surface structures. The above surface image that could contain surface structures is generated from the original and setting all negative values to zero; thus the pores disappear from this image. Similarly, the below surface image is generated by replacing the positive values, where we have surface structures with zero, leaving the image with pores only. Now, the Fuzzy engine is used to characterize each image separately. The earlier technique was designed to deal with positive heights. So in the case of the below surface image the image is actually inverted first (multiplied by -1) before being processed by the fuzzy engine.

The results of the engine for the second image are reverted (given negative values), in order to distinguish them from the true structure detected in the first image.

At this point, the processed results from the “Above surface” image have identified structures, and the results from the “Below surface” image would have identified pores. The last step of the algorithm is to combine the results from each image to generate a final result that characterizes the exact location and boundary for each structure and pore.

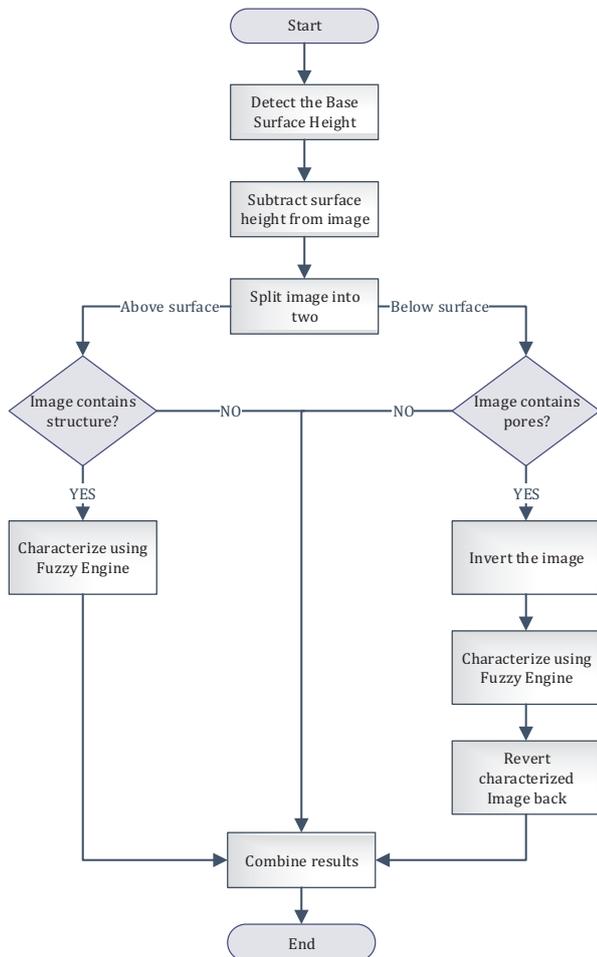


Figure 4: Overall System Architecture

IV. RESULTS ANALYSIS

To demonstrate the effectiveness of the technique, it was applied to varying types of samples and surfaces. Since this work is focused on showing how the original engine can be modified to handle porous surfaces, the results shown in this paper are focused on porous surfaces, shown in section A. Also, an artificial compound test surface that contains both pores and structures is presented in section B.

A. Porous Surfaces

A sample porous surface is shown in Figure 5. This sample here is a porous alumina scanned using and SCD probe [11]. The aim here is to detect the shown pores automatically and characterize their properties. Typically, automatic characterization allows for detecting manufacturing defects

or anomalies without manual inspection, similar to the one circled in the image.

