Applied Computer Science, vol. 18, no. 2, pp. 28–42
doi: 10.35784/acs-2022-11

Submitted: 2022-04-08 | Revised: 2022-05-16 | Accepted: 2022-06-08

Keywords: image enhancement, SEM images, statistical approaches, contrast enhancement

Zaid ALSAYGH[*], *Zohair AL-AMEEN* [0000-0003-3630-2134]*

CONTRAST ENHANCEMENT OF SCANNING ELECTRON MICROSCOPY IMAGES USING A NONCOMPLEX MULTIPHASE ALGORITHM

Abstract

Microscopic technology has recently flourished, allowing unparalleled viewing of microscopic elements invisible to the normal eye. Still, the existence of unavoidable constraints led on many occasions to have low contrast scanning electron microscopic (SEM) images. Thus, a noncomplex multiphase (NM) algorithm is proposed in this study to provide better contrast for various SEM images. The developed algorithm contains the following stages: first, the intensities of the degraded image are modified using a two-step regularization procedure. Next, a gamma-corrected cumulative distribution function of the logarithmic uniform distribution approach is applied for contrast enhancement. Finally, an automated histogram expansion technique is used to redistribute the pixels of the image properly. The NM algorithm is applied to natural-contrast distorted SEM images, as well as its results are compared with six algorithms with different processing notions. To assess the quality of images, three modern metrics are utilized, in that each metric measures the quality based on unique aspects. Extensive appraisals revealed the adequate processing abilities of the NM algorithm, as it can process many images suitably and its performances outperformed many available contrast enhancement algorithms in different aspects.

1. INTRODUCTION

Microscopic technology has lately flourished, allowing to view of different microscopic elements that are invisible to the normal eye (Cocks, Taggart, Rind & White, 2018). Electron microscopes are deemed the most powerful and versatile tools for depicting the microstructures of various materials (Al-Ameen, 2018a). The capacity of a microscope to view small details has dramatically increased in recent years. The scanning electron microscope (SEM) can achieve resolutions of less than 0.4 nm (Vladár, Postek & Ming, 2009). In integrated circuits, biological cells, and other important applications, SEM is becoming increasingly demanded as vital information is frequently extracted from Such images (Feng, Ye & Pease, 2006). The SEM uses high energy with a concentrated beam of electrons to generate a variety of pulses that are used to display the examined object in the form of a digital image (Sutton et al., 2007).

[*] Department of Computer Science, College of Computer Science and Mathematics, University of Mosul, Nineveh, Iraq, zaidalobaidy1988@gmail.com, qizohair@uomosul.edu.iq

Normal humans can observe two items that are 0.2 mm at a distance without the need for magnifying lenses. Modern SEM devices, on the other hand, may achieve a resolution of 1 nm. The SEM on the other hand may enlarge objects to 300,000 times, which is much more than the standard simple microscope that can only enlarge objects to 1,500 times (Wighting, Lucking & Christmann, 2004). The SEM devices produce grayscale images that can be colorized using specific processes to make such images look more practical. Although the SEM devices have thrived, the produced images from such a device are still owning degradations, and one of the most common occurring degradations in SEM is the low-contrast effect (Ohta et al., 2012; Beekman et al., 2019; Sim, Ting, Leong & Tso, 2019; Bennet, Burr, Schmid & Hodoroaba, 2021).

The difference between the lightest and dimmest image regions is what defines the contrast, in that a high difference leads to better contrast and a low difference leads to poor contrast. As a result, the details of an image with high contrast are preserved better than the details in an image with poor contrast (Chen et al., 2018). The low contrast is an unfavorable artifact that decreases the visibility of the details and makes it difficult to extract useful information. Therefore, such an effect must be processed efficiently to produce an output image that owns better visibility and has no processing artifacts (Cakir, Kahraman, Cetin-Atalay & Cetin, 2018). Contrast enhancement (CE) is an approach that is used to improve the distribution of pixels in the image dynamic range. The fundamental goal of CE is to create an output image that is more lucid than its original version and does not include any processing artifacts (Pei, Zeng & Chang, 2004).

Various CE approaches have been presented in the past and among those approaches, the histogram equalization (HE)-based methods have been of high popularity (Hashemi, Kiani, Noroozi & Moghaddam, 2010). For SEM, various CE approaches have been introduced in the past years, and such approaches vary in their ideas. Thus, different approaches are reviewed in Section 2 of this article. Hence, a noncomplex multiphase algorithm is developed for the CE of SEM. Accordingly, it owns two key phases: Firstly, a two-step processing approach is implemented for intensity adjustment. Secondly, a gamma-corrected cumulative distribution function of the log-uniform distribution (GCCDFLUD) method is implemented to further enhance the image. Finally, an automated histogram expansion method is utilized to reallocate the pixels to the full image interval.

The assessment of the proposed algorithm is done by applying it to different real contrast distorted SEM images. Furthermore, it is appraised against different approaches and the accurateness of the outputs is considered along with the processing speed. From the results, the proposed algorithm provided satisfactory performance as it performed the best in many aspects. Finally, the organization of this study goes as follows: Section 2 contains a review of the germane methods; Section 3 includes a full description of the developed algorithm; Section 4 describes the experimentations, comparisons, and results, along with their discussions; Section 5 includes the important conclusions.

