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Brain Early Infarct Detection Using Gamma Correction Extreme-Level Eliminating With Weighting Distribution

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SUMMARY: According to the statistic from World Health Organization (WHO), stroke is one of the major causes of death globally.Computed tomography (CT) scan is one of the main medical diagnosis system used for diagnosis of ischemic stroke. CT scan provides brain images in Digital Imaging and Communication in Medicine (DICOM) format. The presentation of CT brain images is mainly relied on the window setting (window center and window width), which converts an image from DICOM format into normal grayscale format. Nevertheless, the ordinary window parameter could not deliver a proper contrast on CT brain images for ischemic stroke detection. In this paper, a new proposed method namely gamma correction extreme-level eliminating with weighting distribution (GCELEWD) is implemented to improve the contrast on CT brain images. GCELEWD is capable of highlighting the hypodense region for diagnosis of ischemic stroke. The performance of this new proposed technique, GCELEWD, is compared with four of the existing contrast enhancement technique such as brightness preserving bi-histogram equalization (BBHE), dualistic sub-image histogram equalization (DSIHE), extreme-level eliminating histogram equalization (ELEHE), and adaptive gamma correction with weighting distribution (AGCWD). GCELEWD shows better visualization for ischemic stroke detection and higher values with image quality assessment (IQA) module. SCANNING 9999:1–15, 2016. © 2016 Wiley Periodicals, Inc.

Key words: contrast enhancement, histogram equalization, gamma correction, weighting distribution, extreme-level eliminating

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Introduction

Computed tomography (CT) scan is one of the main medical diagnosis system used by doctors and hospitalist to have a better view of patients' brain for detection and diagnosis of brain lesion. CT scan is much ordinary used than magnetic resonance imaging (MRI). This is mainly due to higher availability, lower cost, and shorter time taken (Kwong and Yucel, 2003). Besides that CT scan is suitable for patients who have inserted with surgical clips or metallic fragments as artifacts may occur within the MRI process. CT scan is also much more suitable for patients who are claustrophobic as they may have irrational fear and cannot stay in a confined place for long period.

CT brain images are stored in the Digital Imaging and Communication in Medicine (DICOM) format which includes 12-bits of image and 4-bits of textual information. It is then further examined and analyzed by doctor for lesion detection. However, due to wide dynamic range of CT numbers among the CT brain images, the output of CT brain images may have lower contrast. Low contrast in CT brain images may not be appropriate to extract out the region of interest (ROI) for analyzation and diagnosis of ischemic stroke (Tan *et al.*, 2012a). In fact, normally out of this wide dynamic range, only a particular range of CT numbers is required to reveal the ROI for diagnosis of brain lesion. Hence, in order to visualize the CT brain images, window setting consists of two main parameters namely window width (W) and window center (C) is pre-performed (Hsieh, 2009).

The main objective of window setting is to stretch the range of Hounsfield Unit (HU) on 16-bits DICOM image into the normal 8-bits grayscale range which has the intensity range of 0 (dark region) to 255 (bright region). These windowing parameters are mainly tuned by the expertise for diagnosis of ischemic stroke. The most common parameters proposed and used is window width of 80 HU and window center of 40 HU. Consider an image with grayscale levels of $f(x,y)$, $f_{\min}$ is assigned to 0 and $f_{\max}$ is assigned to 255.

The relationship of window setting and the respective grayscale range is shown in Equation 1.

$$f(x,y) = \begin{cases} 0, & HU(x,y) < C - \frac{W}{2} \\ \frac{HU(x,y) - \left(C - \frac{W}{2}\right)}{W} \times f_{\max}, & C - \frac{w}{2} \leq HU(x,y) \leq C + \frac{W}{2} \\ f_{\max,} & HU(x,y) > C + \frac{W}{2} \end{cases} \quad (1)$$

In addition, good contrast in CT brain images is important for doctor to differentiate between the normal brain tissues and the hypodense area even with just a little density difference (Zohair and Ghazali, 2015). Nevertheless, the existing proposed window setting is not efficient for ischemic stroke detection, as it cannot highlight the hypodense area within the area of the brain.

