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Adaptive Image Enhancement based on Bi-Histogram Equalization with a clipping limit ☆

Jing Rui Tang, Nor Ashidi Mat Isa *

Imaging and Intelligent Systems Research Team (ISRT), School of Electrical and Electronic Engineering, Universiti Sains Malaysia, 14300 Nibong Tebal, Penang, Malaysia

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ABSTRACT

A new approach based on Bi-Histogram Equalization is presented to enhance grayscale images. The proposed Adaptive Image Enhancement based on Bi-Histogram Equalization (AIEBHE) technique divides the input histogram into two sub-histograms, which are at the threshold of the histogram median for mean brightness preservation. Histogram clipping is performed to control the enhancement rate, and then the clipped sub-histograms are equalized and integrated to obtain the enhanced image. The novelty of AIEBHE is its flexibility in choosing the clipping limit that automatically selects the smallest value among histogram bins, mean, and median values, resulting in the conservation of a greater amount of information in the image. Automatic selection of the clipping limit addresses the issue of over-emphasizing of high frequency bins during histogram equalization. Simulation results reveal that AIEBHE technique outperforms other histogram-equalization-based enhancement techniques in terms of detail preservation and mean brightness preservation.

1. Introduction

Image enhancement is one of the major concerns in the field of digital image processing. It aims to produce better image quality with improved interpretability by altering the original input image. Image processing technique is widely used in different application, such as fingerprint recognition [1,2], face recognition [3,4] and many others [5–7]. Despite its effectiveness and ease of computation, conventional histogram equalization (CHE), one of the most widely used image enhancement techniques, suffers from several drawbacks. CHE flattens and stretches the dynamic range of the histogram by remapping the gray-levels based on the probability density function (PDF) of the image [8]. Consequently, this procedure leads to mean brightness shifting and creates artifacts in the resultant image. In addition to mean brightness shifting, the nature of CHE to emphasize histogram bins with high frequency and eliminate those with low frequency results in an over-enhanced and washed-out effect. Histogram bins are arrays that store the number of pixels with the same gray levels. Furthermore, contrast stretching is confined in certain dominated regions, and excessive merging of gray levels of the image leads to the generation of false contours and unnatural enhancement [9]. Certain areas may appear to be too bright in the output image, so-called the saturation effect, which degrades the outlook of the image and causes information loss [10].

Substantial amounts of work have been reported to address the aforementioned drawbacks. However, yielding a high-quality enhanced image in the field of image processing is still a challenge. In this study, we propose an adaptive image

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* Corresponding author. Tel.: +60 45996051; fax: +60 45941023.
E-mail addresses: tjr12_eee039@student.usm.my (J.R. Tang), ashidi@eng.usm.my (N.A. Mat Isa).

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enhancement algorithm, namely Adaptive Image Enhancement based on Bi-Histogram Equalization (AIEBHE). The work is motivated by the idea of maintaining the mean brightness through histogram segmentation while simultaneously controlling the enhancement rate through histogram clipping. The effectiveness of histogram segmentation in maintaining the mean brightness of an image has been proven in several studies [8,11,12]. The utilization of histogram clipping in preserving image details as demonstrated in Refs. [13–16] is the reason behind the introduction of a new approach in CHE to obtain the enhanced image with the advantages of the mentioned techniques.

The rest of this paper is organized as follows: Section 2 discusses some recent related work in image enhancement, specifically the techniques based on histogram equalization. Section 3 presents the proposed AIEBHE in detail. Section 4 outlines the data sample and the performance measurement used. Section 5 discusses the experimental results and discussions. Finally, Section 6 provides the conclusions.

2. Related works

We briefly review several histogram-equalization-based enhancement techniques in this section. To overcome the mean brightness shifting problems of CHE, Kim proposed Brightness Preserving Bi-Histogram Equalization (BBHE) in 1997 [11]. BBHE, which works by dividing the input histogram into two sub-histograms using the mean brightness of the image and independently equalizing the sub-histograms, can preserve the mean brightness while reducing the saturation effect and avoiding unnatural enhancement as well as unwanted artifacts [13]. Following BBHE, Dualistic Sub-image Histogram Equalization (DSIHE) was proposed. It uses median value to separate the histogram of the input image instead of the mean value [8]. The generalization scheme of BBHE and DSIHE, Recursive Mean-Separate Histogram Equalization (RMSHE) [17] and Recursive Sub-image Histogram Equalization (RSIHE) [18] were developed. RSIHE and RMSHE generate 2^r sub-histograms through recursive division of the input histogram more than once based on the mean and median values respectively. The recursive property of RMSHE and RSIHE techniques enables scalable brightness conservation. The common disadvantage of RMSHE and RSIHE is the difficulty of defining the optimal value for r. The number of decomposed sub-histograms is restricted to a number of power of two. When r becomes very large, the output image will be exactly the same as the input image and there will be no enhancement [19].

On the other hand, several studies were conducted on histogram clipping with the concept of limiting the enhancement rate. One of them is Bi-Histogram Equalization with a Plateau Level (BHEPL), which is proposed in year 2009 [13]. BHEPL clips the histogram at its average number of intensity occurrence. An extension of BHEPL, Bi-Histogram Equalization Median Plateau Limit (BHEPLD) was subsequently proposed [14]. Instead of setting a mean number of intensity occurrence, BHEPLD uses the median of occupied intensity as the clipping limit. In 2010, Ooi observed and compared the performance of different combinations in assigning mean and median values as thresholds for histogram separation and clipping [16]. Based on his findings, the best enhancement result is obtained when the input histogram is divided by the median value and when the sub-histograms are clipped with the median value of the occupied intensity. This technique is known as Brightness Preserving Plateau Limits Histogram Equalization (BPPLHE). Another example focusing on preserving the small parts in images was proposed by Abdullah-Al-Wadud [15]. The proposed Modified Histogram Equalization (MHE) technique manipulates the accumulation in the input histogram components before equalizing the histogram.

Meanwhile, another approach uses modified histogram-based image enhancement technique to maintain the details in the image have been performed. An example of the technique that focused on maximizing image entropy is the Adaptive Histogram Equalization Algorithm (AHEA) [9]. Information entropy is used as the objective function to select the optimum value for the adaptive parameter introduced in AHEA. Singh and Kapoor recently proposed Image Enhancement Using Exposure Based Sub Image Histogram Equalization (ESIHE) [20]. ESIHE clips the input histogram at the average number of intensity occurrences and divides the clipped histogram at its exposure threshold.

Various techniques have been proposed in literature to solve the drawbacks of mean brightness shifting and high frequency bin domination nature of the CHE technique. BBHE and RMSHE techniques solve the problem of mean brightness shifting through histogram segmentation at the mean brightness of the image. Segmentation at the median brightness has been proposed for better mean brightness preservation and has been demonstrated by both DSIHE and RSIHE techniques. On the other hand, to overcome the weakness of CHE in emphasizing high frequency histogram bins, MHE technique confines the histogram bins to the average value of the histogram, a technique known as histogram clipping. On the other hand, techniques that combine both histogram segmentation and histogram clipping (i.e., BHEPL, BHEPLD, BPPLHE and ESIHE) share the benefits of preserving mean brightness while eliminating the domination effects of high frequency bins. These techniques segment the input histogram with mean brightness, median brightness, or intensity exposure value, and use either mean or median number of intensity occurrence for the clipping limit. Consequently, all the mentioned techniques are capable of preserving the mean brightness of the input image while restricting histogram bins to either the mean or median value of the occupied intensity.

These techniques, however, have room for further enhancement in future studies. The excellent performance resulting from the idea of integrating histogram segmentation together with histogram clipping and the limitation of BHEPL, BHEPLD and BPPLHE in confining high frequency bins motivate us to propose a new approach to enhance grayscale images. The proposed AIEBHE technique first divides input histogram into two sub-histograms based on the median value of the image to preserve the mean brightness of the image, and then clips the histogram to reduce the domination effect of high frequency

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histogram bins while preserving most of the image details. The novelty of the proposed AIEBHE technique is its flexibility in selecting clipping limits to increase the information details preserved in the resultant image. The minimum value among the histogram bins, mean, and median of histogram bins is set as the clipping limit. This criterion provides flexibility for the proposed AIEBHE to choose the best clipping limit. As proven in the literature done in this study, image enhancement techniques that employ fixed clipping limit either based on histogram bins, mean, or median value of the occupied histogram bins do not produce promising results for all type of images. Thus, by providing this flexibility, the proposed technique is believed to have better capability in choosing the best clipping limit criterion and yielding a resultant image with more image details preserved.