2. RELATED WORK

This part reviews different studies related to improving the contrast of SEM images to deliver a clear grasp of the formerly utilized methodologies in this field. The main aim is to highlight the previously used concepts and determine their advantages and disadvantages so that when developing the proposed algorithm, a wide knowledge of processing concepts would be known so that the development process becomes easier. Moreover, the advantages and disadvantages are considered, in that the advantages are properly exploited, and the disadvantages are carefully avoided. In (Sengee, Sengee & Choi, 2010), a two-phase approach was proposed, in which the large histogram bins that cause the washout artifacts are divided into sub-bins using a neighborhood-based process, in which the adjacent information is arranged accordingly. In the second phase, the processed histogram is separated into two smaller histograms depending on the histogram average value and these two histograms are equalized independently using a refined HE procedure. In (Ma & Han, 2014), a fusion-based algorithm was introduced, which begins by implementing a gradient transform to attain the edge information. Next, the Laplace of Gaussian (LoG) and the median filters are applied to the input image to get the filtered high-frequency information. After that, the image low-frequency components are processed by the contrast limited adaptive histogram equalization (CLAHE) technique. The outputs of the aforesaid three steps are fused to get the output image.

In addition, a hybrid technique was presented by (Lal & Chandra, 2014), in that it starts by applying a modified sigmoid function to modify the image intensities. Then, the outcome is further processed by the CLAHE technique to get the output image. Moreover, a spatial entropy-based algorithm is introduced by (Celik, 2014), in that it computes the spatial entropy of pixels by using the spatial distribution feature of image pixels. Next, entropy is used along with specific statistical measures to redistribute the image intensities and obtain the output. Likewise, a histogram sub-blocking-based algorithm is developed by (Sim, Teh, Tey & Kho, 2016), which starts by normalizing the input image to get its correct confined information. Then, the normalized image is broken into different sub-blocks and each sub-block is enhanced using a generalized HE technique. Using the output, the mid-nodes are computed and then a piecewise equalization approach is applied. Finally, a convolution procedure is implemented to mix the processed sub-blocks and get the output of the algorithm.

Furthermore, a quad HE-based approach is presented by (Shukri, Sim & Leong, 2016), in that it separates the input into two sub-histograms, in that they are separated again into quad-histograms. Then, the four histograms are considered and normalized using a specific probability density function. Finally, a remapping and equalization procedure is implemented depending on a distinct cumulative distribution function to get the output image. Moreover, an improved contrast equalization method was introduced by (Al-Ameen, 2018a), in that it includes two key stages. The first phase includes two-step image intensity rescale procedures that are used to modify the image intensities. The second phase includes two-step processing and remapping procedures that are used to adjust the contrast and remap the intensities to the full range.

In addition, a CLAHE-sigmoid-based algorithm was presented by (Arya, Sharma & Arya, 2019), in that it begins by implementing a modified sigmoid function on the input. Then, a CLAHE approach is implemented depending on the output of the previous step. The output is finally processed by the modified sigmoid function again to get the output image. Lastly, a multi-scale top-hat-based algorithm was proposed by (Mello-Román et al., 2021), in that it initially extracts different bright and dark features of the input image by utilizing the top-hat procedure. Next, the dark and bright scale variations are determined using a specified method. After that, a separate summation of the dark and bright scale variations is obtained.

The last step includes the adjustment of the bright and dark elements, in that the adjusted bright elements are added to the image and the adjusted dark elements are subtracted from the image to get the output.

From the studied methods, different ideas were utilized in the past to process the contrast and obtain satisfactory results. Table 1 describes the examined research articles in chronological sequence, including the authors, years, methodology, difficulty, benefits, and drawbacks. As noticed, the histogram-based methods are the most used. The standard version of histogram equalization is known to deliver an unnatural appearance with brightness amplification. The improved versions of histogram equalization may also have these artifacts but with less effect. Moreover, they may also involve excessive computations to provide the output. As for the statistical-based approaches, they utilize mediocre-intricacy computations making them somewhat rapid in processing the given images. However, insufficient enhancement abilities and the presence of artifacts may be introduced. Moreover, not all the reviewed methods were successful in delivering acceptable quality results as the contrast may be insufficient, brightness amplification may happen, and some artifacts may appear more distinctly. This is deemed undesirable as efficient processing without generating visual flaws is needed. Furthermore, the SEM images are obtained with high resolution and rapid processing is also needed for such images. Hence, providing a plain-structure algorithm that can produce acceptable results with no flaws is highly needed.

Tab. 1. A synopsis of the literature review.

No.	Author & Year	Concept	Intricacy	Pros	Cons
1.	(Sengee et al., 2010)	Bi-histogram equalization	Moderate	Preserve the brightness	Some results own a hazy look
2.	(Ma & Han, 2014)	A mix of statistical, morphological, and image processing operations	High	Increase the contrast and acutance	Unnatural contrast
3.	(Lal & Chandra, 2014)	Sigmoid function with adaptive histogram equalization	High	Good performance in the dark image regions	Many computations
4.	(Celik, 2014)	Spatial entropy	Low	Non-complex method	Does not provide enough enhancement
5.	(Sim et al., 2016)	Sub-blocking multiple peak histogram equalization	Moderate	Makes the dark regions more visible	Brightness amplification
6.	(Shukri et al., 2016)	Minimum Mean Brightness error Bi-histogram equalization	Low	Provides a noticeable CE	Provides unnatural look
7.	(Al-Ameen, 2018a)	Contrast equalization	Low	Non-complex method	Needs further improvements
8.	(Arya et al., 2019)	Modified sigmoid function with limited histogram equalization	High	Good CE	Many computations
9.	(Mello-Román et al., 2021)	Multiscale top-hat transform	High	Balanced CE	Complex method

3. PROPOSED ALGORITHM

This algorithm is created based on the notion that few computations are required to generate satisfactory results, in that it should produce the filter images rapidly with no processing artifacts. This algorithm employs a mix of statistical and image filtering methods in its processing concept. Its concept is as follows: First, a two-stage adjustment procedure is implemented to modify the intensities. Then, a gamma-corrected cumulative distribution function of the log-uniform distribution (GCCDFLUD) approach is implemented to further enhance the image. Finally, an automated histogram expansion approach is used to redistribute the pixels to the full image interval. To better represent the proposed algorithm, the diagram given in Figure 1 explains the steps concisely.

