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Application of the Hough Transform to Dispersion Control of Overlapping Particles and Their Agglomerates

Pavel V. Gulyaev

*Udmurt Federal Research Center of the Ural Branch of the Russian Academy of Sciences,
T. Baramzina str., 34, Izhevsk 426067, Russia*

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Abstract

The dispersion control of micro- and nanoparticles by their images is of great importance for ensuring the specified properties of the particles themselves and materials based on them. The aim of this article was to consider the possibilities of using the Hough transform for dispersion control of overlapping particles and their agglomerates. Analysis of the application of the Hough transform for overlapping particles and their agglomerates showed the following. The particularities of the conventional implementation lead to the preferred registration of large particles, the shift of the centers of overlapping particles, and the distortion of the size values. To use the Hough transform correctly, fine-tuning of all its parameters is required. To automate this process, the dependences of the number and size of particles recorded in the image on the parameters of the Hough transform was investigated. The studies were carried out on test images with a known number and size of particles. The results showed that when the threshold parameters of the Hough transform change, the number of detected particles stabilizes near their optimal values. When the size range of particles detected by the Hough transform changes, the histogram of the particle size distribution changes. In this case, the optimal width of the range is determined by the most stable extremes of the histogram. The maximum center-to-center distance is set at least half of the optimal range. The configuration algorithm is described and implemented. It implies repeatedly running the Hough transform with different combinations of parameters. The algorithm includes stages of coarse and fine-tuning, which allows to getting closer to the optimal parameters. The efficiency of the algorithm has been confirmed on test and real images. Tests have shown that the errors in determining the size and number of particles of the multi-pass Hough transform are on the same level or exceed these indicators for analog methods.

Keywords: scanning probe microscope, SPM image, particles, dispersion control

Адрес для переписки:
Гуляев П.В.
Удмуртский федеральный исследовательский центр УрО РАН,
ул. имени Т. Барамзиной, 34, Ижевск 426067, Россия
e-mail: lucac@inbox.ru

Address for correspondence:
Gulyaev P.V.
Udmurt Federal Research Center of the Ural Branch of the Russian Academy of Sciences,
T. Baramzina str., 34, Izhevsk 426067, Russia
e-mail: lucac@inbox.ru

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Применение преобразования Хафа для контроля дисперсности накладывающихся частиц и их агломератов

П.В. Гуляев

Удмуртский федеральный исследовательский центр Уральского отделения Российской академии наук, ул. имени Т. Барамзиной, 34, г. Ижевск 426067, Россия

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Контроль дисперсности микро- и наночастиц по изображениям имеет большое значение для обеспечения заданных свойств самих частиц и материалов на их основе. Целью данной работы являлось исследование возможностей применения преобразования Хафа для контроля дисперсности накладывающихся частиц и их агломератов. Анализ применения преобразования Хафа для накладывающихся частиц и их агломератов показал следующее. Особенности конвенциональной реализации приводят к предпочтительной регистрации больших частиц, смещению центров перекрывающихся частиц, искажению размеров. Для корректного использования преобразования Хафа требуется точная настройка всех его параметров. Для автоматизации такой настройки исследованы зависимости количества и размера регистрируемых на изображении частиц от параметров преобразования Хафа. Исследования проводились на тестовых изображениях с известным количеством и размерами частиц. Результаты показали, что при изменении пороговых параметров преобразования Хафа число регистрируемых частиц стабилизируется вблизи их оптимальных значений. При изменении диапазона размеров регистрируемых преобразованием Хафа частиц изменяется гистограмма распределения частиц по размерам. При этом оптимальная ширина диапазона определяется по наиболее устойчивым экстремумам гистограммы. Максимальное межцентровое расстояние устанавливается не менее половины оптимального диапазона. Описан и реализован алгоритм настройки, подразумевающий многократный запуск преобразования Хафа с различными комбинациями параметров. Алгоритм включает этапы грубой и точной настройки, позволяющие точнее приблизится к оптимальным параметрам. Работоспособность алгоритма подтверждена на тестовых и реальных изображениях. При этом погрешности определения размеров и количества частиц многопроходового преобразования Хафа находятся на одном уровне или превосходят данные показатели у методов-аналогов.