In addition to standard public images, this study also tackles the feasibility of the proposed technique in enhancing medical images, specifically, cervical cell images. The proposed algorithm is free of any parameter tuning and is easy to implement because it does not involve complex mathematical equations. The details of AIEBHE are presented in the following section.

3. The proposed technique: AIEBHE with a clipping limit

Consider an input grayscale image X with intensity levels in the dynamic range of $[0, L-1]$, where L is the number of gray levels. The PDF of the image, $p(k)$, is defined as:

$$p(k) = \frac{H(k)}{n} \tag{1}$$

where $H(k)$ is the occurrence of intensity k in the image, and n is the total number of pixels in the image.

The cumulative density function (CDF), $c(k)$ is defined as:

$$c(k) = \sum_{i=0}^{k} p(i) \quad \text{for} \quad k = 0, 1, \ldots, L-1 \tag{2}$$

The transformation function of CHE, $f(k)$ is defined as:

$$f(k) = X_0 + (X_{L-1} - X_0) \cdot c(k) \tag{3}$$

where X_0 and X_{L-1} represent the minimum and maximum gray levels respectively. Based on (3), CHE remaps the input image into the whole dynamic range $[X_0, X_{L-1}]$ and spreads out the distribution of gray levels to achieve the effect of contrast enhancement.

The proposed AIEBHE algorithm involves three stages: histogram segmentation, sub-histogram clipping, and sub-histogram equalization. Histogram segmentation is performed to preserve the mean brightness of the input image by dividing the input histogram into two sub-histograms using a threshold value, λ. In this study, the threshold value used is the median value, which is the same as in DSIHE technique. The threshold divides the input histogram with a gray level range of $[0, L-1]$ into two sub-histograms (i.e., the lower histogram $H_{low}(k)$ and the upper histogram $H_{up}(k)$) with the ranges $[0, \lambda - 1]$ and $[\lambda, L-1]$ respectively. The PDF of each sub-histogram is represented by Eqs. (4) and (5) respectively.

$$p_{low}(k) = \frac{H_{low}(k)}{n_{low}}, \quad \text{for } k = 0, 1, \ldots, \lambda - 1 \tag{4}$$

$$p_{up}(k) = \frac{H_{up}(k)}{n_{up}}, \quad \text{for} \quad k = \lambda, \lambda + 1, \ldots, L-1 \tag{5}$$

where n_{low} is the total number of pixels in the lower histogram, and n_{up} is the total number of pixels in the upper histogram.

Histogram clipping is performed to restrict the enhancement rate of histogram equalization. As mentioned in the Introduction, CHE suffers from over-stretching the high frequency histogram components. This drawback can be seen in Eq. (3), where the enhancement is heavily dependent on the CDF of the image. Consequently, the enhancement rate is proportional to the rate of CDF as shown in Eq. (6). Restricting the value of $p(k)$ can achieve the purpose of restricting the enhancement rate.

$$p(k) = \frac{d}{dk} c(k) \tag{6}$$

The clipping limit in AIEBHE is the minimum value among the histogram bins, average number of intensities, and median value of occupied intensities, as shown in Eq. (7).

$$\text{Clipping limit} = \min\{p(k), \text{mean}[p(k)], \text{median}[p(k)]\} \tag{7}$$

The main difference between the proposed AIEBHE technique compared with other techniques that use either the average number of intensities or the median value of occupied intensities is the clipping limit. From (7), we can derive (8) and (9) to perform sub-histogram clipping.

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$$new\_p_{low}(k) = \min\{p_{low}(k), \mathrm{mean}[p_{low}(k)], \mathrm{median}[p_{low}(k)]\}, \quad \text{for} \quad k = 0, 1, \ldots, \lambda - 1 \tag{8}$$

$$new\_p_{up}(k) = \min\{p_{up}(k), \mathrm{mean}[p_{up}(k)], \mathrm{median}[p_{up}(k)]\}, \quad \text{for k} = \lambda, \lambda + 1, \ldots, L - 1, \tag{9}$$

CHE is then applied on the clipped lower and upper histograms using (10), and the resulting sub-histograms are integrated to yield the final enhanced image.

$$f(k) = \begin{cases} X_0 + (X_{\lambda-1} - X_0) \cdot \sum_{k=0}^{\lambda-1} new\_p_{low}(k), & \text{for} \quad k = 0, 1, \ldots, \lambda - 1 \\ X_\lambda + (X_{L-1} - X_\lambda) \cdot \sum_{k=\lambda}^{L-1} new\_p_{up}(k), & \text{for} \quad k = \lambda, \lambda + 1, \ldots, L - 1 \end{cases} \tag{10}$$

As a result, histogram components greater than the minimum value between the mean and median values will be limited to that value, and therefore avoid the domination of these components during the histogram equalization process.

Fig. 1 shows the changes in the histogram at each stage. In the first stage, we construct the input histogram and compute the median brightness, λ of the histogram. Input histogram is divided by λ during histogram segmentation as demonstrated in Fig. 1(b). Then, histogram clipping is performed with the choice of clipping limit made according to the flow chart shown in Stage 2. Unlike other conventional techniques that use either mean or median values as the clipping limit, the proposed AIEBHE technique introduces flexibility in selecting the clipping limit. If a histogram bin of a particular intensity is relatively large, thus tending to dominate the equalization process, its value will be limited to the minimum value between the mean and median value. Mean value well represents a data set without the presence of outliers in the data set. Outliers are observations that lie outside the overall pattern of a distribution. They are statistical values that are significantly different from the others in the sample [21]. If the mean value is the average number of intensity occurrence, outliers demonstrate a significant effect on the mean value compared with the median value, which is the median value of non-zero histogram bins of the image. Therefore, median value is a better choice to represent a data set with outliers.

The idea of automatically choosing the smallest value among histogram bins, mean, and median value as the clipping limit to restrict the enhancement rate is the main contribution of this paper. This flexibility better preserves image details during the enhancement and increases the robustness of the proposed technique compared with other conventional techniques, because it takes into consideration both cases with and without outliers while eliminating the domination effect of large histogram bins during histogram equalization. The implementation of different clipping limits is shown in Fig. 1(c). Instead of a straight horizontal line representing a constant value, the clipping limit is indeed a function as indicated in Eq. (7). In the final stage (e.g., Stage 3), CHE is performed on both the clipped sub-histograms as illustrated in Fig. 1(d). The resultant sub-histograms are then integrated to produce the final enhanced image. Fig. 2 illustrates the flow of the proposed AIEBHE technique.

4. Data sample and performance evaluations

In this section, the data sample used to investigate the performance of AIEBHE technique is discussed first. Then, the qualitative and quantitative analyses used for results evaluation are discussed in details.

4.1. Data sample

The proposed AIEBHE technique and the other seven histogram-based image enhancement techniques for comparison are tested with 70 benchmark images downloaded from the public image database [22] and 70 cervical cell sample images

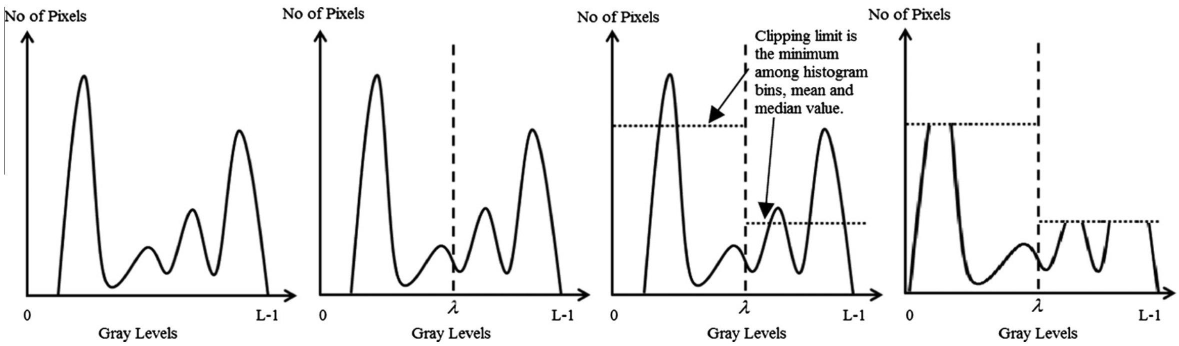


Fig. 1. (a) Input histogram and histogram at (b) Stage 1, (c) Stage 2 and (d) Stage 3.