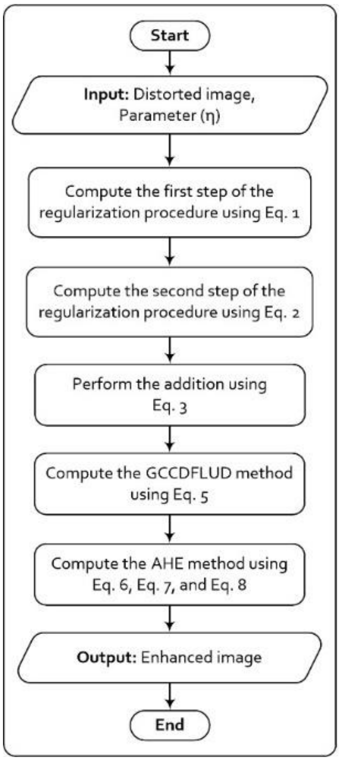

Fig. 1. Diagram of the proposed algorithm.

Explaining the proposed noncomplex multiphase (NM) algorithm in detail, the two-stage adjustment procedure is initially used to modify the poor intensities in the image in a non-linear way, better rescale such intensities, and restrain the extreme values. The two-step regularization procedure can be computed using these equations (Al-Ameen, 2018a):

$$W_{(i,j)} = \frac{O_{(i,j)}}{\left(\text{mean}\left(\left|O_{(i',j')}\right|^{\eta}\right)\right)^{1/\eta}} \tag{1}$$

$$M_{(i,j)} = \frac{W_{(i,j)}}{\left(\text{mean}\left(\min\left(\eta, \left|W_{(i',j')}\right|\right)^{\eta}\right)\right)^{1/\eta}} \tag{2}$$

where i and j are image coordinates, $W_{(i,j)}$ is the output of the first step, $O_{(i,j)}$ is a given input image, $O_{(i',j')}$ is the transpose of $O_{(i,j)}$, $M_{(i,j)}$ is the output of the first step, $W_{(i',j')}$ is the transpose of $W_{(i,j)}$, *mean* is the average, *min* is the lowest value, η is an enhancement parameter, in that it should be ($\eta > 0$), as a higher value leads to more enhancement. Next, the values of $M_{(i,j)}$ are increased by a small value τ to avoid getting the values of zero, in that the log is computed for the image in an upcoming step, and adding the value of τ helps to avoid computing the log of zero which is infinity. Here, $\tau = 0.1$, and the addition is done using the following equation:

$$T_{(i,j)} = M_{(i,j)} + \tau \tag{3}$$

Next, a gamma-corrected cumulative distribution function of the log-uniform distribution method is applied to further modify the image intensities and control the enhancement process as well. The log-uniform distribution is a statistical approach that is used to distribute values in a curvy non-linear way (Hamming, 1970). In image processing, it is proven that curvy transforms can be used to process the intensity of an image (El Malali et al., 2020). Thus, it is used and modified in this study to process the images as a vital stage. The original cumulative distribution function of the log-uniform distribution can be computed as follows (Hamming, 1970):

$$L_{(i,j)} = \frac{\log\left(T_{(i,j)}\right) - \log(y)}{\log(z) - \log(y)} \tag{4}$$

where, y is the lowest value in $T_{(i,j)}$, while z is the highest value in $T_{(i,j)}$. the above equation is further modified to control the amount of enhancement. The modified version of the above equation can be computed as follows:

$$Q_{(i,j)} = \left(\frac{\log\left(T_{(i,j)}\right) - \log(y)}{\log(z) - \log(y)}\right)^{\eta} \tag{5}$$

where, $Q_{(i,j)}$ is the output of the GCCDFLUD method. At this point, the image intensities are redistributed in a curvy way and are not distributed to the full range. Hence, an automated histogram expansion (AHE) method is implemented to well-distribute the pixels to the full image range. The AHE method can be computed as follows (Al-Ameen, 2020):

$$E_{(i,j)} = \kappa \cdot Q_{(i,j)} - \omega \tag{6}$$

$$\kappa = \frac{1}{\max\left(Q_{(i,j)}\right) - \min\left(Q_{(i,j)}\right)} \tag{7}$$

$$\omega = \frac{\min\left(Q_{(i,j)}\right)}{\max\left(Q_{(i,j)}\right) - \min\left(Q_{(i,j)}\right)} \tag{8}$$

where κ and ω are the extension parameters, $E_{(i,j)}$ is the final output of the proposed algorithm, and *max* represents the highest value.

4. RESULTS AND DISCUSSION

In this segment, the outcomes of comparisons, experiments, and related remarks are presented to analyze and demonstrate the true processing capabilities of the developed NM algorithm with a dataset of various real low-contrast SEM images. The dataset of this study was collected from different internet websites, in that the images are made available freely online. From these websites, almost 200 images were collected, in that these images are grayscale, and their sizes vary where the smallest has the size of 500×500 and the largest have the size of 3000×3000. The first website is http://www.dartmouth.edu, which includes different raw SEM images which are available freely online. The second website is https://www.ualberta.ca, which also includes different high-resolution SEM images. The third source of SEM images is from the consistence website, which can be accessed at https://www.consistence.nl/gallery/.