Ключевые слова: сканирующий зондовый микроскоп, СЗМ-изображение, частицы, контроль дисперсности

Адрес для переписки:
Гуляев П.В.
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ул. имени Т. Барамзиной, 34, Ижевск 426067, Россия
e-mail: lucac@inbox.ru

Address for correspondence:
Gulyaev P.V.
Udmurt Federal Research Center of the Ural Branch of the Russian Academy of Sciences,
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Introduction

The micro- and nanoparticles dispersion control is important to ensure the specified properties of particles and materials based on them. Traditionally, various types of microscopy associated with obtaining high-resolution images are used to dispersion control. Conventional methods [1] of processing such images imply segmentation, identification of objects and measurement of their sizes. Threshold filtering (binarization [2, 3]) and contour analysis [4]) are the most common segmentation tools. However, the use of these tools reduces the accuracy of determining the size of overlapping particles and particles with varying degrees of brightness. There are more complex segmentation methods, for example, parametric [5], variational [6], neural network [7]. These methods have significant limitations in application (complexity of implementation, high demands on computing resources) and are not always available in open libraries such as OpenCV.

The disadvantage of conventional image processing procedures is the necessity of manual parameter settings. At the same time, for automation of dispersion control, it is advisable to use methods with automatic parameters setting [8]. In addition, as shown in [9], conventional methods for segmentation of overlapping and touching particles do not always determine their real contours. In this case, structural methods that can take into account the hidden part of the particle contour are more effective. Such methods include surface curvature detectors [10] and geometric shape detectors based on the Hough transform. Unlike curvature detectors, the Hough transform has found much wider application in commercial [11] and free software [12]. The aim of this article was to consider the possibilities of using the Hough transform for particle dispersion control.

Problem definition

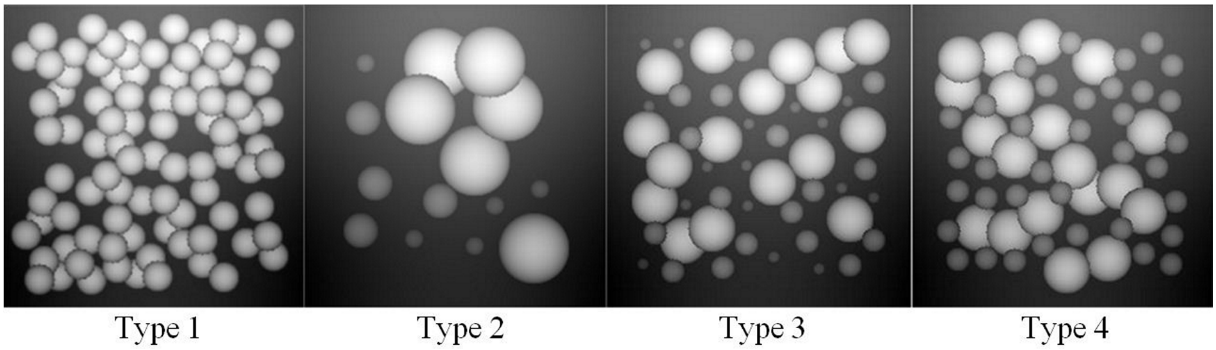
The scheme for calculating the distribution of il-luThe simplest case [13] of particle dispersion monitoring implies manual parameters adjustment and manual results filtering, more complex – the use of additional add-ons, such as neural networks [14], filters [15]. However, this approach reduces the availability of the resulting software. The main task of this work is to develop an algorithm for automatically adjusting the parameters of the Hough transform without modifying the conventional implementation of the transform. This implementation generally includes the following procedure.

