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CONTRAST ENHANCEMENT OF CT BRAIN IMAGES USING GAMMA CORRECTION ADAPTIVE EXTREME-LEVEL ELIMINATING WITH WEIGHTING DISTRIBUTION

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Abstract. *Stroke is one of the top leading causes of fatality globally among people whose ages are above 60 years old. Computed tomography (CT) scan is the primary medical diagnosis equipment operated by radiologist and doctor for inspection of stroke cases. Window setting is always used for presentation of CT and magnetic resonance imaging (MRI) brain image. Besides, contrast enhancement techniques are also implemented to improve the contrast of CT brain image. Nevertheless, it is very difficult for radiologist and doctor to diagnose the brain image especially on early stroke cases. The main reason is because the ordinary window parameters and some of the existing contrast enhancement techniques cannot provide a good contrast for highlighting the region of interest (ROI) or hypodense area during the stroke diagnosis. Therefore, by implementing the concept of local histogram equalization (LHE), a new histogram modification technique called gamma correction adaptive extreme-level eliminating with weighting distribution (GCAELEWD) is proposed. This new technique is used to increase the difference of intensities on CT brain images. Moreover, this new approach is competent to preserve the local change of brightness in input image while extending the dynamic range of an input image.*
Keywords: Image processing, CT brain image, Contrast enhancement, Gamma correction

1. **Introduction.**

According to World Heart Federation (WHF), stroke has a huge impact to the society as it is also the second leading cause of disability just after dementia [1]. Besides, stroke claims around 5 million lives a year globally [2]. Generally, stroke can be categorized into two main classes which are hemorrhagic stroke and ischemic stroke. Hemorrhagic stroke occurs when there is leakage of blood vessel within the brain whereas ischemic stroke happens when there is blockage of blood supplies to the brain [3,4]. However, ischemic stroke is the majority as it occupied 87% out of the total stroke cases. Early detection and treatment of stroke can save a person from suffering permanent brain damage [5]. In this 21st century, computed tomography (CT) scan is still more favorable while compared to magnetic resonance imaging (MRI) on ischemic stroke diagnosis predominantly due to convenience, quick process and affordability [6]. In addition, CT scan is also much suitable for patients who have inserted with surgical clips or metallic fragments. Other than that, CT scan is also suitable for patients who are claustrophobic as they cannot stay in a confined place for long period. 16-bits digital imaging and communication in medicine (DICOM) format is the standard used to keep the captured CT brain images [7,8]. Hence, in order to present the DICOM image, window parameter is implemented to extend the dynamic scope of Hounsfield unit (HU) to the common 8-bits grayscale image.

Nonetheless, the ordinary window parameters with window width and window center of 80 HU and 40 HU may not be able to give a perfect contrast in CT brain image [9]. Besides, window setting is also very case dependence as it requires the manual tuning of radiologists to obtain a good result. Consequently, it may not be effective in highlighting the region of interest (ROI) on ischemic stroke diagnosis. Other than improving the contrast of CT brain images with window setting, intravenous contrast agent is also normally applied with contrast CT scan to have better visualization. Nevertheless, intravenous contrast agent tends to introduce some side effects such as severe pain or vomit. Due to these limitations, different contrast enhancement techniques have been proposed by researchers to enhance the CT brain image for diagnosis of stroke cases. Histogram equalization (HE) is mainly utilized to grow the contrast of an image by changing the input image histogram [10-12]. In other words, HE technique works by manipulating the cumulative density function (CDF) of the whole input image and transforms it to a new gray level for the enhanced image.

Global histogram equalization (GHE) and local histogram equalization (LHE) are two categories of HE technique [13-16]. GHE improves the intensity's difference of the entire image with space invariant transformation to be appertained to each pixel. On the other hand, LHE performs block-overlapping HE with space invariant transformation and obtains the information of gray level using sub-block. The advantage of LHE while compared with GHE is that it has better preservation on the local change of input brightness for ordinary grayscale image. However, HE technique can cause over improvement and hardly maintain the average brightness of the input images. Therefore, brightness preserving bi-histogram equalization (BBHE) is then suggested to retain the average brightness of the input image [17]. BBHE is performed by using the input mean value to split the input image histogram into two portions. Nonetheless, since BBHE is formulated from GHE, the enhanced image may not adapt to the local change of brightness for the input image. Next, dualistic sub-image histogram equalization (DSIHE) technique is also proposed [18]. Similar to BBHE technique, DSIHE works by first separating the input image histogram into two portions. The only difference is that it separates the input image histogram by aiming at the highest Shannon's entropy value of the output image. This DSIHE technique has potential to give better results when there are large areas with almost the identical intensity value. However, DSIHE can produce a very dark enhanced CT brain image and it is not practical for stroke diagnosis.