From this website, different unprocessed images were collected that own different sizes and are beneficial for this study. The fourth and final source of images is particle technology, which can be accessed at https://www.particletechlabs.com. The collected images are sorted, numbered, and in some cases cropped to be properly utilized. To truly measure the filtering abilities of the NM algorithm, a comparison is made with different algorithms namely, recursive mean-separate histogram equalization (RMSHE) (Chen & Ramli, 2003), dynamic histogram equalization (DHE) (Abdullah-Al-Wadud et al., 2007), adaptively increasing the value of histogram equalization (AIVHE) (Lu, Hsu & Wang, 2009), fuzzy-contextual contrast enhancement (FCCE) (Parihar, Verma & Khanna, 2017), swift algorithm (SWIFT) (Al-Ameen, 2018b), and improved contrast equalization (ICE) (Al-Ameen, 2018a). The comparison outcomes are evaluated using three no-reference quality evaluation methods, in that each metric detects the quality of the assessed images using special traits.

The used metrics are visual contrast measure (VCM) (Jang et al., 2011), blind pseudo-reference image (BPRI) (Min et al., 2017), and blind reference-less image spatial quality evaluator (BRISQUE) (Mittal, Moorthy & Bovik, 2012). The VCM is a metric that utilizes local statistical methods to measure the visual contrast in an image. The smaller output of VCM indicates better visual contrast. Moreover, the BPRI is a metric that utilizes a pseudo-reference approach with the image structural information to determine the naturalness. The smaller output of BPRI indicates better naturalness. In addition, the BRISQUE metrics utilize a set of statistical measures to measure the quality of the apparent luminance and contrast. The smaller output of BRISQUE indicates better visual luminance and contrast. The computer used in this study has the specifications of an intel core I3-2328M 2.20 GHz processor and 4 GB of memory. MATLAB 2018a is the programming environment that is used for developing the algorithm, running the comparison algorithms, and the image evaluation methods. Figures 2 to 4 demonstrate different empirical results of the proposed algorithm. Figures 5 to 8 illustrate the comparison outcomes. Tables 2 to 5 represent the recorded image evaluation scores and runtimes. Figures 9 to 12 depict the average performances of Tables 2 to 5 as graphical charts. From Figure 2 to Figure 4, it is noticed that the outcomes of the NM algorithm are of acceptable visual quality, as they own improved contrast, preserved brightness, and no obvious processing errors, and they appear more credible to the viewer. Accordingly, when comparing the unprocessed image with its processed version, it seems as if a coat of mist has been diminished.

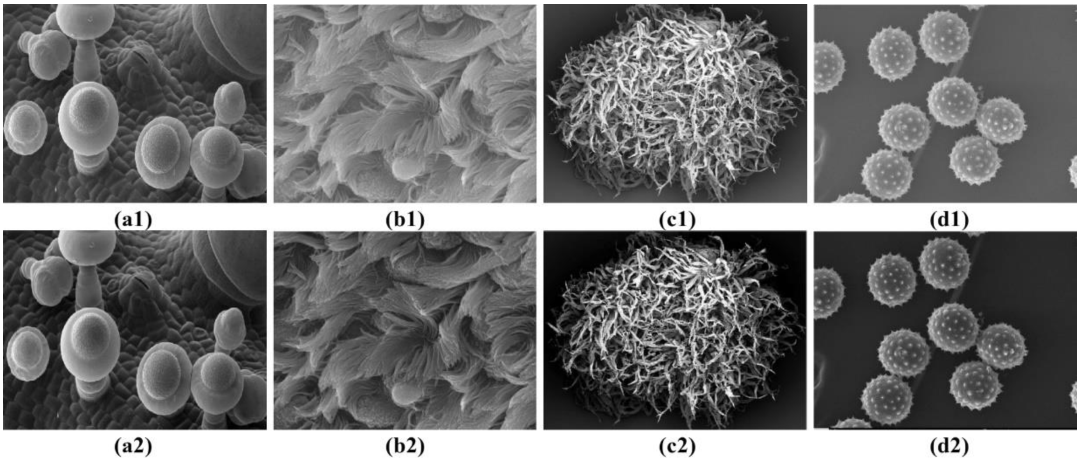

Fig. 2. The outcomes of the developed NM algorithm – (a1–d1) real contrast-distorted images, (a2–d2) results of the NM algorithm with η = 3.9, 4.9, 5, and 5.3, respectively