1. To find the boundaries of objects in the image, contours are allocated using the Canny method.
2. The brightness gradient for the boundary points is calculated.
3. Rays perpendicular to the tangent to the boundary points and directed along the brightness gradient are plotted.
4. Candidate centers of circles are localized. These include the image pixels through which the largest number of rays have passed.
5. The dimensions of the circles are determined. Non-zero points are located around the candidate centers at a distance taking values from the minimum to the maximum allowable radius. The final radius of the circle is defined by the largest number of boundary points removed from the candidate center by the value of this radius.

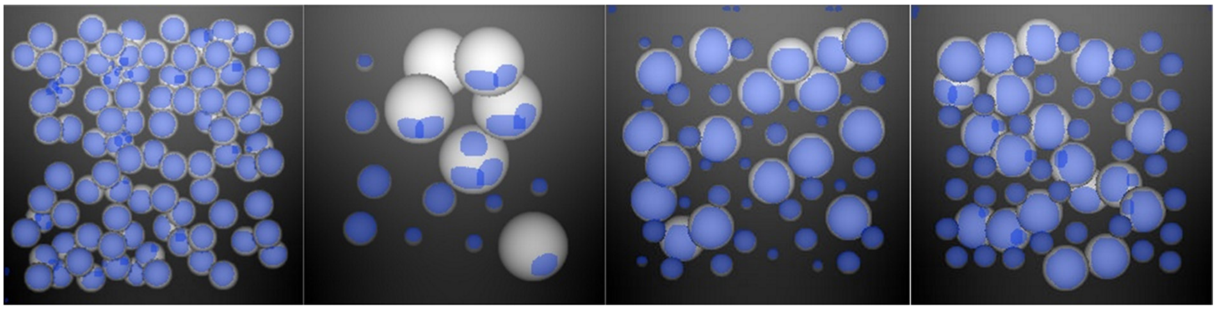
The conventional implementation of the Hough transform in conditions of superposition of particles with a large size range, as well as in the presence of noise, may have the following disadvantages.

1. Incorrect localization of particle centers caused by in local gradient calculating errors (especially on small, low-contrast particles).
2. Inaccurate determination of the particle size in agglomerates caused by the fact that only one circle is assigned to each candidate center.
3. There is a preferred registration of large circles (pseudo-circles, fragments of circles), since for them the threshold of correspondence (coincidence) to the candidate center turns out to be greater than for small circles.

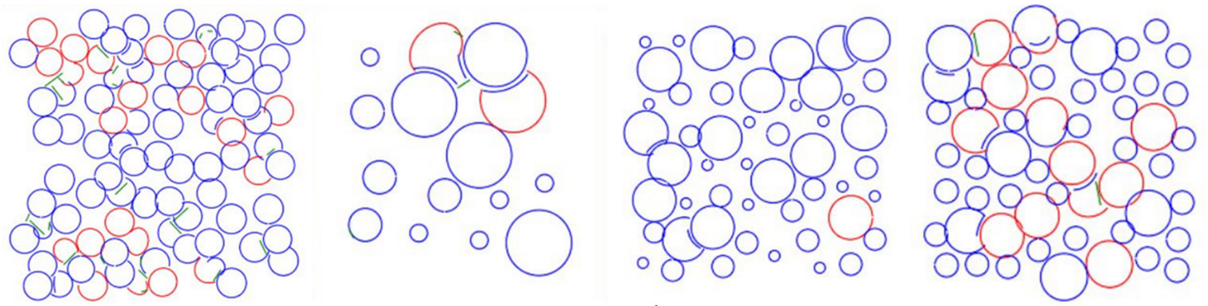
These disadvantages are partially eliminated by manually adjusting the parameters of the Hough transform. However, to do this, it is necessary to change up to five parameters at the same time, and this increases the processing time and the risks of human influence on the results. At the same time, there are examples of particle size control algorithms that do not require manual adjustment. These include neural networks, for example, ParticlesNN [16], and the ELSD method (ellipse and line segment detector, a detector of line segments and ovals) [8]. The results of segmentation of images of overlapping particles (Figure 1*a*) using these methods are presented in Figure 1*b*,c and in Tables 1, 2. Four types of test images were used for evaluation: type 1 – a set of densely packed particles of the same size; type 2 – particles of three standard sizes with a low density of placement; type 3 – particles of three standard sizes with high density of placement; type 4 – particles of two standard sizes with a high density of placement.