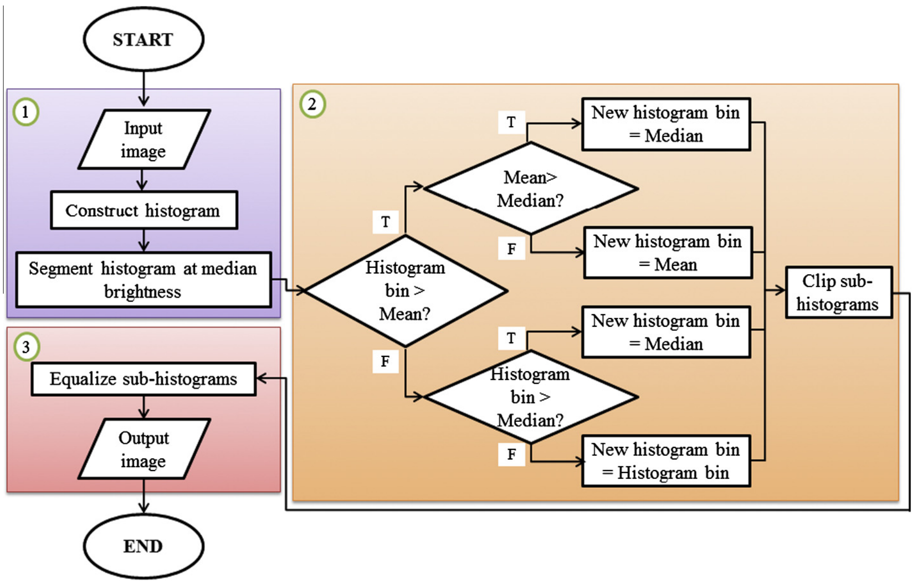


Fig. 2. Flow chart of the proposed AIEBHE technique. [*]*Note*: 1 = Histogram segmentation, 2 = Hostogram clipping, 3 = Histogram equalization.

obtained from Hospital Universiti Sains Malaysia, Kelantan, Malaysia. The cervical cell sample images comprises 15 images magnified using $\times 10$ objective, 15 images magnified using $\times 40$ objective, and 40 cropped images with a single cell. To evaluate the efficiency of the proposed technique, the other seven histogram-equalization-based techniques, including RSIHE [18], BHEPL [13], BHEPLD [14], BPPLHE [16], MHE [15], ESIHE [20], and AHEA [9], are implemented. To further investigate the mean brightness preservation ability of AIEBHE technique, the technique is compared with RSIHE even though the number of sub-histograms is not equal to the proposed technique. The scale *r* of RSIHE is set as two, and thus four sub-histograms are generated.

The proposed AIEBHE technique is evaluated in terms of detail preservation, mean brightness preservation, and image quality. Three images, namely *City*, *Plane*, and *Couple*, downloaded from a public image database [22] are used as test images. The resultant images enhanced by AIEBHE and the seven other techniques are presented in Figs. 3–5. Qualitative and quantitative analyses are performed, and the details of these analyses are discussed in the following subsections.

4.2. Qualitative analysis

Qualitative analysis involves evaluating the image enhancement results visually. The quality of the resultant images will decide the capability of the techniques. Qualitative analysis can focus on the amount of image details, level of contrast, homogeneity of regions, and naturalness of the image.

4.3. Quantitative analysis

Five quantitative evaluations, namely entropy, peak signal-to-noise ratio (PSNR), average absolute mean brightness error (AMBE), contrast, and computational time are employed. The details of each evaluation, including the functions and purposes, are described in the following subsections.

4.3.1. Assessment of detail preservation

Introduced by Shannon [23], entropy is often applied to evaluate the amount of details in the image [14,20,24]. A higher entropy value is desired because the higher the entropy value, the greater the amount of information contained in the image. The entropy of an image is independent of the other image since comparison on the information contained is done based on the same image before and after the processing. The entropy of the gray level grayscale image is calculated using (11). Thus, the entropy of the entire image is defined by Eq. (12) as the summation of all the individual entropies at every gray level [9].

$$e(k) = -p(k)\log_2 p(k) \tag{11}$$

$$\text{Entropy} = \sum_{i=0}^{L-1} e(i) = -\sum_{i=0}^{L-1} p(i)\log_2 p(i) \tag{12}$$

4.3.2. Assessment of mean brightness preservation

Average Mean Brightness Error (AMBE) is employed as the objective function to evaluate the ability of the proposed AIEBHE technique in mean brightness preservation [13,14,24]. Ideally, the mean brightness of the enhanced image should be equal to the mean brightness of the input image, in which the value of AMBE is zero. A small AMBE is thus desired because it computes the difference of the mean brightness between the input and resultant images, as shown in Eq. (13).

$$\mathrm{AMBE} = |\bar{J} - \overline{K}| \tag{13}$$

where $\bar{J}$ and $\overline{K}$ are the mean intensity of the input and enhanced images respectively.

4.3.3. Assessment of image quality and contrast enhancement

A good image enhancement technique should yield an image that retains its natural look. Specifically, the technique should not heavily magnify the noise level of the input image. PSNR is commonly used for evaluating image quality [14,18]. It measures how much the enhanced image has degraded when referred to the input image, as expressed in Eq. (14).

$$\mathrm{PSNR} = 10\,\log_{10}\left[\frac{(L-1)^2}{\frac{1}{n}\sum_u\sum_v|U(u,v) - V(u,v)|^2}\right] \tag{14}$$

where $U(u, v)$ is the intensity of the input image at a two-dimensional (2-D) position (u, v), and $V(u, v)$ is the intensity of the resultant image at the same position.

In addition to PSNR, we compute the deviation of gray levels to evaluate the contrast improvement. The image contrast function as shown in Eq. (15) has been used in Refs. [25,26].

$$C_{contrast} = \frac{1}{WH}\sum_{u=1}^{W}\sum_{v=1}^{H} g^2(u,v) - \left|\frac{1}{WH}\sum_{u=1}^{W}\sum_{v=1}^{H} g(u,v)\right|^2 \tag{15}$$

where W and H are the width and height of the image respectively, and $g(u, v)$ is the intensity of the pixel at a 2-D position (u, v). A greater $C_{contrast}$ is desired because it indicates a larger dynamic range of gray levels and has better contrast.

$C_{contrast}$ is then taken logarithm to convert it into decibel (dB) unit using:

$$C^{*}_{contrast} = 10\,\log_{10} C_{contrast} \tag{16}$$

4.3.4. Assessment of algorithm complexity

Apart from evaluating the proposed AIEBHE technique in the resultant image, we perform complexity analysis to examine the complexity of the proposed algorithm in computational time [13,14]. Given that complexity evaluation in computational time depends on the platform used, the computational time required for all algorithms should be measured under a homogeneous platform condition for fair comparison [27]. In this paper, the mean computational times of all algorithms are measured using a PC Intel Core i5 3.30 GHz with 4.00 GB RAM employing Windows 7 with Matlab version R2012a implementation. A shorter computational time indicates that the algorithm is simpler in implementation.

5. Results and discussion

In this section, we first present the simulation results for the proposed AIEBHE technique and the seven other CHE-based techniques. We then perform experiments on medical microscopy images (specifically, cervical cell images) to further investigate the robustness and feasibility of the proposed technique.

5.1. Simulation results and discussion

The simulation results obtained for three test images are presented in Figs. 3–5 respectively. We evaluate the performance of the resultant images according to several criteria. We compare the information details of the image as well as the contrast of the enhanced image with those of the input image. The homogeneity of the image regions and the naturalness of the images are also included as performance evaluation criteria. We also observe the histograms of the images. In general, a good image should have a uniformly distributed histogram without the presence of spikes. As discussed in Ref. [14], the entropy of an image is at a maximum only when the probability distribution of the intensity values of an image is uniform. The presence of spikes is therefore undesired in a good histogram. Histogram spikes are a result of a large number of pixels having the same intensity [24]. The merging of two separate and different gray levels can also lead to the creation of spikes in the histogram [28]. Thus, histogram spikes are considered as artifacts in the image [29]. In addition to observing the resultant images and their corresponding histograms, we also present the quantitative results of these test images in Table 1.

The test image *City* in Fig. 3(a) has relatively good contrast. All the techniques are similar in terms of contrast measurement, which ranges from 68.750 dB to 70.197 dB, proving that the enhanced images are not far off from one another in contrast. In fact, the histogram distributions of all the images look alike. In terms of detail preservation, the proposed AIEBHE technique outperforms all other techniques in entropy value. This quantitative result is supported by the histograms, which

Table 1
Quantitative analyses for three test images.