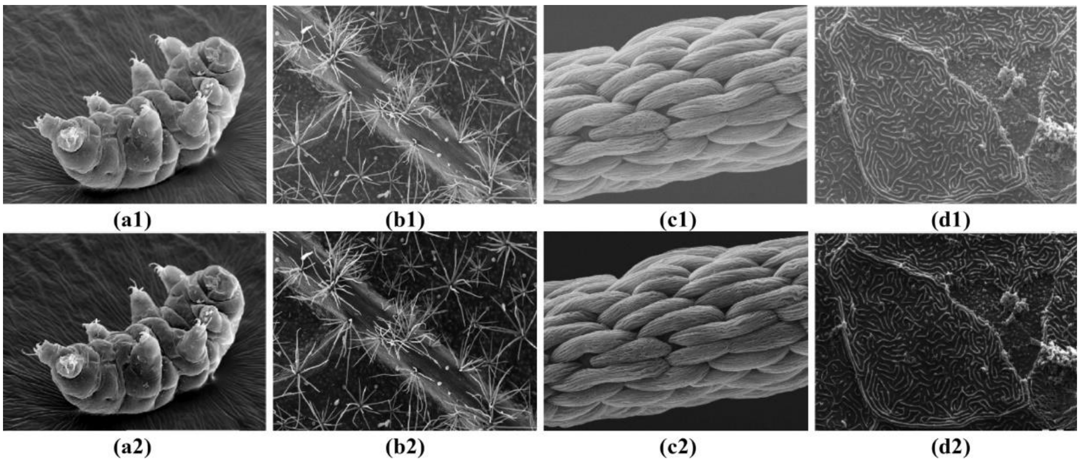

Fig. 3. The outcomes of the developed NM algorithm – (a1–d1) real contrast-distorted images, (a2–d2) results of the NM algorithm with η = 4.5, 5.2, 5.3, and 6.5, respectively

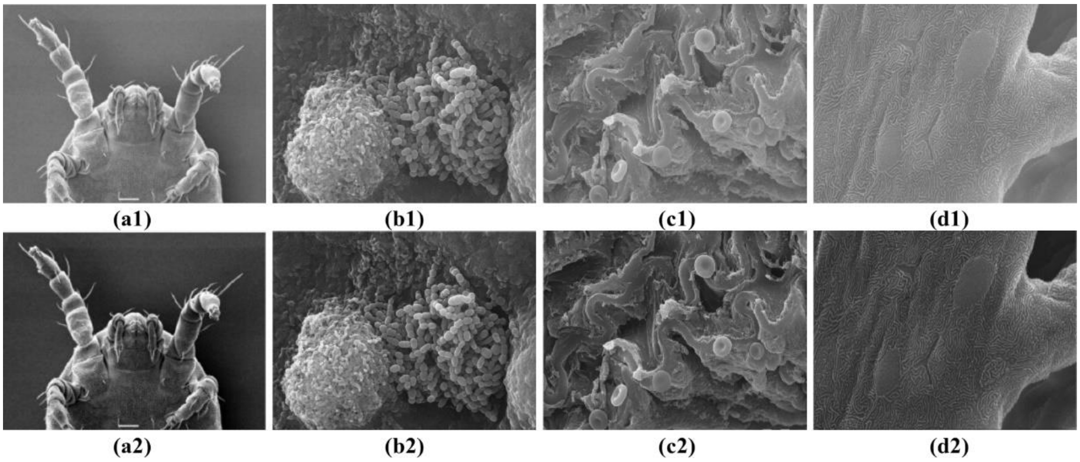

Fig. 4. The outcomes of the developed NM algorithm – (a1–d1) real contrast-distorted images, (a2–d2) results of the NM algorithm with η = 2.4, 3.9, 4.9, and 5.9, respectively

The details stood out better and the images became visually pleasing. Likewise, the NM algorithm showed promising performances as it was successful in processing many images obtained from different sources. The NM algorithm depends on the value of η, in that if it is properly chosen by the operator, the quality of the output would be desirable. From Figure 5 to Figure 12 and Table 2 to Table 5, it is spotted that dissimilar outcomes are obtained, as different algorithms in concept were implemented with numerous SEM images. The FCCE algorithm provided good contrast but amplified the brightness in different regions and darkened other regions making the image appear with an unusual look. That's why it scored low in all three metrics and was the slowest method. In addition, the SWIFT algorithm delivered a balanced performance concerning brightness and contrast, as the contrast is adjusted, and the brightness is slightly increased. Yet, it did not reach the scores of the proposed NM as it scored high in all three metrics with a slight difference from the NM algorithm. Yet, it ranked the 6th fastest method.

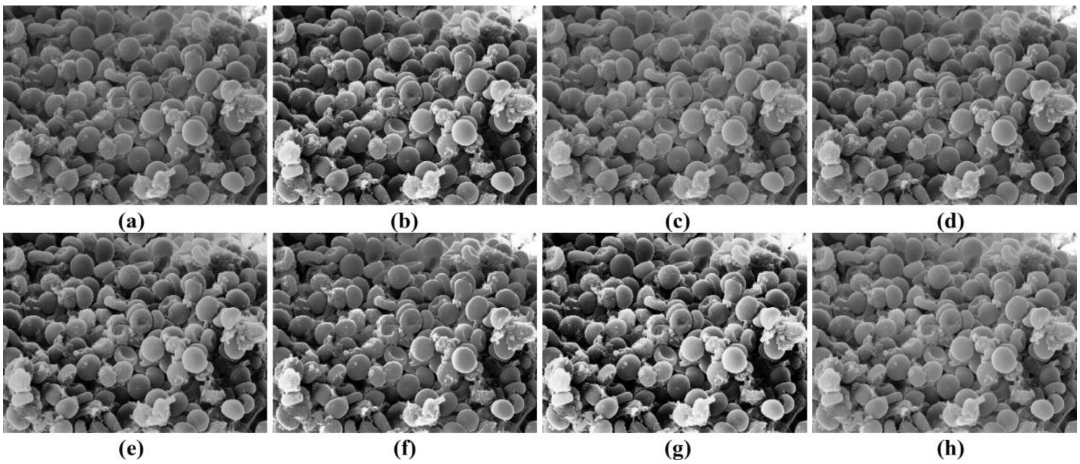

Fig. 5. The comparison outcomes (Batch -1-) – (a) real contrast-distorted SEM image, images (b–h) are processed by: (b) FCCE, (c) SWIFT, (d) ICE, (e) AIVHE, (f) RMSHE, (g) DHE, and (h) proposed NM