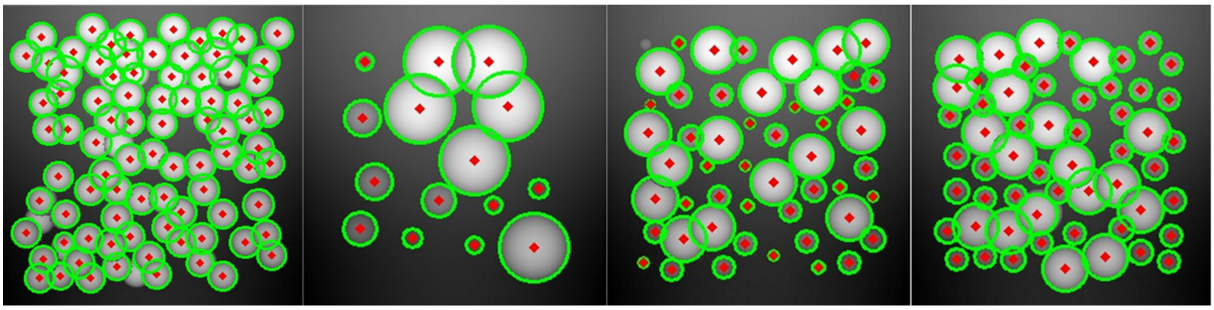
a



b



c



d

Figure 1 – Particles detection in the source images (*a*) using a neural network (*b*), the ELSD method (*c*) and the multi-pass Hough transform (*d*)

The 256×256 test images were formed from a background relief $F[x,y]$, simulating the non-ideality of the scanner, and a particle image $Q[x,y]$ with radius R_0 and coordinates (x_0, y_0, z_0):

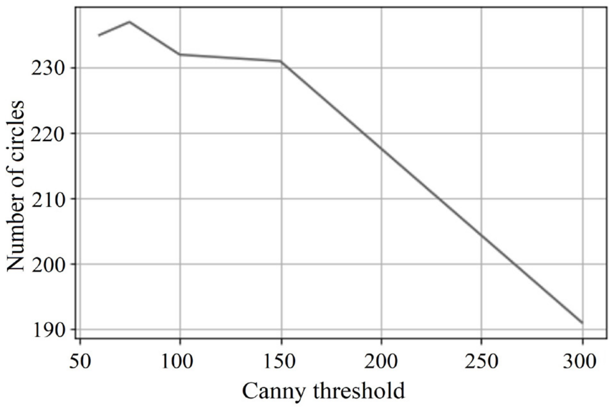
$$F[x,y] := 255 - 2R_0 +$$
$$+\left(R_0/\left(2\sin\left(0{,}5x\pi/128\right)\right) + R_0/\left(2\cos\left(0{,}5y\pi/128\right)\right)\right);$$

$$\forall x,y : (x-x_0)^2 + (y-y_0)^2 < R_0^2;$$
$$Q[x,y] = z_0 + 2\sqrt{R_0^2 - (x-x_0)^2 - (y-y_0)^2}.$$