Technique	Entropy (bit)	PSNR	AMBE	Contrast (dB)
Test image City				
Input image	7.322	–	–	70.167
RSIHE [18]	7.124	27.048	7.006	69.737
BHEPL [13]	7.264	29.083	3.253	69.974
BHEPLD [14]	7.268	29.009	2.952	69.994
BPPLHE [16]	7.270	29.101	3.131	69.982
MHE [15]	7.264	28.732	0.319	**70.197**
ESIHE [20]	7.264	29.033	**0.134**	70.185
AHEA [9]	7.220	20.561	21.273	68.750
AIEBHE	**7.276**	**29.102**	3.162	70.002
Test image Plane				
Input image	6.452	-	-	69.813
RSIHE [18]	6.305	17.339	13.166	69.245
BHEPL [13]	6.411	18.104	4.710	69.635
BHEPLD [14]	6.439	23.120	4.392	**70.020**
BPPLHE [16]	6.445	**23.217**	**4.231**	69.637
MHE [15]	6.383	14.490	25.968	68.620
ESIHE [20]	6.380	18.242	11.224	69.326
AHEA [9]	6.438	16.845	23.385	68.727
AIEBHE	**6.447**	**23.217**	**4.231**	69.837
Test image Couple				
Input image	7.058	–	–	68.793
RSIHE [18]	6.956	23.216	3.163	69.013
BHEPL [13]	7.015	23.238	7.118	69.281
BHEPLD [14]	7.041	28.684	3.305	69.022
BPPLHE [16]	7.043	29.033	**1.464**	68.893
MHE [15]	6.995	20.695	14.129	**69.740**
ESIHE [20]	7.011	24.646	1.288	68.879
AHEA [9]	**7.057**	**30.481**	3.038	69.004
AIEBHE	7.043	29.033	**1.464**	68.893

show that the image processed using AIEBHE yields fewer spikes than any other image, particularly in the middle section of the histograms. In the image processed using AIEBHE, the small details highlighted with boxes, such as the sign board, are well preserved. Contrast is also sufficiently enhanced because the image appears to be natural with high homogeneity. This observation is supported by the fact that the image processed using AIEBHE has the highest PSNR value. The findings also prove that the mean brightness preservation of AIEBHE is comparable to that of the other techniques.

The second test image, *Plane,* appears to have low contrast since few regions of the image appear to be totally white or totally black. Intensity distribution appears to be concentrated at the middle part of the histogram. The proposed AIEBHE technique produces an enhanced image with the highest entropy value, thereby preserving more details in the image than the other techniques. The writing on the airplane wing is legible and the edges of the plane can be clearly seen, as shown in Fig. 4(i). We hardly find significant histogram spikes in the histogram of the image processed using AIEBHE. The proposed AIEBHE technique produces a histogram similar to those of the BHEPL, BHEPLD, and BPPLHE techniques. In fact, the resultant images of these techniques demonstrate a similar contrast enhancement measurement. The image processed using AHEA appears to lose its naturalness owing to the shifting effect of mean brightness, which leads to it having the largest AMBE value. By contrast, the image processed using AIEBHE technique has a mean brightness that is the closest to that of the input image. The resultant image enhanced using the AIEBHE technique has a smooth texture with few non-homogenous regions, and is thus ranked first in terms of PSNR measurement.

For the third test image, *Couple,* as shown in Fig. 5(a), the proposed AIEBHE technique produces the image closest to the input image in terms of brightness. The overall appearance of the image looks very similar to the input image, an observation supported by the resultant image having the lowest AMBE value. Quantitative analysis reveals that the AIEBHE technique performs comparably to the BPPLHE technique. The small contrast range of all images (i.e., 0.861 dB) indicates that all the resultant images are about the same in terms of contrast. In fact, the distributions of the histograms of all images are similar and cover the entire dynamic range. Furthermore, AIEBHE technique produces an image with a homogeneous texture. Most of the image area, for instance, the carpet, appears to have a smooth texture with few small regions. The image processed using AIEBHE has the second-largest PSNR value, indicating that the technique does not significantly amplify the noise level in the image during the enhancement process. Although the contrast enhancement of the proposed technique is less significant than that of the other techniques in the test image *Couple*, most of the details of the image are well preserved, and the resultant image has the second-largest entropy value. The detail preservation can be seen in the ornamental ironwork, and the telephone as highlighted with boxes. The image processed using AHEA has a histogram with the best spread among all the other techniques because it does not have any significant spikes. To support the findings from these test images,

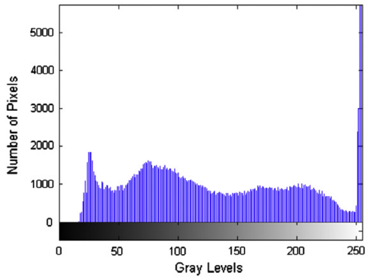
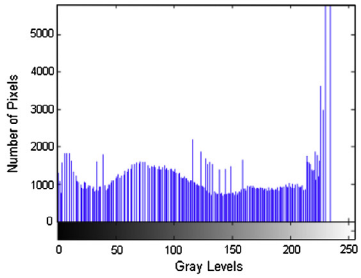
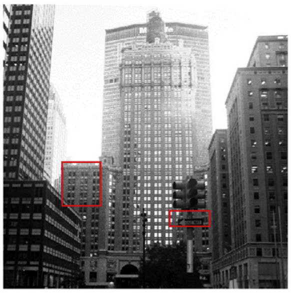
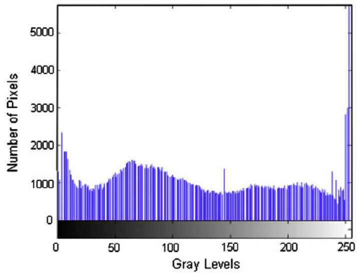
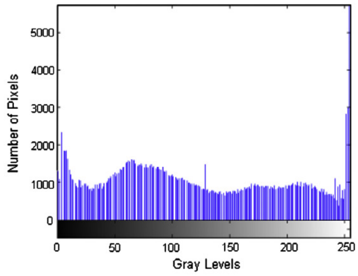
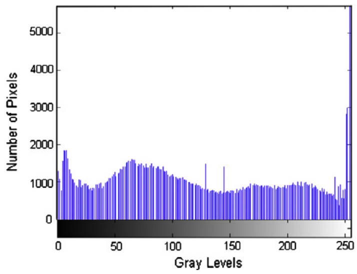
Technique	Image	Histogram
(a) Original		
(b) RSIHE		
(c) BHEPL		
(d) BHEPLD		
(e) BPPLHE		

Fig. 3. (a) Test image *City* enhanced using: (b) RSIHE, (c) BHEPL, (d) BHEPLD, (e) BPPLHE, (f) AHEA, (g) MHE, (h) ESIHE, and (i) proposed AIEBHE technique.