In the past few decades, image processing technique has been widely used in various fields. Object recognition as one of the image processing technique is used to help visually impaired person in detecting generic object either indoor or outdoor environment (Jafri and Arabnia, 2013; Jafri *et al*., 2014). Moreover, a special computer input device for medically impaired users has also been developed (Arabnia, '92). Other than that, Jafri and Arabnia (2008) also proposed a better human recognition system with fusion of face and gait.

Image processing tools such as contrast enhancement techniques are widely used to improve the contrast on the CT brain images for ischemic stroke detection. There are various contrast enhancement techniques proposed to enhance the CT brain images and to aid the doctor on ischemic stroke detection. The most common proposed technique is the histogram equalization (HE). This technique is the easy and most simple way of improving the overall contrast of an input image. Basically, it is done by stretching the dynamic range of an input image to achieve a uniform distribution on the output image. However, there are some drawbacks from this HE technique. HE tends to be over enhanced in certain situation and causes unwanted noise existed (Sim *et al*., 2015). Noise on CT brain images can affect the ischemic stroke diagnosis process and may also lead to wrong interpretation.

In order to overcome the drawbacks of HE technique, various modified HE methods have been proposed by researchers. Brightness preserving bi-histogram equalization (BBHE) separates the original image into two sub-images by using the image mean gray level (Kim, '97). The main purpose of this method is to preserve the input brightness. Furthermore, dualistic sub-image histogram equalization (DSIHE) is also suggested. DSIHE has the same concept as BBHE by separating the input image into two sub-images. The only difference is that DSIHE uses Shannon's entropy value for histogram division instead of the mean value (Wang *et al*., '99; Sim *et al*., 2015). However, these two techniques may produce some artifacts depending on the difference of gray level distribution. BBHE and DSIHE also have lower efficiency in enhancing CT brain images as CT brain images are mainly occupied by the two extreme-levels which are intensity 0 (dark region) and 255 (bright region).

In order to eliminate the two extreme-levels which mainly occupied by background and also the skull on the CT brain images, another technique namely extreme-level eliminating histogram equalization (ELEHE) is proposed (Tan *et al*., 2012b). This ELEHE technique eliminates the two extreme gray levels before the equalization process is applied. ELEHE is used to stretch the other gray levels as much as possible while remaining the extreme gray levels at the same level. Nevertheless, ELEHE technique also tends to over enhance the normal brain tissue on CT brain images. The intensity of normal brain tissue becomes darker in some cases and very close to the hypodense area (lesion). Thus, this will definitely cause the analyzation process to be harder.

Another recently proposed contrast enhancement technique is the adaptive gamma correction with weighting distribution (AGCWD) (Huang *et al*., 2013). Instead of using the normal transfer function of HE for contrast enhancement, this AGCWD implements the gamma correction as the transfer function. AGCWD is widely implemented in grayscale and color images in recent years. However, due to the two extreme-levels on CT brain images which occupied more than half of the image pixel, AGCWD technique might produce some artifacts. Moreover, AGCWD tends to make the lesion area to be less intensified in some cases, and increases the overall brightness of the CT brain images which is unwanted in the examination process.

Thus, in this paper, a new contrast enhancement method for medical imaging based on the details of

ELEHE technique and AGCWD technique is formulated and named as gamma correction extreme-level eliminating with weighting distribution (GCELEWD). The difference on the use of ELEHE and AGCWD technique is carefully studied. Comparison on CT brain images for ischemic stroke detection is being done with few contrast enhancement approaches such as BBHE, DSIHE, ELEHE, AGCWD, and the new proposed technique. The performance of GCELEWD is also compared with some image quality assessment (IQA) model. CT brain images with various cases are used to test and confirm the performance of above techniques.