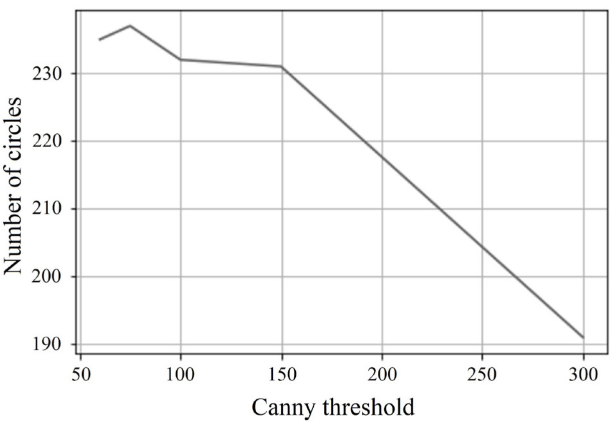
As Figure 1 shows, even the most modern means of dispersion control require some refinement:

neural networks – additional training; the ELSD method – filtering of neighboring results. This gives reason to consider that the development of algorithms for automatic adjustment of the Hough transform parameters may be of great practical importance due to the wide use of this transformation.

The conventional implementation of the Hough transform, presented in the OpenCV library, involves setting five parameters: the center-to-center distance, the minimum $R_{\min}$ and maximum $R_{\max}$ radii of particles, the Canny threshold p_1 and the Hougt accumulator threshold p_2. The value of p_1 determines the sensitivity of the Canny detector (the higher the value of p_1, the lower the sensitivity). The value of p_2 determines the sensitivity of the Hough transform (the lower the value of p_2, the more circles are registered). Studies have shown that the graphs of the dependence of the number N of registered circles on the values of p_1, p_2 have stabilization zones outlined with a dashed line in Figure 2, which was obtained during image processing type 3 Figure 1*a*. These zones correspond to the optimal values of p_1, p_2.



a

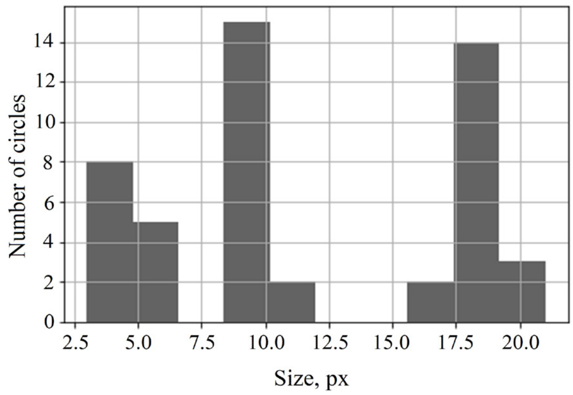


b

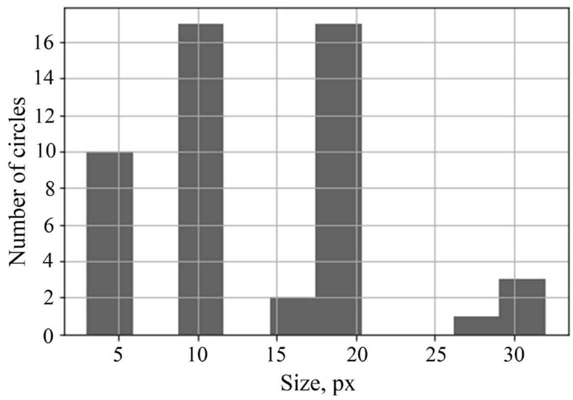
Figure 2 – Examples of graphs of the dependence of the number of detected particles (image type 4 in Figure 1*a*): *a* – from the Canny threshold; *b* – from the Hough threshold

Determining the size range and center-to-center distance

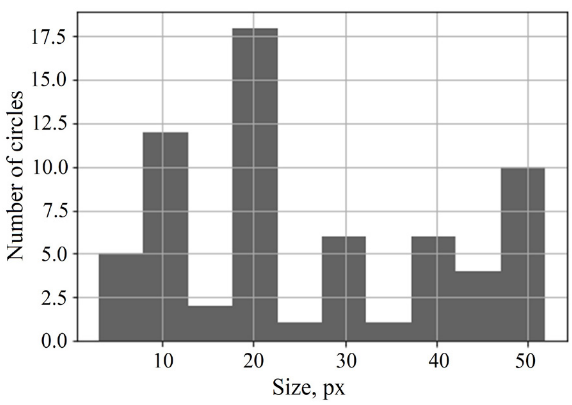
The range of the detected particles sizes (minimum $R_{\min}$ and maximum $R_{\max}$ sizes) significantly affects the results of the dispersion control. Too large a range of sizes in the presence of agglomerates and overlapping particles leads to the registration of pseudo-circles near the maximum values of the range. In this case, you can use the analysis of the histogram of the particle size distribution in pixels of the image (*px*). In particular, when changing the range in the histogram, those peaks (marked with arrows in Figure 3) that correspond to real particles will be stable.