Pizer et al. proposed contrast-limited adaptive histogram equalization (CLAHE) technique which is one of the LHE to prevent from over enhancement and noise amplification [19]. Furthermore, extreme-level eliminating adaptive histogram equalization (ELEAHE) method is also proposed mainly for enhancing CT brain image [20]. This ELEAHE technique is considered as one of the LHE approaches specifically formulated for enhancing CT brain image. ELEAHE is actually the localized version of extreme-level eliminating histogram equalization (ELEHE) technique. Essentially, it is done by dividing image into non-overlapped, equal sized sub-blocks and proceeds with the elimination of the two extreme-levels in every sub-block before the transfer function (TF) of HE is implemented. For reconstruction of image, ELEAHE applies the bilinear interpolation method to determining the optimum value for all pixels across the image. Nevertheless, the region of normal brain soft tissue turns gloom in the output of ELEAHE enhanced image. Consequently, this may lengthen the time taken for diagnosis.

In recent years, other than the ordinary transfer function of HE, transfer function of gamma correction (GC) is also used in adaptive gamma correction with weighting distribution (AGCWD) and normalized gamma-corrected contrast-limited adaptive histogram equalization (NGCCLAHE) to enhance the normal grayscale and medical images [21,22]. Nevertheless, AGCWD technique may not show good visualization for stroke diagnosis as it is mainly developed for enhancing the normal grayscale and color images. Furthermore, there is also contrast enhancement technique which requires the use of un-sharp mask filter and Otsu method that has been proposed in 2016 [23]. In addition, extreme-level eliminating brightness preserving bi-histogram equalization (ELEBBHE) technique is also proposed in 2016 for enhancing CT brain images [24]. In summary, there are still limitations from existing contrast enhancement techniques applied on CT brain images in which most of it tend to intensify the area of normal brain soft tissue and cause over enhancement. The normal brain soft tissue on the enhanced image by existing contrast enhancement techniques is being darkened and closed to the intensity of the hypodense area. On the other hand, over enhancement includes loss of skull, loss of part of brain soft tissues and the hypodense area on the enhanced image.

Thus, a new histogram modification method based on LHE approach called gamma correction adaptive extreme-level eliminating with weighting distribution (GCAELEWD) is developed to overcome the limitations of existing contrast techniques in enhancing CT brain image. Besides, by taking the advantage of LHE approach and considering the drawbacks of ELEAHE technique, GCAELEWD technique is able to overcome the limitations of existing contrast enhancement techniques and give good enhancement while preserving the local change of input brightness on CT brain image. The rest of this paper is ordered as follows. In Section 2, the fundamental principle of HE technique is discussed. Then, the new GCAELEWD is presented in Section 3. Section 4 shows the experimental results and the conclusion is given in Section 5.

2. **Principles of Histogram Equalization Technique.**

Histogram equalization (HE) technique is widely used predominantly due to rapidity and simplicity of application. It is applied to stretching the dynamic range of an input image. Consider an input image I consists of total number of pixels n and intensity level z. The input probability density function (PDF) can be computed as shown in Equation (1).

$$PDF(I_z) = \frac{n_z}{n} \tag{1}$$

where $z = 0, 1, \ldots, Z-1$, n_z constitutes the whole summation of pixels value at intensity level I_z and $I_z \in \{I_0, I_1, \ldots, I_{Z-1}\}$. The input cumulative density function (CDF) can be acquired by Equation (2).

$$CDF(I_z) = \sum_{a=0}^{z} PDF(I_a) \tag{2}$$

The transfer function can be acquired just after the input CDF is obtained and it is shown in Equation (3).

$$TF = (I_{Z-1} - I_0)(CDF(I_z)) + I_0 \tag{3}$$

where I_{Z-1} is the maximum intensity level and I_0 is the minimum intensity level of an image. Since $CDF(I_{Z-1}) = 1$ and $I_0 = 0$, the transfer function of HE can be simplified as Equation (4).

$$TF = CDF(I_z) \tag{4}$$

3. **Gamma Correction Adaptive Extreme-Level Eliminating with Weighting Distribution.** Gamma is normally used to relate the pixel's luminance and its numeric value. Essentially, gray level transfer function is used to apply on the input image to enhancing the low luminance images. In this section, the algorithm of gamma correction adaptive extreme-level eliminating with weighting distribution (GCAELEWD) is presented. This new proposed histogram modification technique is further developed from a GHE method called gamma correction extreme-level eliminating with weighting distribution (GCELEWD) technique [25]. Basically, GCAELEWD is formulated to overcome the drawbacks of existing techniques on enhancing CT brain images. GCAELEWD is also able to preserve the local change of brightness in the input image.

Consider an input image M with the size of $X \times Y$ and intensity level L, the algorithm of GCAELEWD technique is discussed as follows.

1) The input image is partition into $R \times C$ equal area and non-overlapped sub-tiles. A zero array Nil with the area of $R \times C$ is set.