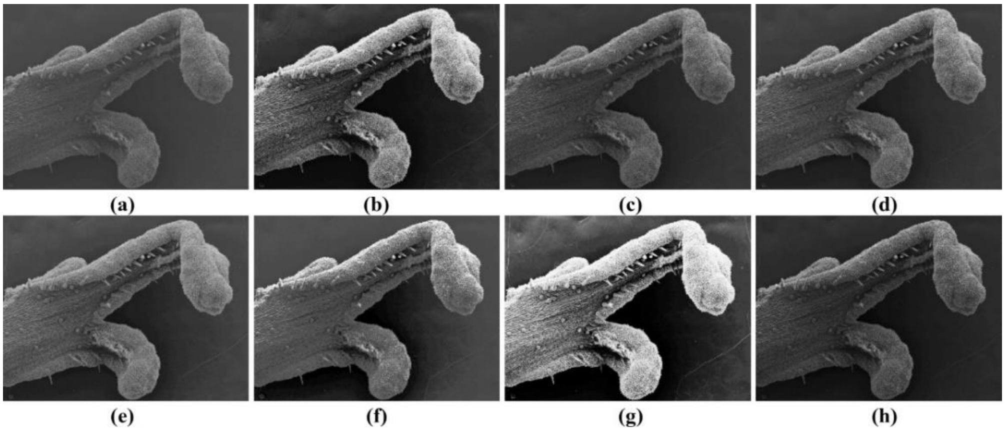

Fig. 6. The comparison outcomes (Batch -2-) – (a) real contrast-distorted SEM image, images (b–h) are processed by: (b) FCCE, (c) SWIFT, (d) ICE, (e) AIVHE, (f) RMSHE, (g) DHE, and (h) proposed NM

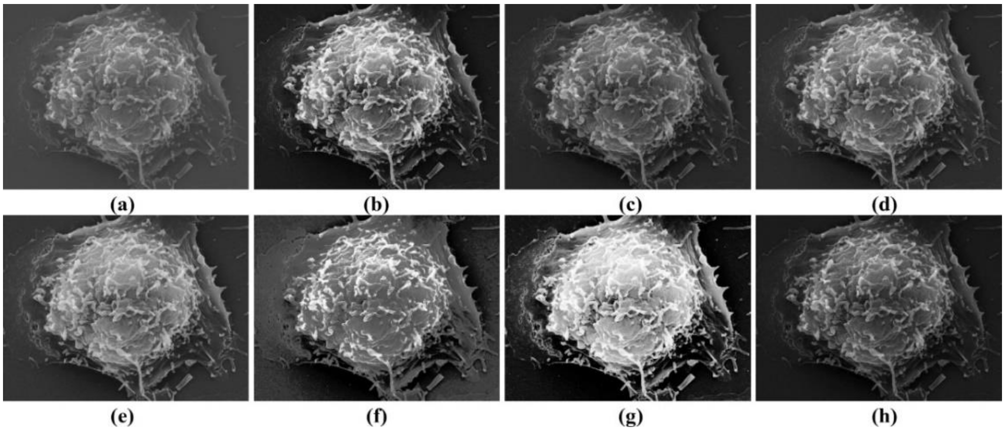

Fig. 7. The comparison outcomes (Batch -3-) – (a) real contrast-distorted SEM image, images (b–h) are processed by: (b) FCCE, (c) SWIFT, (d) ICE, (e) AIVHE, (f) RMSHE, (g) DHE, and (h) proposed NM

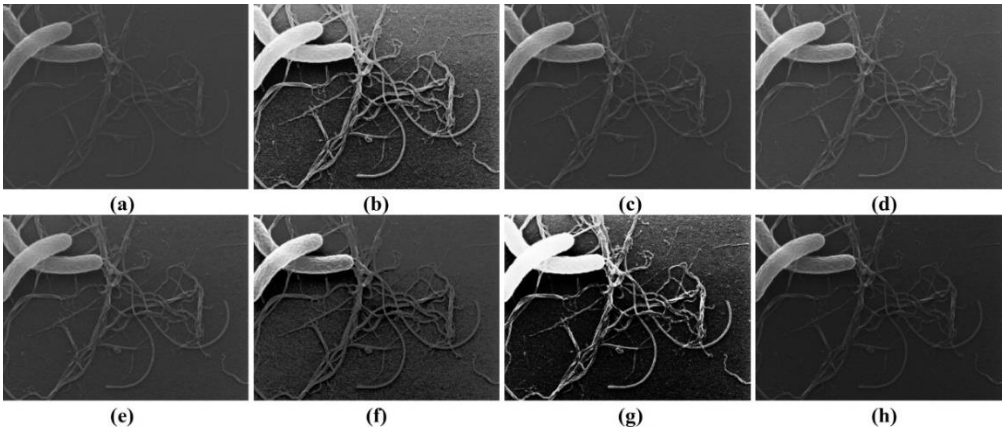

Fig. 8. The comparison outcomes (Batch -4-) – (a) real contrast-distorted SEM image, images (b–h) are processed by: (b) FCCE, (c) SWIFT, (d) ICE, (e) AIVHE, (f) RMSHE, (g) DHE, and (h) proposed NM

Moreover, the ICE algorithm delivered a reasonable performance as well but with marginally greater brightness than SWIFT with a regulated contrast, as it scored above moderate in all three metrics and was ranked the 3rd fastest method. Furthermore, the AIVHE algorithm delivered a somewhat sensible performance, with more need for contrast enhancement and brightness adjustment. Therefore, it scored moderately in all three metrics and was ranked the 5th fastest method.