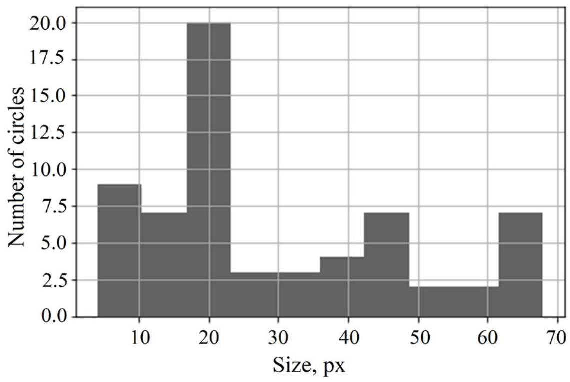
a



b



c



d

Figure 3 – Histograms of particle size distribution for the image type 3: *a* – range 0–20; *b* – range 0–30; *c* – range 0–50; *d* – range 0–70

After specifying the size range of the recorded circles, the minimum center-to-center distance is set at a level that is at least half of the width of the range.

Parameters setting algorithm

Based on the studies described above, the algorithm for setting the parameters of the Hough transform (multi-pass Hough transform) can be formulated as follows.

Step 1. The p_1 value is adjusted. The image is processed with different p_1 values in the range from 1 to 300 in increments (50), with a minimum value of $p_2 = 1$. The stabilization zone is determined automatically based on the minimum change in the number of particles N with a change in p_1 (minimum of the first derivative). If there are several stabilization zones, p_1 is determined according to the minimum extremum of the number of particles (circles).

Step 2. Coarse adjustment of p_2 is carried out. The image is processed with different p_2 values in the range from 1 to 100 in increments (10). The range of the p_2 value is set in accordance with the stabilization zone (zone of minimal change) of the particles number.

Step 3. A histogram of the particle size distribution is formed. The range of particle sizes and the center-to-center distance is determined.

Step 4. Fine-tuning of p_2 is performed within the previously set range. The value of p_2 is increased with a small step (1) to stabilize the number of particles (clusters).

The results of comparing the multi-pass Hough transform with analogous methods are presented in tables 1, 2 (the results are obtained on test images presented in Figure 1*a*). The value of ε_N in Table 1 was defined as the relative deviation of the number of detected particles N from the true value of N_0:

$$\varepsilon_N = |N - N_0| / N_0 .$$

The value of ε_R in Table 2 was defined as the relative deviation of the average measurement value $\overline{R}$ from the true value of the radius $\overline{R}_0$:

$$\varepsilon_R = \left|\overline{R} - \overline{R}_0\right| / \overline{R}_0 .$$

Table 1

Relative error ε_N of determining the number of particles

Particle size determination method	Image (Figure 1*a*)			
	Type 1	Type 2	Type 3	Type 4
ParticlesNN	0.477	0.266	0.120	0.200
ELSD	0.136	0.200	0.060	0.127
Multi-pass Hough transform	0.022	0	0.020	0.018