2) Starting from the first sub-tile, GCELEWD technique is implemented. By eliminating the two extreme-levels, PDF of a sub-block is given in Equation (5).

$$PDF(M_{l_s}) = \frac{n_{l_s}}{n} \tag{5}$$

where s represents a specific sub-tile, $l_s = 1, 2, \ldots, L-2$, n_{l_s} constitutes the whole summation of pixel values of a sub-tile at intensity level M_{l_s} and $M_{l_s} \in \{M_{1_s}, M_{2_s}, \ldots, M_{L-2_s}\}$.

3) Weighting distribution function (WDF) is implemented to flatten the enhancement and a new PDF is given in Equation (6).

$$PDF_{WDF}\left(M_{l_s}\right) = PDF_{\max_s}\left(\frac{PDF\left(M_{l_s}\right) - PDF_{\min_s}}{PDF_{\max_s} - PDF_{\min_s}}\right)^{\alpha} \tag{6}$$

where α is the adjusted parameter which is in the range of 0 to 1, $PDF_{\max_s}$ represents the maximum PDF value of image histogram at specific sub-tile s and $PDF_{\min_s}$ represents the minimum PDF value of image histogram at a sub-tile.

From Equation (6), it can be noted that a low α value will produce a blur and darker enhanced image, whereas a high α value will produce an over enhancement image.

4) Thus, sigmoid function is employed to obtain the optimum value of α for enhancing CT brain images. It is used to normalize the nonlinear function of WDF in Equation (6). In short, sigmoid function is used to ensure that the PDF is normalized accordingly with a smooth continuous function. From sigmoid function, the adjusted parameter, α, can be represented as Equation (7).

$$\alpha = \max\left\{\sum_{l_s=0}^{L-1} \frac{1}{\left(1 + e^{-PDF(M_{l_s})}\right)}\right\} = 0.50 \tag{7}$$

5) In this case, the parameter alpha (α) is set accordingly to 0.50 as shown in Equation (7) and proposed by the GHE, GCELEWD technique. CDF can be obtained from Equation (8).

$$CDF_{WDF}\left(M_{l_s}\right) = \sum_{l_s=1}^{l_s} PDF_{WDF}\left(M_{l_s}\right) \tag{8}$$

where $l_s = 1, 2, \ldots, L-2$, M_{l_s} is the normalized gray intensity level on each sub-block, and PDF_{WDF} is the PDF after weighting distribution function is applied.

6) This CDF is further normalized into the output scope of $[0, 1]$ before the transfer function of GCAELEWD technique is applied. The normalization process is shown in

Equation (9).

$$CDF_n(M_{l_s}) = \frac{CDF_{WDF}(M_{l_s})}{\sum_{l_s=1}^{l_s} PDF_{WDF}(M_{l_s})} \tag{9}$$

7) Transfer function (TF) of GCAELEWD technique as shown in Equation (10) is implemented on the sub-tile and the value is stored in the array Nil.

$$TF_{GCAELEWD}(M_{l_s}) = \frac{CDF_n(M_{l_s}) + M_{l_s}^{1-CDF_n(M_{l_s})}}{2} \tag{10}$$

where $l_s = 1, 2, \ldots, L-2$, M_{l_s} is the normalized gray intensity level on each sub-block, and CDF_n is the normalized CDF of each sub-block on the input image.

8) Steps 2 to 7 are to redo for the rest of the sub-tiles until all the values for every sub-tile are kept in the array Nil.

9) The produced image is reconstructed with bilinear interpolation technique to approximate the optimum value for all pixels across the image. The reason is that it can eliminate the blocking effect between each sub-tile. By using bilinear interpolation technique, each sub-tile is further classified into four tiny tiles as shown in Figure 1. TF of GCAELEWD technique is used to define the mapping function of each sub-tile. The rest of the pixels are allocated with maximum of four mapping functions of sub-tile possess center pixels nearest to them. These pixels are then mapped with interpolated values. From Figure 1, the pixels in the edges sub-tiles (colored dark gray) are mapped with the TF of its own sub-tile. In addition, linear interpolation is performed for the pixels in boundary sub-tiles (colored light gray) whereas bilinear interpolation technique is performed on pixels in the center sub-tiles (colored white).