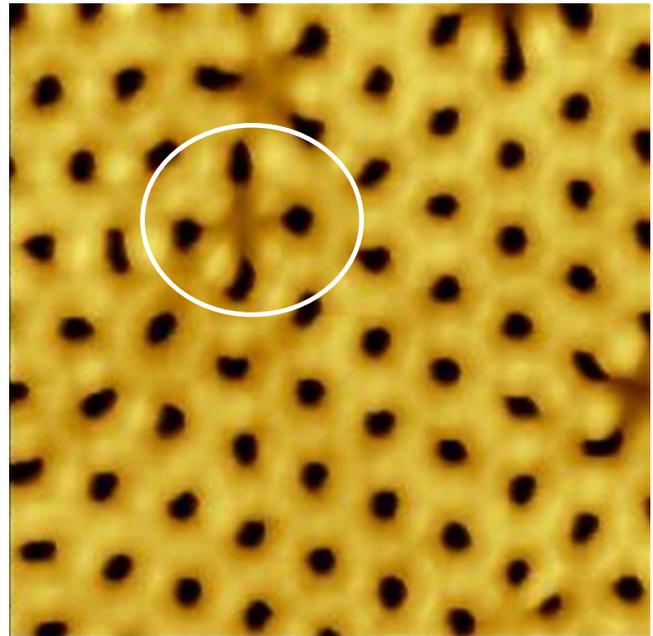


Figure 5: AFM topography of porous alumina made using SCD probe [11]

Once the flat pixels of the image are identified, a histogram distribution of the height of the flat pixels is generated, shown in Figure 6. The maxima on the moving average is used to identify the height of the base surface, in this example it is around 178.

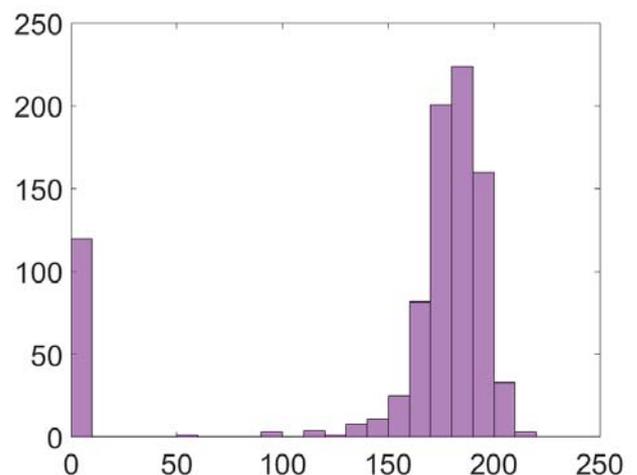


Figure 6: Histogram of the height distribution of flat pixels

After the height value is subtracted from the original image data the image would look similar to the one shown in Figure 7.

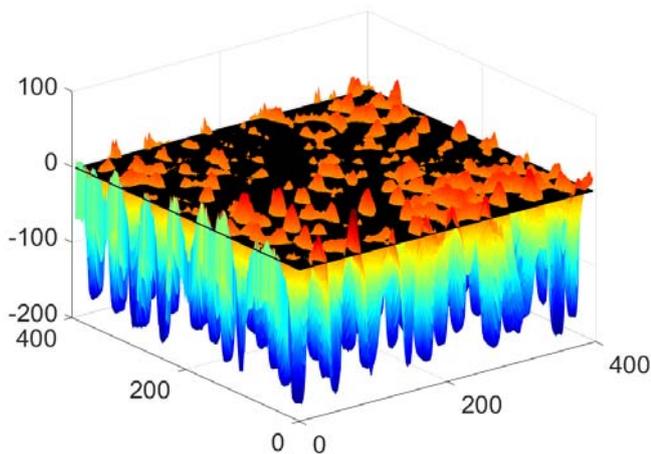


Figure 7: 3D reconstruction of the surface after subtracting the base surface height

The next step of the technique is to take the below surface part, flip it to look like the image shown in Figure 8. The defected area can be seen in the figure; where four pores have expanded in size. The processed image can now be fed to the fuzzy engine to properly identify and isolate the pores.