Tab. 2. The recorded accuracies and their averages by the BPRI metric

Methods	Fig. 5	Fig. 6	Fig. 7	Fig. 8	Average
FCCE	0.0133	0.0164	0.0109	0.0364	0.01925
SWIFT	0.0096	-1.05E-04	0.0101	0.019	0.009649
ICE	0.0115	0.003	0.0117	0.0228	0.01225
AIVHE	0.0092	0.0099	0.0116	0.0251	0.01395
RMSHE	0.0083	0.0174	0.0108	0.0278	0.016075
DHE	0.009	0.0272	0.0141	0.0347	0.02125
Proposed NM	0.0123	-0.0049	0.0071	0.0179	**0.0081**

Tab. 3. The recorded accuracies and their averages by the BRISQUE metric

Methods	Fig. 5	Fig. 6	Fig. 7	Fig. 8	Average
FCCE	0.3385	40.1115	15.2681	41.2206	24.234675
SWIFT	-0.5849	28.5376	10.0693	36.4228	18.6112
ICE	0.4441	29.9195	10.3777	36.6058	19.336775
AIVHE	1.2809	33.1953	15.4099	40.0946	22.495175
RMSHE	0.2925	35.1319	25.4102	37.0675	24.475525
DHE	2.4419	47.1025	20.8524	45.413	28.95245
Proposed NM	-0.033	29.4091	8.9988	35.9838	**18.589675**

Tab. 4. The recorded accuracies and their averages by the VCM metric

Methods	Fig. 5	Fig. 6	Fig. 7	Fig. 8	Average
FCCE	1944.6	1.97E+03	1.44E+03	1.61E+03	1741.825
SWIFT	1.23E+03	807.3552	762.6877	338.4481	784.79775
ICE	1.25E+03	1.02E+03	968.6738	483.8228	931.37415
AIVHE	1.50E+03	1.11E+03	1.08E+03	436.2752	1032.1438
RMSHE	1.83E+03	1.44E+03	1.44E+03	721.4281	1357.107025
DHE	2.33E+03	3.02E+03	1.90E+03	1.52E+03	2190.00
Proposed NM	1346.3	787.9635	732.6598	255.0645	**780.49695**

Tab. 5. The application times and their averages (in seconds) for the comparison algorithms

Methods	Fig. 5	Fig. 6	Fig. 7	Fig. 8	Average
FCCE	0.789711	0.700735	0.604065	0.541752	0.65906575
SWIFT	0.197413	0.505441	0.344469	0.21442	0.31543575
ICE	0.100958	0.12412	0.106676	0.110124	0.1104695
AIVHE	0.101407	0.084859	0.32177	0.078892	0.146732
RMSHE	0.097669	0.094901	0.117599	0.087891	0.099515
DHE	0.102309	0.158808	0.12121	0.111865	0.123548
Proposed NM	0.097171	0.082195	0.087944	0.076719	**0.086005**

What is more, the RMSHE algorithm delivered an undesirable performance as it introduced brightness amplification and unusual contrast to the filtered images. The brightness in some areas appears massively amplified and the contrast looks unnatural with some processing artifacts. That is why it scored below moderate in all three metrics but was the 2nd fastest method. As for the DHE algorithm, it massively increased the brightness and delivered uncommon contrast. The overall look of the image is ruined, and many details were lost due to brightness amplification and the extreme darkening that happens in some areas. Therefore, it scored the lowest in all three metrics and was ranked the 4th fastest method. As for the proposed NM algorithm, it showed a clear superiority in performance over the comparison algorithms as its outcomes own balanced contrast, preserved brightness, and an overall acceptable appearance, in addition to being the fastest in runtimes. This is a noteworthy achievement as its structure is simple, yet it was able to perform better than many existing algorithms. Despite the above-mentioned primary advantages, it has one disadvantage being parameter η must be determined manually. In future work, a suitable optimization method can be utilized to automatically assess the value of η.