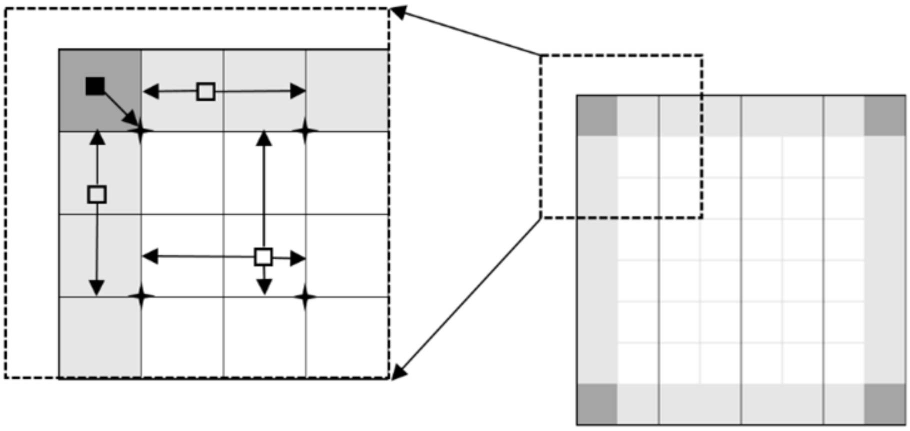

Figure 1. Bilinear interpolation technique on pixels of a sub-block

After the process of reconstruction of image, GCAELEWD enhanced image can be obtained. The main difference of GCAELEWD and the existing ELEAHE technique is the types of transfer function used in each sub-block. In ELEAHE technique, transfer function of HE is used in each sub-block whereas the new transfer function of GCAELEWD technique is used in the sub-block of GCAELEWD technique. The general review of this new GCAELEWD technique is shown in Figure 2.

4. **Results and Discussions.** To examine the performance on enhancing CT brain image, GCAELEWD technique is compared with HE, BBHE, CLAHE and ELEAHE techniques. This new GCAELEWD technique is tested on 300 datasets of non-contrast CT brain image collected from hospitals. The window setting for all the images obtained are set to default with window width of 80 HU and window center of 40 HU. The enhanced

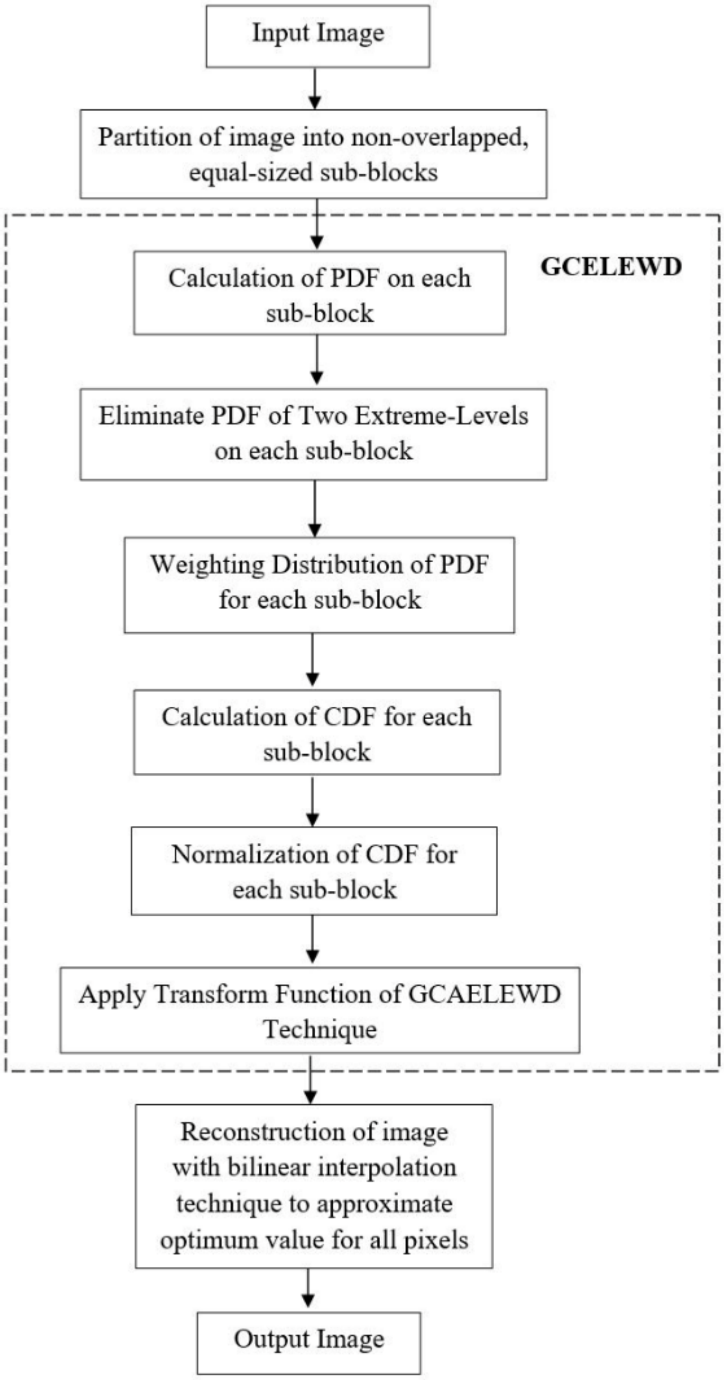

Figure 2. The overview of gamma correction adaptive extreme-level eliminating with weighting distribution technique

CT brain images of various techniques are shown in Figure 3 to Figure 5. The evaluation of performance can be mainly categorized into two categories which are qualitative test and quantitative test.