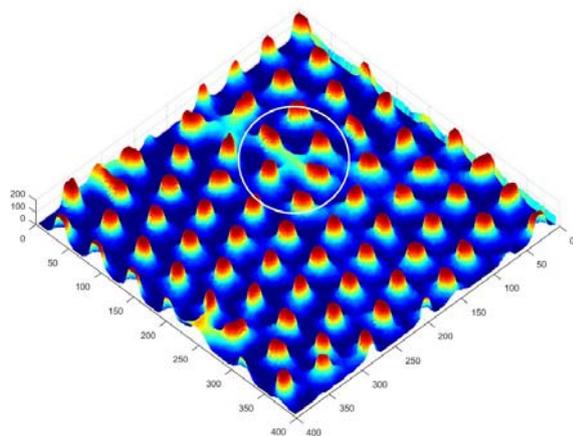


Figure 8: 3D reconstruction on the surface after it is flipped

The fuzzy engine processes the image and isolates each pore, the engine assigns a unique random color per pore to help visualize the results, as shown in Figure 9.

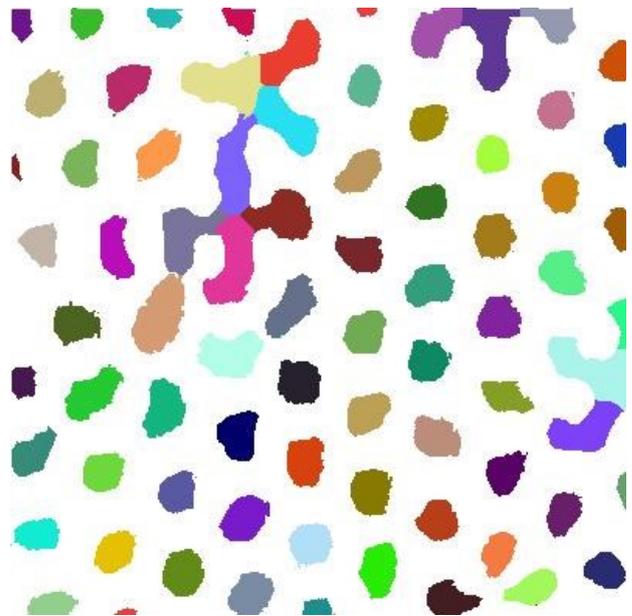


Figure 9: Pores identified by the Fuzzy Engine

With the size of each pore now available, the system can now bin the size of the pores, as shown in Figure 10. It can be seen that there are pores whose size has exceeded the expected size of a normal pore. This can be used to automatically trigger an inspection on the AFM image.

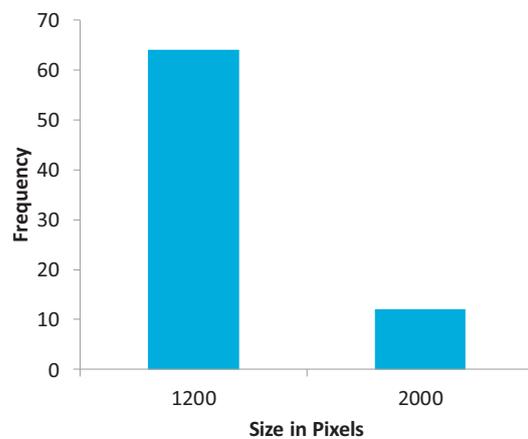


Figure 10: Binning of the pore size to detect defects

B. Compound Test Surface

The algorithm was also tested on a test artificial surface that was generated to contain both pores and structures. The surface is shown in Figure 11.

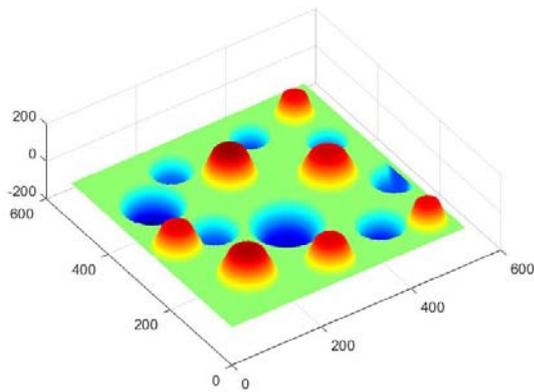


Figure 11: Test surface containing pores and structures

Upon running the algorithm, the algorithm is able to identify the seven surface structures, shown in Figure 12-a, and the surface pores shown in Figure 12-b. the results from both of these images are combined together in Figure 12-c to generate a full characterization of the surface.