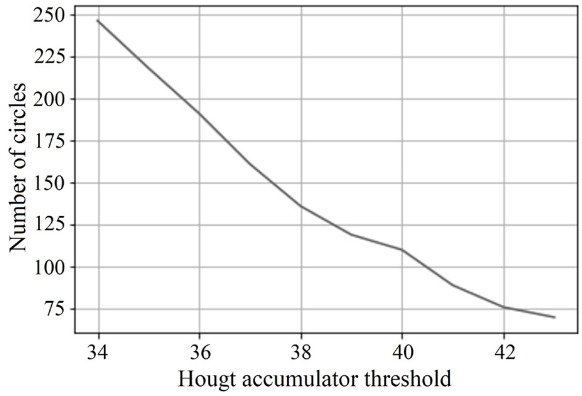
Table 2

Relative error ε_R of the particle radius determination

Particle size determination method	Image (Figure 1*a*)			
	Type 1	Type 2	Type 3	Type 4
ParticlesNN	0.037	0.061	0.526	0.489
ELSD	0.043	0.058	0.036	0.007
Multi-pass Hough transform	0.022	0.037	0.031	0.015

Tables 1, 2 show that the accuracy indicators ε_N, ε_R of the multi-pass Hough transform on the test images are on the same level or exceed these indicators for analog methods.

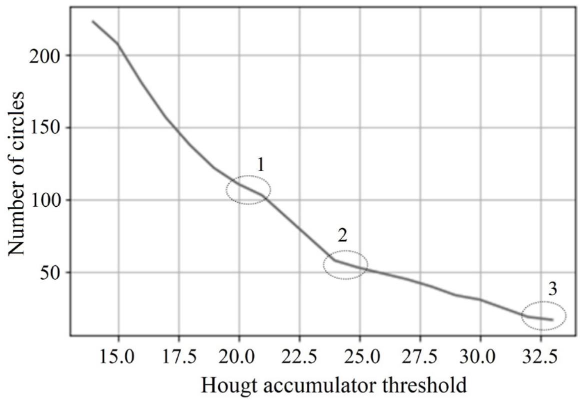
For real images (Figures 4, 5), the stabilization zones available on the dependence graphs $N(p_1)$, $N(p_2)$ may be relatively narrow and not obvious.



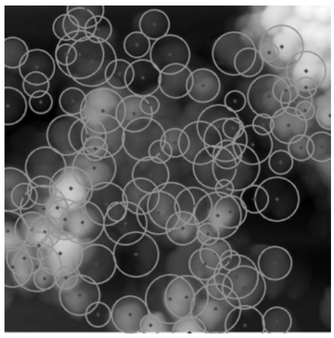
a

b

Figure 4 – Relative stabilization of the number of silver nanoparticles (*a*) and results of particles detection in the image (*b*). Image from the NT-MDT Spectrum Instruments website: https://www.ntmdt-si.com/resources/scan-gallery



a



b

Figure 5 – Zones of relative stabilization of the number of erythritol particles when the parameter $\boldsymbol{p}_2$ is changed (*a*) and results of particle separation in the image (*b*). Image from the NT-MDT Spectrum Instruments website: https://www.ntmdt-si.com/resources/scan-gallery

Therefore, it is advisable to accompany the adjustment of these parameters by monitoring the absolute and relative values of the particles number. In particular, in Figure 4*a*, the relative stabilization zone is located in the range p_2 = 38–40 and is characterized by a minimal change in the particles number. At the same time, an estimation of the target range of the absolute value of the particles number can be obtained using the minimum $R_{\min}$ and maximum $R_{\max}$ values from the histogram, as well as the image sizes $S{\times}S$ in pixels:

$$N_{\min} = \left(S/R_{\min}\right)^2; \; N_{\max} = \left(S/R_{\max}\right)^2.$$

Figure 5*a* shows three stabilization zones, from which the first zone was automatically selected, focusing on the minimum deviation from the permissible number of particles $N_{\min}$ = 164. The corresponding result is shown in Figure 5*b*.

Conclusion

The performed studies allowed to obtain the following results. When changing the threshold parameters of the Hough transform, zones of detected particles number stabilization are observed, which determine the optimal values of the transformation parameters. At the same time, the histograms of the particle size distribution show distinct peaks corresponding to the marginal sizes of the detected particles and determining the range and minimum center-to-center distance of the Hough transform. Based on the results obtained, an algorithm has been developed for automatically adjusting the parameters of the Hough transform.