Problems Formulation

According to the statistic from World Health Organization (WHO), 15 million people suffer from stroke each year (Gund *et al.*, 2013). Thus, diagnosis and detection of ischemic stroke is very important as it could save a person's life. Since, it is much easier for doctor and hospitalist to diagnose the ischemic stroke cases from better enhanced CT brain images, contrast CT scan and contrast enhancement techniques as image processing tools are always chosen to improve the contrast. Intravenous contrast agent that implemented with contrast CT scan can also be injected into the patient to improve the overall contrast during the CT scan process. However, it may still cause some side effects such as severe pain or vomit (Andreucci *et al.*, 2014).

Due to the side effects from intravenous contrast agent for contrast CT scan, contrast enhancement technique as image processing technique is still the main and preferred approach for detection of ischemic stroke cases. Other than that this is always chosen as time and simplicity is considered. Hence, many contrast enhancement methods have been used to enhance the contrast of CT brain images and to highlight the hypodense area. Different modified HE techniques such as BBHE, DSIHE, and ELHE can be used to enhance the CT brain images. Nevertheless, as mentioned earlier, BBHE and DSIHE may produce some artifacts due to sudden changes of gray levels within the CT brain images.

Although ELEHE is able to stretch the overall gray levels of the CT images while maintaining the two extreme-levels, it may still over enhance the area of normal brain tissue. AGCWD which is depended on the transfer function of gamma correction can perform well in normal grayscale and color images, but slightly poor in CT brain images for ischemic stroke detection. AGCWD will cause some unwanted noise to exist on the CT brain images.

Contrast Enhancement Using Histogram Equalization

Histogram equalization (HE) is an easy and efficient way in improving the overall contrast of an image. HE has been widely applied in various fields with grayscale images, such as photography firm, semiconductor firm, and also medical related field. Basically, HE is implemented to pull the dynamic range of an original image (Gonzalez and Woods, 2008). Consider an input image f with T gray discrete levels, and the probability density function $pdf(f_T)$ is shown in Equation 2.

$$pdf(f_t) = \frac{n_t}{n}, \tag{2}$$

where $t = 0,1,2,...,T-1$, n_t represents the total number of pixels value at gray level f_t and $f_t \in \{f_0, f_1, f_2, ..., f_{T-1}\}$.

From this probability density function, the cumulative density function (CDF) can be calculated by Equation 3.

$$cdf(f_t) = \sum_{a=0}^{t} pdf(f_a), \tag{3}$$

where $cdf(f_{T-1}) = 1$ and the transform function of HE based on CDF can be represented in Equation 4.

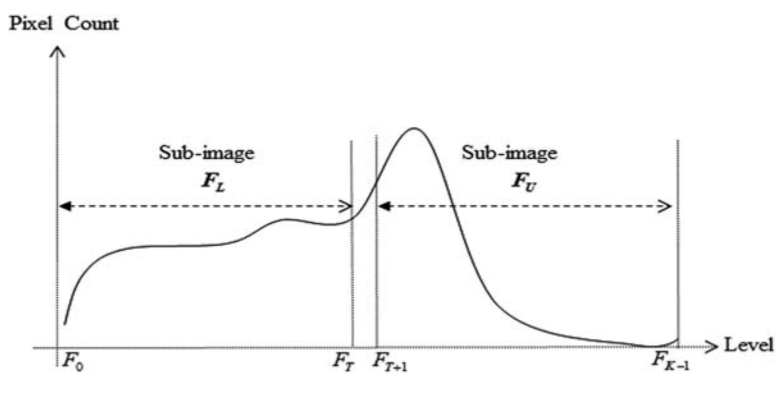


Fig 1. Sub-image histogram of brightness preserving bi-histogram equalization and dualistic sub-image histogram equalization.