Qualitative test is done based on the observation and perception of the whole enhanced image. In other words, it is used to determine the clarity and difference of the damaged tissue and the normal tissue with our human bare eye. On the other hand, measure of enhancement by entropy (EMEE) [26,27], structure similarity index (SSIM) [28] and universal image quality index (UIQI) [29] are used for the quantitative test. Loss of correlation, luminance distortion and contrast distortion are three considerations of UIQI.

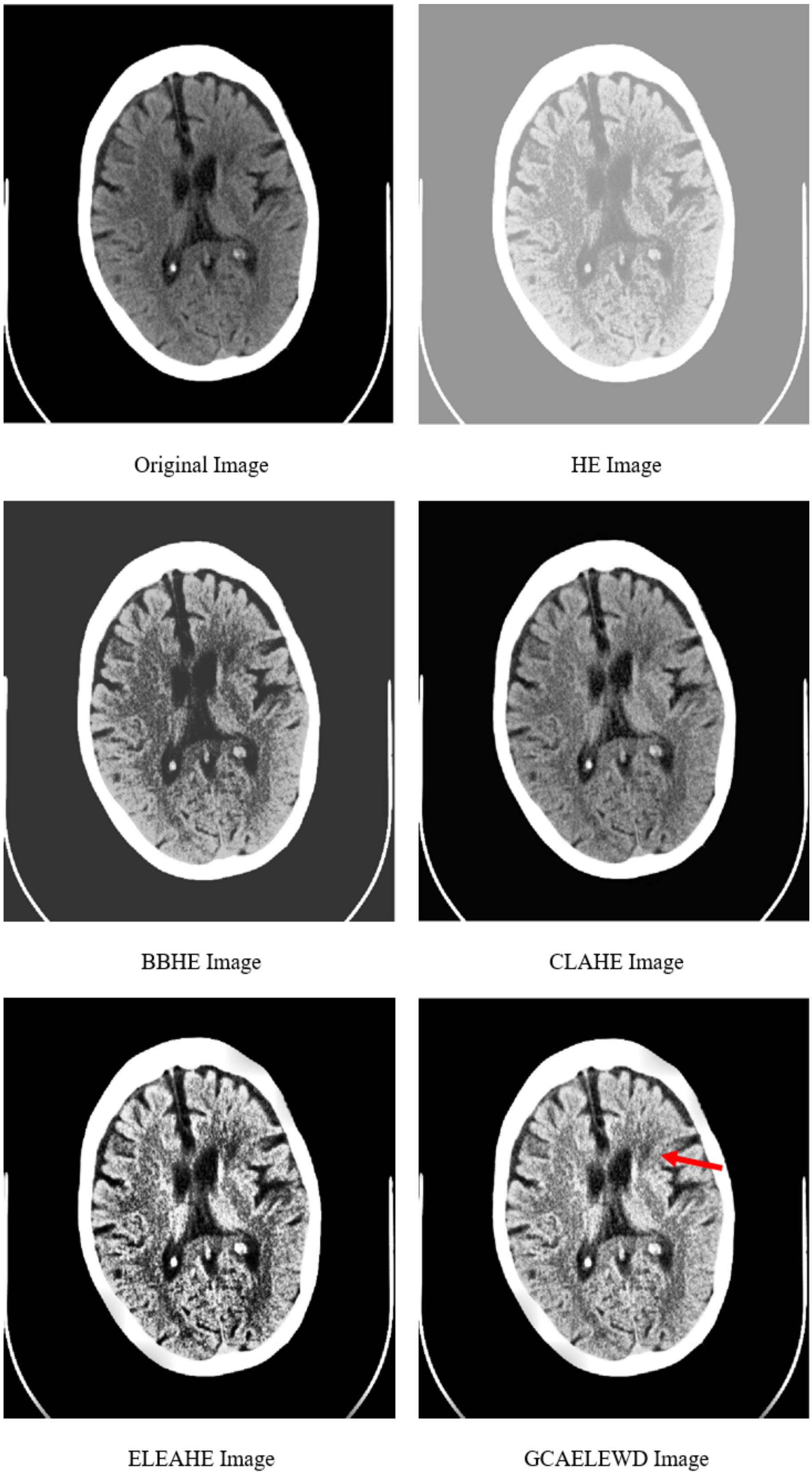

FIGURE 3. Comparison of different histogram modification methods on sample CT brain image I