V. CONCLUSION

In conclusion, this paper presented an expended technique that is able to characterize surfaces that contain pores as well as structures. The technique presented has the advantage of not needing manual human intervention to set a threshold. The technique has been applied to real AFM images and was able to successfully characterize the images and even catch small defects and anomalies in these images.

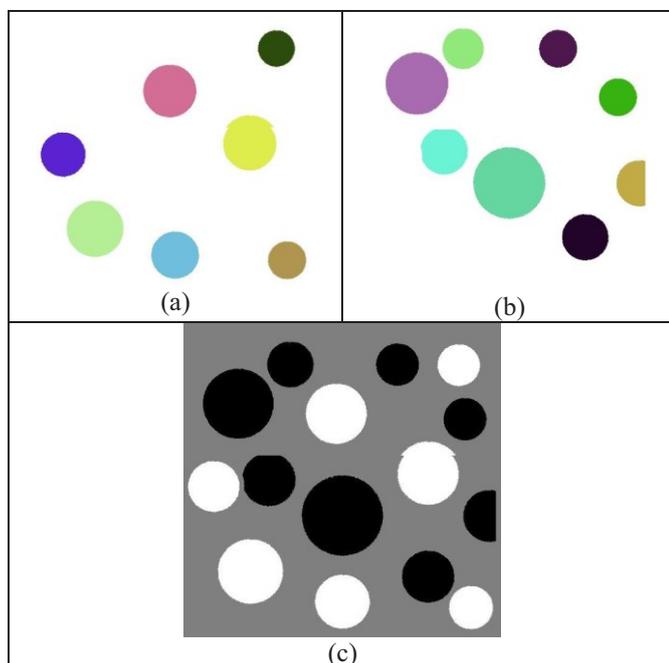


Figure 12: Results of test surface: (a) Surface Structures (b) Pores (c) Combined results

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- [1] A. A. Al-Mousa, "A new systematic and quantitative approach to characterization of surface nanostructures using fuzzy logic," Santa Clara University, 2010.
- [2] D. L. N. D. J. N. N. G. G. M. R. Amjed Al-Mousa, "Analysis of atomic force microscopy data for surface characterization using fuzzy logic," *Materials Characterization*, vol. 62, no. 7, pp. 706-715, 2011.
- [3] E. d. V. B. d. S. J. F. V. F. G. F. E. d. S. J. J.B. da Silva Jr.a, "Statistical analysis of topographic images of nanoporous silicon and model surfaces," *Microelectronics Journal*, vol. 36, pp. 1011-1015, 2005.
- [4] G.-C. W. T.-M. L. Y. Zhao, *Characterization of Amorphous and Crystalline Rough Surfaces: Principles and Applications*, San Diego: Academic Press, 2001.
- [5] G. Bertrand, "On topological watersheds," *Journal of Mathematical Imaging and Vision*, vol. 22, no. 2-3, pp. 217-230, 2005.
- [6] G. Bertrand, "Some properties of topological greyscale watersheds," in *procs. SPIE Vision Geometry XII*, 2004.
- [7] M. Corp., "MATLAB Online Help, V7.5 R2007b.," [Online]. Available: <http://www.matlab.com>.
- [8] J. Canny, "A Computational Approach To Edge Detection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 8, pp. 679-714, 1986.
- [9] T. Lindeberg, "Detecting Salient Blob-Like Image Structures and Their Scales with a Scale-Space Primal Sketch: A Method for Focus-of-Attention," *International Journal of Computer Vision*, pp. 283-318, 1993.
- [10] B. S. Mehmet Sezgin, "Survey over image thresholding techniques and quantitative performance evaluation," *Journal of Electronic Imaging*, vol. 13, pp. 13 - 20, 2004.
- [11] [Online]. Available: <http://www.scdprobes.com/images/pa.jpg> .