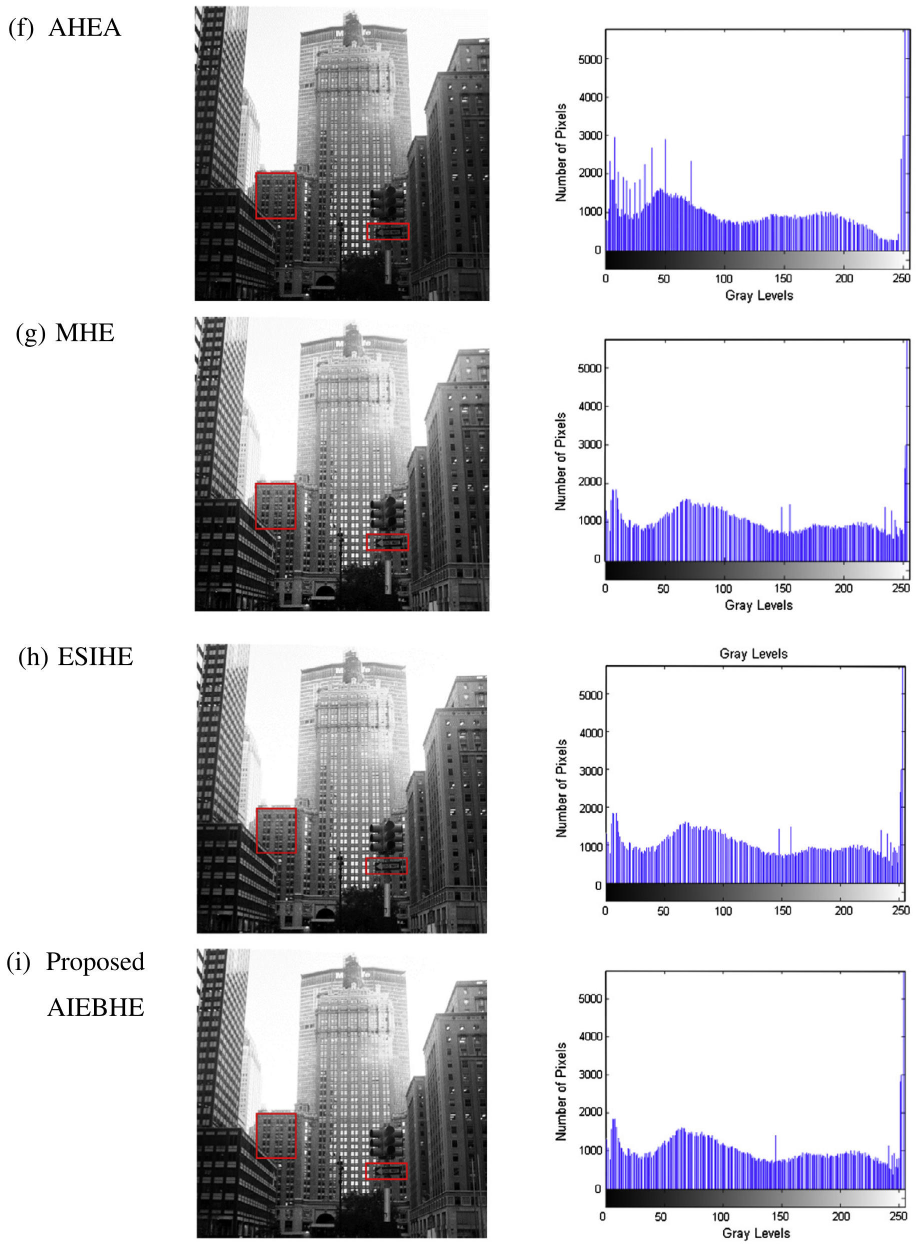


Fig. 3 (*continued*)

Appendix A shows the results for 10 additional images. In general, the results indicate that the proposed AIEBHE technique is the best technique both qualitatively and quantitatively.

The performance of the proposed technique for the three test images is encouraging. We further justify the capability and the performance of the proposed AIEBHE technique with the four objective evaluation functions using 70 test images. We also compute the average computational time for each algorithm. Table 2 presents the average values of these quantitative analyses for 70 test images. The best value for each analysis is written in boldface. Table 2 suggests that the proposed AIEBHE technique demonstrates outstanding performance compared with the other seven HE-based techniques. On the average, the image processed using AIEBHE contains the second-highest amount of information, slightly less than the image processed using AHEA which is specifically designed to preserve the entropy value of the image. Moreover, the proposed technique ranks first in terms of PSNR value, implying that it outperforms all the other techniques. This highest PSNR value shows that the images enhanced using AIEBHE are least degraded. These enhanced images have natural appearances with minimum artifacts compared with those enhanced using the other techniques. In addition to the highest PSNR value, the proposed AIEBHE technique possesses the lowest value for AMBE measurement. Its AMBE value is even better than that of RSIHE

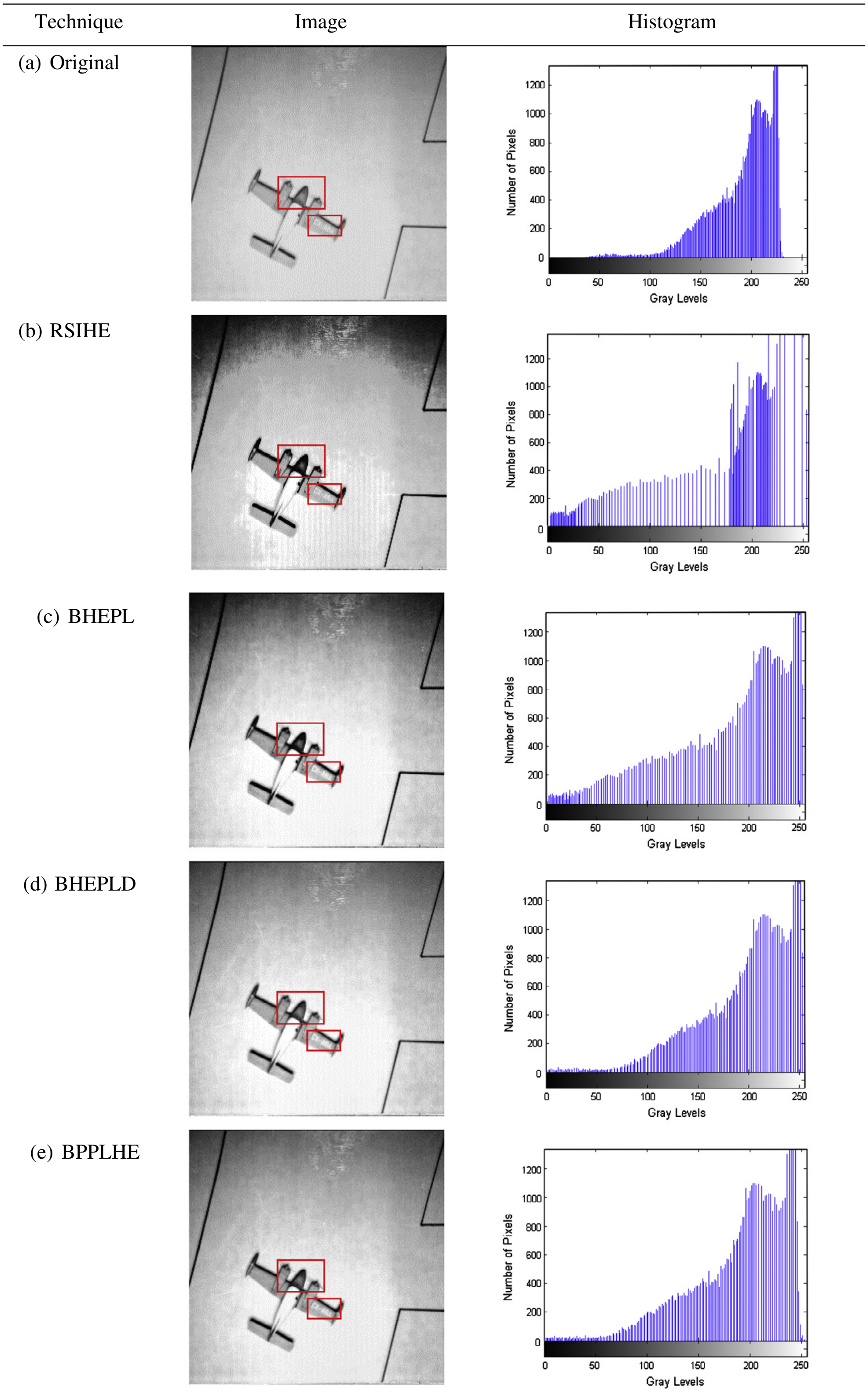


Fig. 4. (a) Test image *Plane* enhanced using: (b) RSIHE, (c) BHEPL, (d) BHEPLD, (e) BPPLHE, (f) AHEA, (g) MHE, (h) ESIHE, and (i) proposed AIEBHE technique.