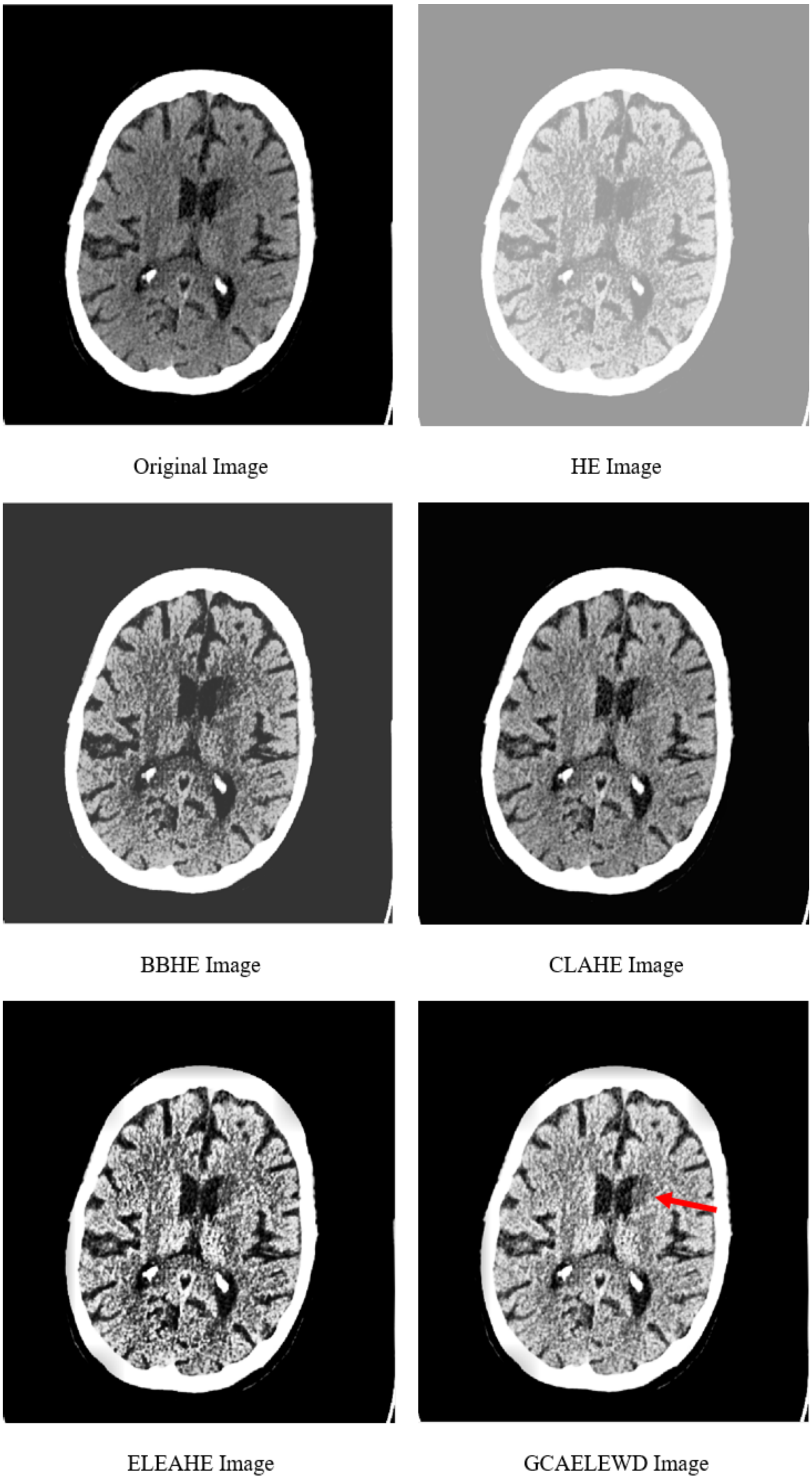

Figure 4. Comparison of different histogram modification methods on sample CT brain image II