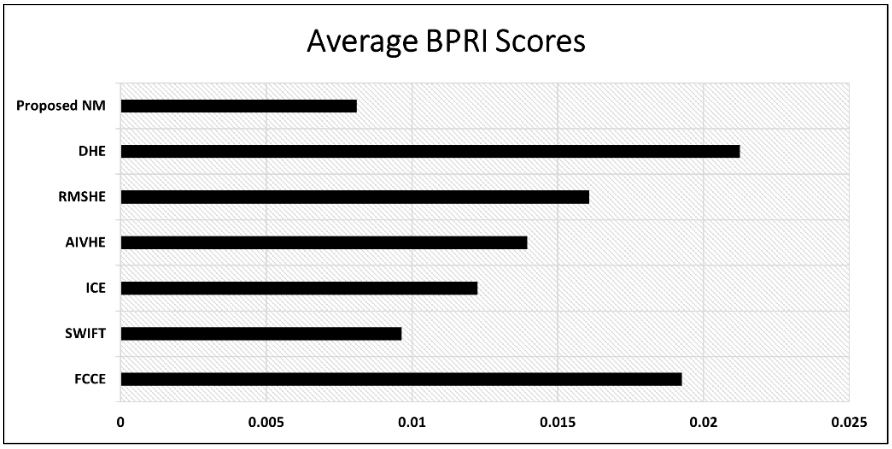

Fig. 9. The average BPRI scores

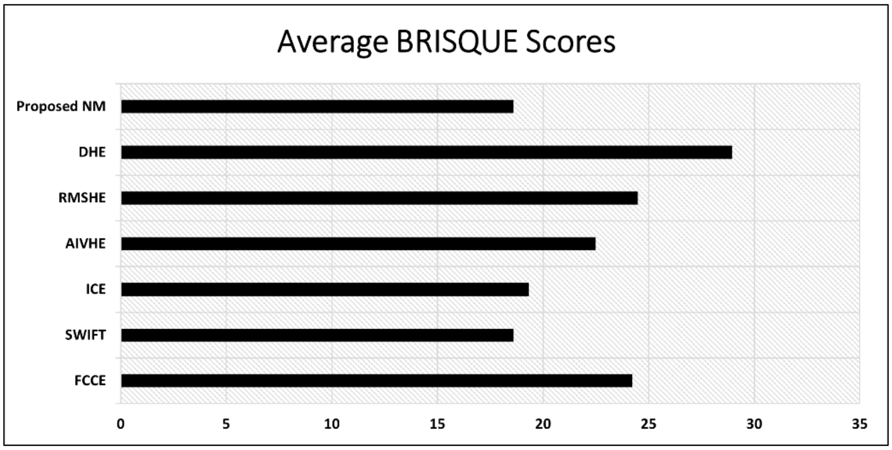

Fig. 10. The average BRISQUE scores

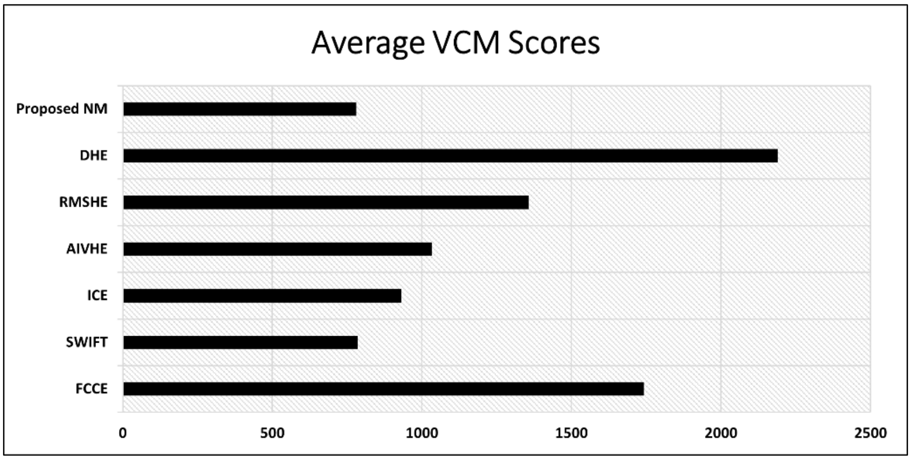

Fig. 11. The average VCM scores

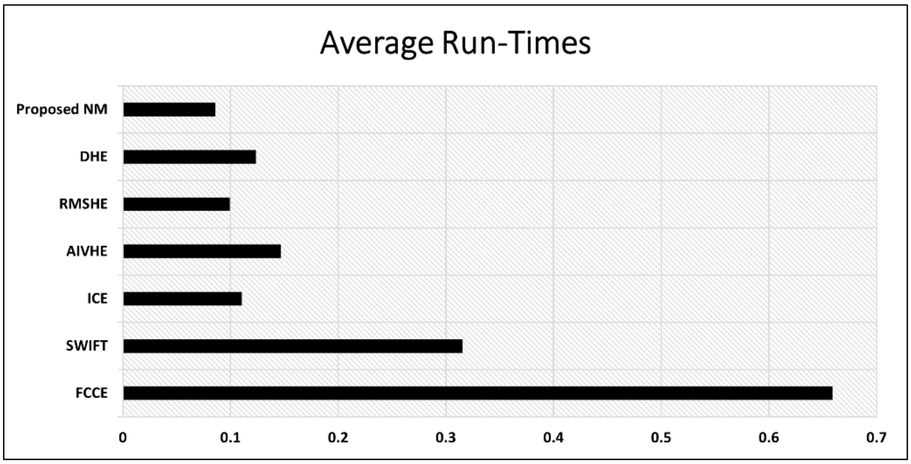

Fig. 12. The average run times

5. CONCLUSION

A simple-structure algorithm is presented in this paper to increase the observed contrast. In the proposed algorithm, a two-step regularization procedure is initially implemented to non-linearly modify the intensities. Then, a GCCDFLUD approach is implemented to further enhance the image and suppress high pixel values. Finally, an automated histogram expansion method is used to redistribute the pixels to the full image interval. Different real-contrast distorted images, evaluation methods, and comparison algorithms were utilized in this study for efficiency evaluations. The obtained results by the proposed algorithm have acceptable quality and surpassed the comparative algorithms in dissimilar facets as the attained results became more visually appealing, looked natural and it did not introduce any unnatural appearance or undesirable effects. Moreover, The NM algorithm outperformed the comparison methods in terms of runtimes, visual contrast, apparent luminance, and naturalness as indicated by the utilized VCM, BPRI, BRISQUE metrics, and processor time.

The outcomes of this study are significant because a noncomplex algorithm was able to well-process different SEM images and avoid the drawbacks of different more advanced algorithms. As for future works, the NM algorithm may be further modified by using some specialized statistical approaches to be utilized with other image datasets that are valuable in different scientific applications. Likewise, it can be made entirely automated by using specialized artificial intelligence techniques.

Funding

This research did not receive any funding.

Conflicts of Interest

The authors declare that we don't have any conflict of interest regarding this study.

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