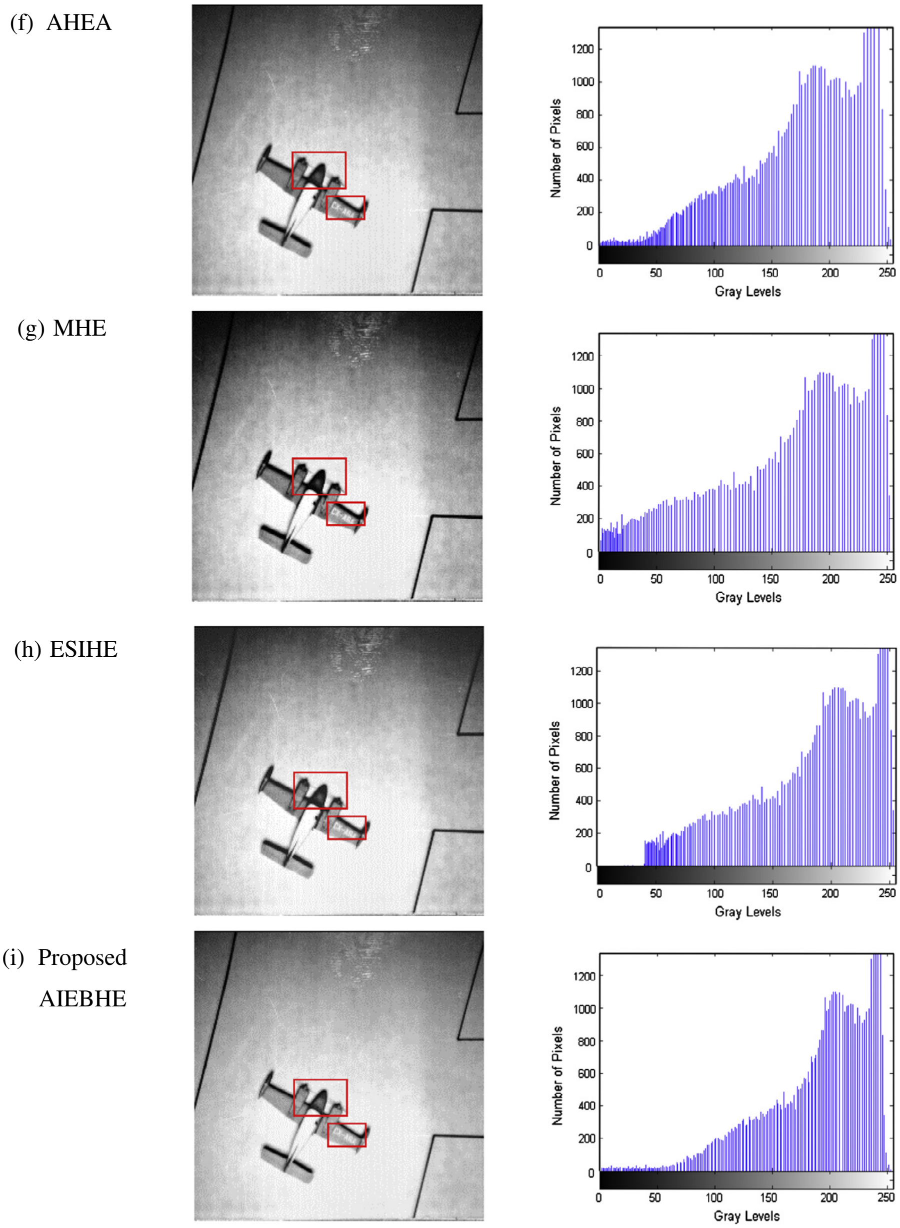


Fig. 4 (*continued*)

technique, although which is designed specifically to maintain the mean brightness of the image. The lowest AMBE value reveals that the resultant images enhanced with AIEBHE have a mean brightness nearest to the input image. All techniques perform similarly in terms of overall contrast enhancement (i.e., 66.408–66.911 dB), which indicates that AIEBHE demonstrates comparable performance with all the other techniques in this aspect. The computational times required by all techniques range from 0.331 s to 0.414 s. The small difference in computational time range (i.e., 0.083 s) proves that the processing times by these techniques are comparable. This finding also shows that the techniques do not differ significantly in terms of complexity. Although the proposed AIEBHE technique requires an additional 6.04% of computational time on the average compared with the shortest computational time demonstrated by AHEA technique, the former significantly outperforms the latter in terms of PSNR (with an improvement of 12.14%) and AMBE (with an improvement of 73.36%) and has a slightly lower entropy measurement of 0.29%.

Apart from the average value, we further analyze the performance of AIEBHE using the Wilcoxon signed-rank test and present the pairwise performance comparison results of each image. Wilcoxon signed-rank test is an analogue of the paired *t*-test in non-parametrical statistical procedures; it aims to detect significant differences between the behavior of two

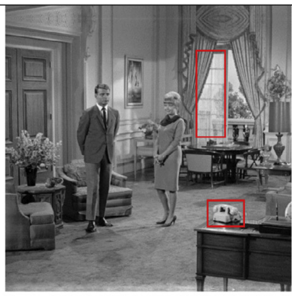
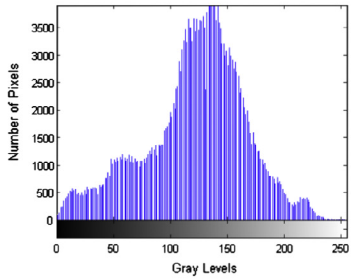
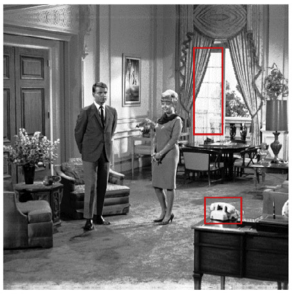
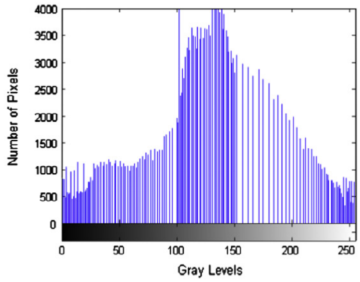
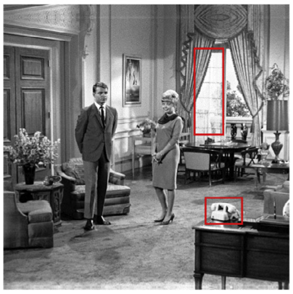
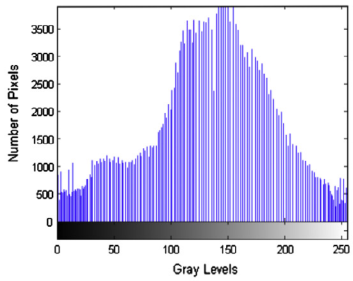
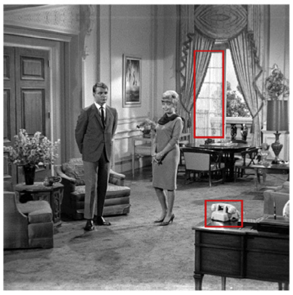
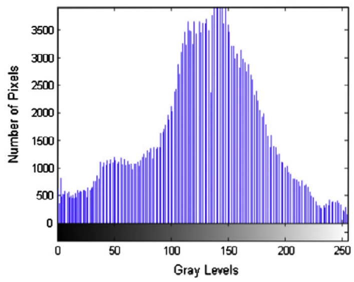
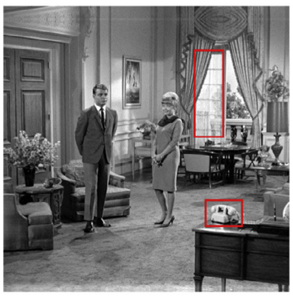
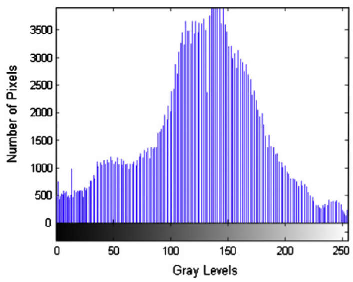
Technique	Image	Histogram
(a) Original		
(b) RSIHE		
(c) BHEPL		
(d) BHEPLD		
(e) BPPLHE		

Fig. 5. (a) Test image *Couple* enhanced using (b) RSIHE, (c) BHEPL, (d) BHEPLD, (e) BPPLHE, (f) AHEA, (g) MHE, (h) ESIHE, and (i) proposed AIEBHE technique.