References

1. ISO 13322-1:2014. Particle size analysis – Image analysis methods. Part 1: Static image analysis methods. 2nd ed.; Publisher: International Organization for standardization, Switzerland, 2014.

2. Chaki N, Shaikh SH, Saeed K. A Comprehensive Survey on Image Binarization Techniques. Exploring Image Binarization Techniques. Studies in Computational Intelligence. Springer, New Delhi. 2014;560:5-15.
DOI: 10.1007/978-81-322-1907-1_2

3. Sezgin BS. A survey over image thresholding techniques and quantitative performance evaluation. Journal of Electronic Imaging. 2004;13(1):146-165.
DOI: 10.1117/1.1631315

4. Ramadevi Y, Sridevi T, Poornima B, Kalyani B. Segmentation and Object Recognition Using Edge Detection Techniques. International Journal of Computer Science and Information Technology. 2010;2:153-161.
DOI: 10.5121/IJCSIT.2010.2614

5. Navon E, Miller O, Averbuch A. Color image segmentation based on adaptive local thresholds. *I*mage and Vision Computing. 2005;23(1):69-85.
DOI: 10.1016/j.imavis.2004.05.011

6. Bui K, Fauman J, Kes D, et. al. Segmentation of scanning tunneling microscopy images using variational methods and empirical wavelets. Pattern Analysis and Applications. 2020;23:625-651.
DOI: 10.1007/s10044-019-00824-0

7. Ronneberger O, Fischer Ph, Brox T. U-Net: Convolutional networks for biomedical image segmentation. Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. Lecture Notes in Computer Science. Springer, Cham. 2015;9351:234-241.
DOI: 10.1007/978-3-319-24574-4_28

8. Pătrăucean V, Gurdjos P, von Gioi RG. A Parameterless Line Segment and Elliptical Arc Detector with Enhanced Ellipse Fitting. Computer Vision – ECCV 2012. Lecture Notes in Computer Science, Springer, Berlin. 2012:7573:572-585.
DOI: 10.1007/978-3-642-33709-3_41

9. Gulyaev PV. Measurement of the length of objects on scanning probe microscope images using curvature detectors. Measurement Techniques. 2021;64(1):21-27.
DOI: 10.1007/s11018-021-01890-9

10. Gulyaev PV, Shelkovnikov EYu, Tyurikov AV. Peculiarities of surface curvature detectors usage for nanoparticles size analysis. Chemical Physics and Mesoscopy. 2013;15(1):138-143. (In Russ.).

11. MountainsSPIP. [Electronic Resource]. Available at: https://www.digitalsurf.com/software-solutions/scanning-probe-microscopy/ [Accessed 07.05.2023].

12. OpenCV. [Electronic Resource]. Available at: https://opencv.org/ [Accessed 07.05.2023].

13. Zhelebovskiy AA, Sumin AA, Dmitrichenkov NV. Application of the Hough algorithm for sorting polydisperse microparticles. Proceedings of XVI International Scientific and Technical Conference, June 28–July 02, 2021. Moscow: Publishing House "Pero". 2021;80-85: 260 p.

14. Lebedev SA, Ososkov GA. Fast algorithms for ring recognition and electron identification in the CBM RICH detector. Physics of particles and nuclei letters. 2009;6(2):161-176.
DOI: 10.1134/S1547477109020095

15. Atherton TJ, Kerbyson DJ. Size invariant circle detection. Image and Vision Computing. 1999;17(11): 795-803. **DOI:** 10.1016/S0262-8856(98)00160-7

16. Okunev AG, Mashukov MY, Nartova AV, Matveev AV. Nanoparticle Recognition on Scanning Probe Microscopy Images Using Computer Vision and Deep Learning. Nanomaterials. 2020;10(7)(1285).
DOI: 10.3390/nano10071285