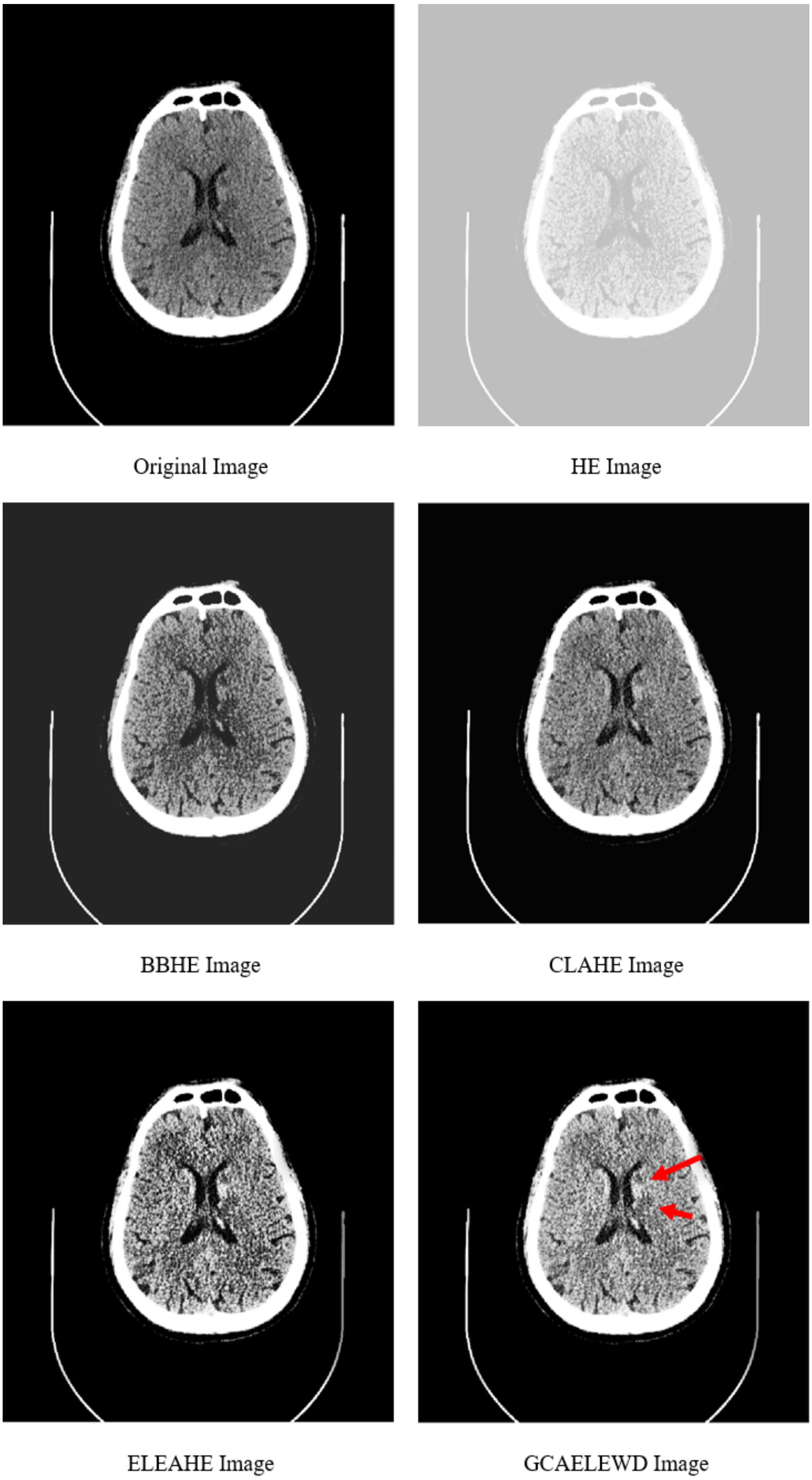

FIGURE 5. Comparison of different histogram modification methods on sample CT brain image III

The value of SSIM and UIQI is normalized into the range of 0 to 1. Meanwhile, if the value is closer to 1, it means good quality result, and value closer to 0 means bad quality result. The experimental results of all the qualitative tests are shown in Table 1 and Figure 6.

Table 1. Comparison of different contrast enhancement methods on measure of enhancement by entropy, structure similarity index and universal image quality index

Technique / CT Brain Image	Original	HE	BBHE	CLAHE	ELEAHE	GCAELEWD
EMEE						
Set I	4.2433	0.0427	0.1453	0.5182	4.6898	4.2974
Set II	3.2022	0.0331	0.0983	0.3781	3.5029	3.2674
Set III	3.5704	0.0175	0.1391	0.3888	3.8114	3.6235
SSIM						
Set I	–	0.3236	0.3605	0.5821	0.8547	0.8950
Set II	–	0.3591	0.4085	0.5984	0.8789	0.9300
Set III	–	0.1602	0.2572	0.4922	0.9343	0.9588
UIQI						
Set I	–	0.3089	0.4149	0.4315	0.9641	0.9524
Set II	–	0.3656	0.4326	0.4614	0.6059	0.9770
Set III	–	0.1938	0.2799	0.3060	0.8473	0.9820