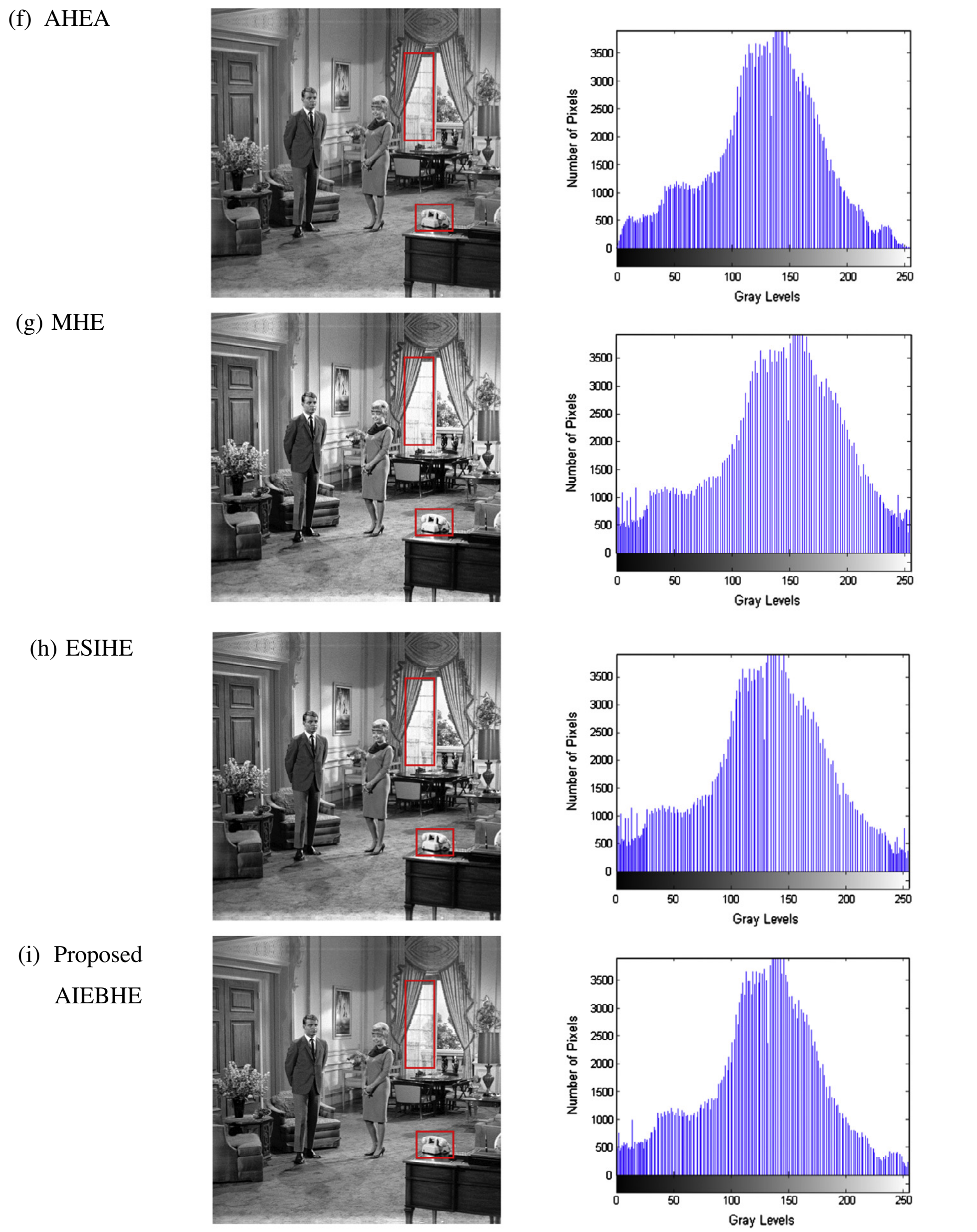


Fig. 5 (*continued*)

Table 2
Average values of quantitative analyses for 70 test images.

Technique	Year	Entropy (bit)	Entropy (%)	PSNR (dB)	AMBE	Contrast (dB)	Time (s)
RSIHE [18]	2007	6.888	97.58	23.108	4.959	66.457	0.414
BHEPL [13]	2009	6.990	99.04	21.999	7.133	66.543	0.346
BHEPLD [14]	2010	7.013	99.39	24.086	4.650	66.417	0.347
BPPLHE [16]	2010	7.014	99.40	24.362	4.380	66.408	0.344
MHE [15]	2012	6.977	98.87	19.250	18.160	**66.911**	0.332
ESIHE [20]	2013	6.981	98.92	23.313	8.781	66.565	0.350
AHEA [9]	2012	**7.037**	**99.72**	21.802	16.172	66.481	**0.331**
AIEBHE	–	7.016	99.43	**24.449**	**4.308**	66.413	0.351

Table 3
Wilcoxon signed-rank test between AIEBHE and the other seven algorithms.

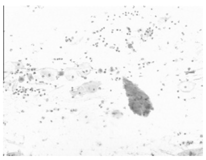
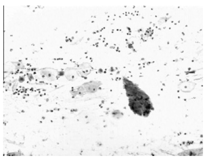
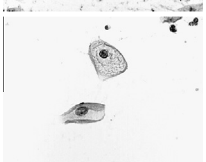
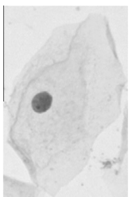
Proposed AIEBHE vs.	Entropy (bit)			PSNR (dB)			AMBE			Contrast (dB)			Computational time (s)		
	R^+	R^-	*p*-Value	R^+	R^-	*p*-Value	R^+	R^-	*p*-Value	R^+	R^-	*p*-Value	R^+	R^-	*p*-Value
RSIHE [18]	2485.0	0.0	**0**	1594.0	891.0	**0**	1386.0	1099.0	**0**	1298.0	1187.0	**0**	1940.0	545.0	**0**
BHEPL [13]	2415.0	70.0	**0**	2277.0	208.0	**0**	1846.0	639.0	**0**	780.0	1705.0	0	705.0	1780.0	0
BHEPLD [14]	1669.5	815.5	**0**	1622.0	863.0	**0**	1352.0	1133.0	**0**	1182.0	1303.0	0	723.0	1762.0	0
BPPLHE [16]	1741.5	743.5	**0**	1753.5	661.5	**0**	1213.5	1201.5	**0**	1512.5	902.5	0	1745.0	740.0	**0**
MHE [15]	2462.0	23.0	**0**	2477.0	8.0	**0**	2422.0	63.0	**0**	821.0	1664.0	0	69.0	1866.0	0
ESIHE [20]	2422.0	63.0	**0**	1583.0	902.0	**0**	1815.0	670.0	**0**	1151.0	1334.0	0	1215.5	1269.5	0
AHEA [9]	268.0	2217.0	0	1923.0	562.0	**0**	2391.0	94.0	**0**	1269.0	1216.0	**0**	501.0	1984.0	0

algorithms [30]. The proposed technique is used as the controlled technique, and the level of significance used for the statistical test is 0.05. R^+ and R^- denote the sum of ranks in which AIEBHE technique outperforms and underperforms the other techniques respectively. Table 3 illustrates the analysis result of the Wilcoxon signed-rank test. The best value for each analysis is written in boldface. Wilcoxon signed-rank test compares all the 70 images individually in terms of entropy, PSNR, AMBE, contrast, and computational time. AIEBHE performs excellently in terms of entropy, PSNR, and AMBE measurements. It outperforms six of the seven techniques in terms of entropy measurement and significantly outperforms all techniques in terms of PSNR and AMBE measurements. The results of the statistical test are consistent with the results shown in Table 2, in which AIEBHE preserves the mean brightness and details of the image while retaining the naturalness of the image with slight tolerance in contrast enhancement. Table 3 also shows that the complexity of our proposed technique is higher than the other five HE-based techniques given that AIEBHE technique tends to incur higher computational overhead than these techniques. The computation of both mean and median values in AIEBHE eventually consumes excessive computational resources compared with the other techniques, which only involve the computation of one of those values. Despite having slightly higher complexity, the simulation results shown in Tables 3 and 4 reveal that our proposed technique significantly outperforms these five techniques in terms of PSNR and AMBE measurements. Our technique is also far better than those techniques in terms of entropy value, except for AHEA, which is designed specifically for entropy preservation. These observations suggest that, compared with the other algorithms, AIEBHE technique achieves better a trade-off between performance improvement and computational complexity. To further investigate the robustness of AIEBHE technique, we perform a case study where AIEBHE technique is used to enhance cervical cell image, as presented in the following section.

5.2. Case study

In this section, we implement AIEBHE technique on the cervical cell sample images shown in Table 4 to evaluate its performance in enhancing medical images. The problem of image enhancement in such images is encountered ubiquitously. Direct segmentation on cervical cell images is a challenging task because these images usually have low contrast. Table 4 shows the results of the quantitative analyses on examples of the simulation results. The first row show image magnified using $\times 10$ objective, the second row $\times 40$ objective, and the last row is the cropped image. Table 4 depicts that the proposed

Table 4
Cervical cell image enhancement using AIEBHE technique.

Magnification	Original image		Resultant image	
×10 Objective		Entropy = 3.174; Contrast = 25.626		Entropy = 3.173; PSNR = 23.180; AMBE = 7.532; Contrast = 30.908
×40 Objective		Entropy = 2.883; Contrast = 23.084		Entropy = 2.882; PSNR = 27.071; AMBE = 3.796; Contrast = 27.922
Cropped image		Entropy = 5.287; Contrast = 23.964		Entropy = 5.286; PSNR = 26.224; AMBE = 0.566; Contrast = 29.007

AIEBHE technique has high potential in enhancing cervical cell images. The edges of both nucleus and cytoplasm become clearer and sharper with overall contrast enhancement. Most details of the cells are well preserved with a relatively high entropy value given that a false contour can hardly be detected in the enhanced images. AIEBHE also has enhanced the cervical cell images to a sufficient level without greatly amplifying the noise level on the image. The resultant images appear with a mean brightness close to that of the input image. The relatively high PSNR values and the low AMBE value confirm our observations of the enhanced images. For further investigation on the robustness of our algorithm in medical image application, we implement AIEBHE technique on 70 cervical cell sample images obtained from Hospital Universiti Sains Malaysia, Kelantan, Malaysia.