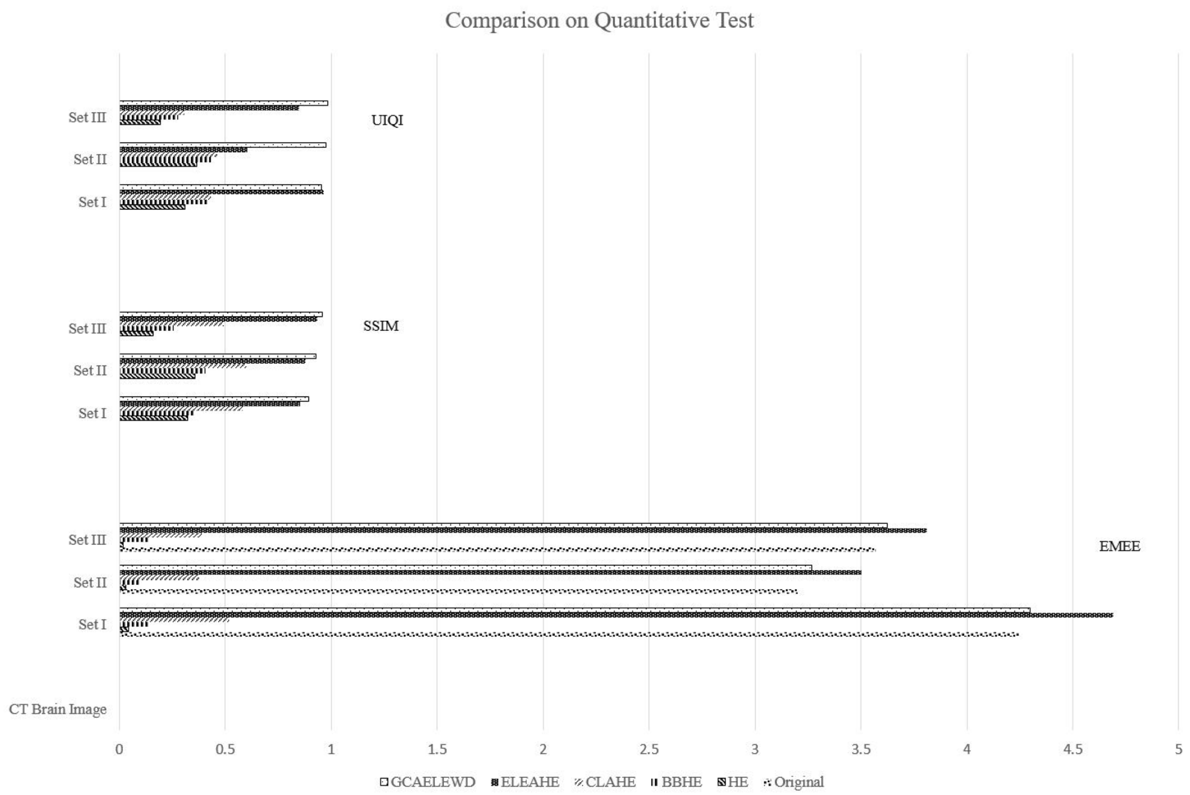

Figure 6. Histogram of comparison on quantitative test

4.1. **Discussion of qualitative test.** It is very tedious for medical practitioners to examine on ischemic stroke cases from poor contrast CT brain images. From Figure 3 to Figure 5, GCAELEWD technique gives better visualization as compared to the rest of the techniques. GCAELEWD enhances the whole image and the region of interest (ROI). Although ELEAHE technique has almost the similar contrast as GCAELEWD technique, it may darken the regular brain soft tissue. This will definitely increase the error on diagnosis process. Moreover, it can be clearly seen that the HE and BBHE techniques failed to preserve the original background brightness.

The background of HE and BBHE technique enhanced images become brighter. Furthermore, CLAHE technique has almost the similar contrast as the original image and it cannot provide a great difference of contrast between ROI and the regular brain soft tissue in some cases. On the other hand, GCAELEWD technique has also overcome the two main limitations of existing contrast enhancement techniques as it does not intensify the area of normal brain soft tissues and it does not produce an over enhanced image. Furthermore, the hypodense area on GCAELEWD can be easily observed compared with the rest of the compared techniques. Thus, GCAELEWD can be used as an aiding tool to shorten the time taken for ischemic stroke diagnosis.

4.2. **Discussion of quantitative test.** From Table 1 and Figure 6, GCAELEWD technique has high EMEE, high UIQI and the highest SSIM value for all three sets of CT brain images. Eventually, a high EMEE value denotes that the image has achieved high level of enhancement. GCAELEWD technique provides the highest UIQI value for sets II and III. Therefore, it can be said that GCAELEWD has obtained a high luminance and contrast on the enhanced image. Contrarily, the lowest EMEE, SSIM and UIQI value can be seen on the HE technique which is initially proposed to stretch the image histogram into dynamic range.

Although, the EMEE value of the GCAELEWD technique is slightly lower than ELEAHE technique that is specifically proposed for enhancing CT brain images, by comparing the enhanced images, it still surpasses the ELEAHE technique in terms of visualization for diagnosis of ischemic stroke. The predominant factor is due to GCAELEWD technique which allows better differentiation of contrast in between the regular brain soft tissue and damaged tissue nor the ventricles of the brain. In short, GCAELEWD technique is able to produce a high luminance and contrast image for aiding the stroke diagnosis process.

5. **Conclusion.** Poor contrast CT brain image tends to increase the chances of misinterpretation on stroke diagnosis especially for early stroke cases. In this paper, a new contrast enhancement technique for CT brain image founded from the principle of LHE is developed. This new developed GCAELEWD method is competent to enhance the whole image and ROI while preserving the local change of input brightness. GCAELEWD has also overcome both of two main limitations of existing contrast enhancement techniques. Other than implementing the ordinary transfer function of HE, this new developed GCAELEWD method has also implemented a new transfer function of GCAELEWD on each sub-block for computation. For reconstruction of image, bilinear interpolation technique is used to eliminate the blocking effect between sub-tiles. The qualitative and quantitative tests clearly show that GCAELEWD technique outperforms the rest of the compared techniques. Thus, this GCAELEWD technique can be used to aid the doctors and radiologists on stroke diagnosis instead of the original image.

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