Fig. A1. Images enhanced using different techniques (first column: original images; enhanced image using: second column: RSIHE; third column: BHEPL; fourth column: BHEPLD; fifth column: BPPLHE; sixth column: MHE; seventh column; ESIHE; eighth column: AHEA; ninth column: proposed AIEBHE); test images from the first row to tenth row are *Lady1*, *Houses*, *Lady2*, *Lake*, *Lady3*, *Pepper*, *Lena*, *Road*, *Lakeside*, and *Toothbrush*, respectively.

AIEBHE technique demonstrates superior performance in retaining image details, achieving an average entropy of 99.90% out of 70 cervical cell sample images. The average PSNR value is 23.926 dB. This high PSNR measurement indicating that the enhanced cervical cell images appear to be natural with homogeneous regions. In terms of mean brightness preservation, the AMBE value of AIEBHE is approximately 3.6 (i.e., 3.561), which is not significantly close to zero. This result may be due to the nature of the gray level distribution of the cervical image itself. The AMBE value may be improved by selecting a better threshold for optimum histogram segmentation. The contrast of the enhanced image improved by 15.46% compared with the input image. These results further support our observation in Table 4, where the contrast enhancement is significant for all the images. Overall, AIEBHE technique has great potential as an image enhancement technique for standard images and medical microscopic images, particularly for cervical cell images.

6. Conclusion

This study proposed a new variant of CHE technique. CHE is well known to be suffered from shifting of mean brightness and over-emphasizing on high frequency bins of the image. This inevitably alters the appearance of the resultant image and leads to loss of image details. The proposed AIEBHE technique aims to minimize these two drawbacks of CHE by integrating both histogram clipping and histogram segmentation into CHE. The novelty of AIEBHE technique is its flexibility in choosing either mean or median value to eliminate the domination effect of high frequency histogram components in histogram equalization. The integration of histogram clipping in the algorithm enables the restriction on enhancement rate. Moreover, histogram segmentation contributes in mean brightness preservation.

Extensive simulation results reveal that AIEBHE performs excellently in preserving the image details while maintaining the mean brightness of the image. The resultant images of the proposed technique appear to be more natural and they are visually pleasing. More importantly, the proposed algorithm is free of any tuning parameters and hence avoids cumbersome computation. Its robustness enables its usage in a wide variety of images, including medical images. To further improve AIEBHE technique, the clipping limit can be formulized as a function of entropy. The selection of clipping limit for every gray level could be done in such a way that it maximized the entropy of the image and thus preserve more image details. Furthermore, the AIEBHE technique could be modified so that it is applicable on color images as well. It is also possible to modify AIEBHE according to image characteristics so that it can be used to enhance more medical images, not limited to cervical cell images.

Table A.1
Entropy values for 10 test images.

Image	Techniques						
	RSIHE	BHEPL	BHEPLD	BPPLHE	MHE	ESIHE	AHEA	AIEBHE
Lady1	7.525	7.590	7.591	7.591	7.580	7.590	**7.628**	7.590
Houses	7.349	7.408	7.427	7.429	7.380	7.408	**7.477**	7.438
Lady2	7.154	7.216	7.220	7.220	7.227	7.219	7.226	**7.266**
Lake	6.982	7.072	**7.112**	7.078	7.032	7.063	7.085	7.082
Lady3	7.399	7.450	7.444	7.449	7.445	7.429	7.454	**7.497**
Pepper	7.377	7.455	7.470	7.469	7.453	7.444	7.473	**7.520**
Lena	7.461	7.516	7.516	7.501	7.500	7.497	**7.565**	7.508
Road	7.229	7.307	7.318	7.315	7.271	7.291	**7.380**	7.325
Lakeside	7.582	7.676	7.699	7.713	7.662	7.663	**7.739**	7.713
Toothbrush	7.459	7.529	7.520	7.517	7.529	7.528	**7.605**	7.528

Table A.2
PSNR values for 10 test images.

Image	Techniques							
	RSIHE	BHEPL	BHEPLD	BPPLHE	MHE	ESIHE	AHEA	AIEBHE
Lady1	26.286	23.927	23.880	23.960	22.780	23.886	**27.203**	23.990
Houses	25.584	23.341	23.577	**26.509**	21.389	23.185	23.737	24.437
Lady2	19.293	17.402	20.220	20.366	13.891	17.811	16.188	**20.414**
Lake	21.985	21.339	22.588	22.665	18.002	**24.764**	23.383	22.924
Lady3	22.429	22.112	22.129	22.149	21.064	22.422	22.676	**23.397**
Pepper	23.936	21.760	**23.971**	21.612	20.249	23.081	21.752	21.940
Lena	24.800	23.479	24.015	24.647	18.515	24.720	24.631	**25.799**
Road	22.213	21.404	21.539	21.554	20.345	21.068	20.768	**23.502**
Lakeside	**31.101**	29.208	29.528	29.241	29.529	29.141	26.533	29.255
Toothbrush	24.895	23.237	22.902	23.180	22.848	23.452	**27.498**	23.488

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Table A.3
AMBE values for 10 test images.

Image	Techniques							
	RSIHE	BHEPL	BHEPLD	BPPLHE	MHE	ESIHE	AHEA	AIEBHE
Lady1	1.007	1.469	1.366	0.824	6.284	1.605	5.105	**0.673**
Houses	0.909	2.407	5.448	**0.180**	8.285	3.611	4.267	2.627
Lady2	**9.109**	17.753	11.241	10.709	42.211	15.850	33.557	11.074
Lake	2.674	**0.220**	3.257	2.618	18.735	7.172	2.027	2.157
Lady3	4.838	4.135	5.425	5.290	8.908	10.777	12.921	**3.473**
Pepper	4.551	7.818	9.428	9.803	15.887	**0.812**	10.845	9.272
Lena	5.109	6.214	5.314	2.684	23.591	2.531	9.878	**2.465**
Road	2.589	5.748	9.202	8.848	**0.937**	2.125	20.670	7.766
Lakeside	**1.899**	5.278	5.210	5.919	2.569	2.082	10.858	5.896
Toothbrush	2.037	3.334	2.915	1.066	6.619	0.740	8.637	**0.434**

Table A.4
Contrast values for 10 test images.

Image	Techniques							
	RSIHE	BHEPL	BHEPLD	BPPLHE	MHE	ESIHE	AHEA	AIEBHE
Lady1	68.599	68.646	68.639	68.588	**68.987**	68.656	68.148	68.601
Houses	67.937	67.961	67.712	67.860	68.071	68.134	67.800	**68.764**
Lady2	67.138	67.849	67.305	67.260	**69.582**	67.698	69.003	67.291
Lake	63.707	**65.069**	63.167	63.228	63.457	62.774	63.273	63.269
Lady3	66.376	66.421	66.336	66.345	66.092	**67.371**	65.824	66.469
Pepper	65.688	65.914	66.027	66.053	66.016	65.408	66.125	**66.464**
Lena	64.328	**65.761**	64.341	64.097	64.415	63.656	64.725	64.117
Road	68.170	67.886	67.609	67.638	**68.483**	68.401	66.645	67.733
Lakeside	69.514	69.298	69.302	69.253	69.480	69.255	68.910	**69.524**
Toothbrush	69.437	69.367	69.398	69.514	69.148	69.535	68.968	**69.557**

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Appendix A

Enhancement results of 10 test images using RSIHE, BHEPL, BHEPLD, BPPLHE, MHE, ESIHE, AHEA, and AIEBHE
See Fig. A.1 and Tables A.1–A.4

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Jing Rui Tang received her B. Eng. in Mechatronic Engineering with First Class Honors from Universiti Sains Malaysia (USM), Malaysia in 2012. She is currently a Ph.D. candidate at School of Electrical and Electronic Engineering, USM, and is attached to the Imaging and Intelligent System Research Team (ISRT). Her research interests include digital image processing and intelligent diagnostic systems.

Nor Ashidi Mat Isa received his B. Eng. degree in Electrical and Electronic Engineering with First Class Honors and his Ph.D. degree in Electronic Engineering from USM in 1999 and 2003 respectively. Currently, he serves as an Associate Professor at the School of Electrical and Electronic Engineering, USM. His research interests include image processing, neural network and intelligent systems.

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