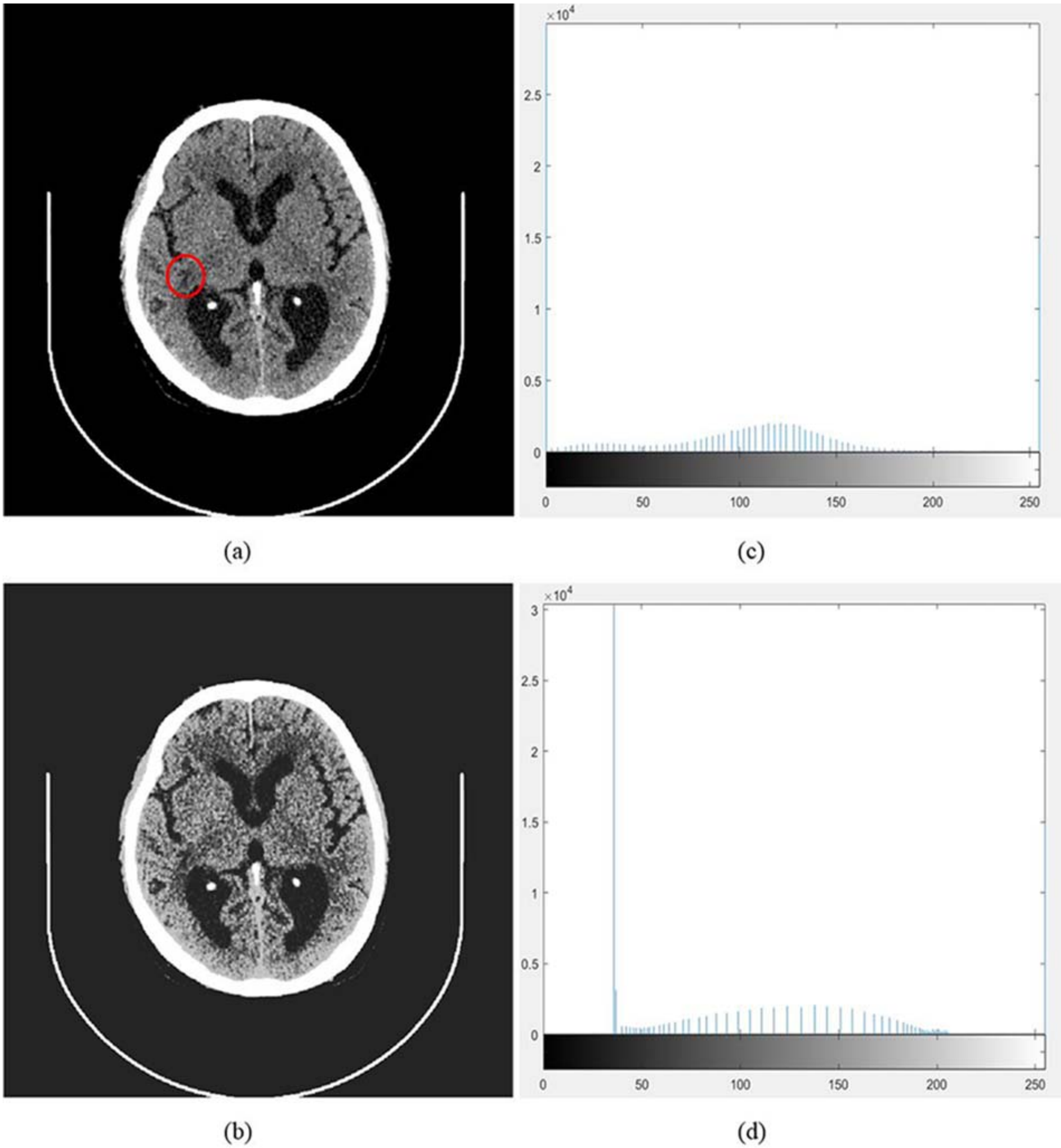


Fig 2. CT brain image (a) original image (b) image after brightness preserving bi-histogram equalization (c) histogram of original image (d) histogram of image after brightness preserving bi-histogram equalization.

$$TF(f) = [(f_{T-1} - f_0)cdf(f_t)] + f_0 \qquad (4)$$

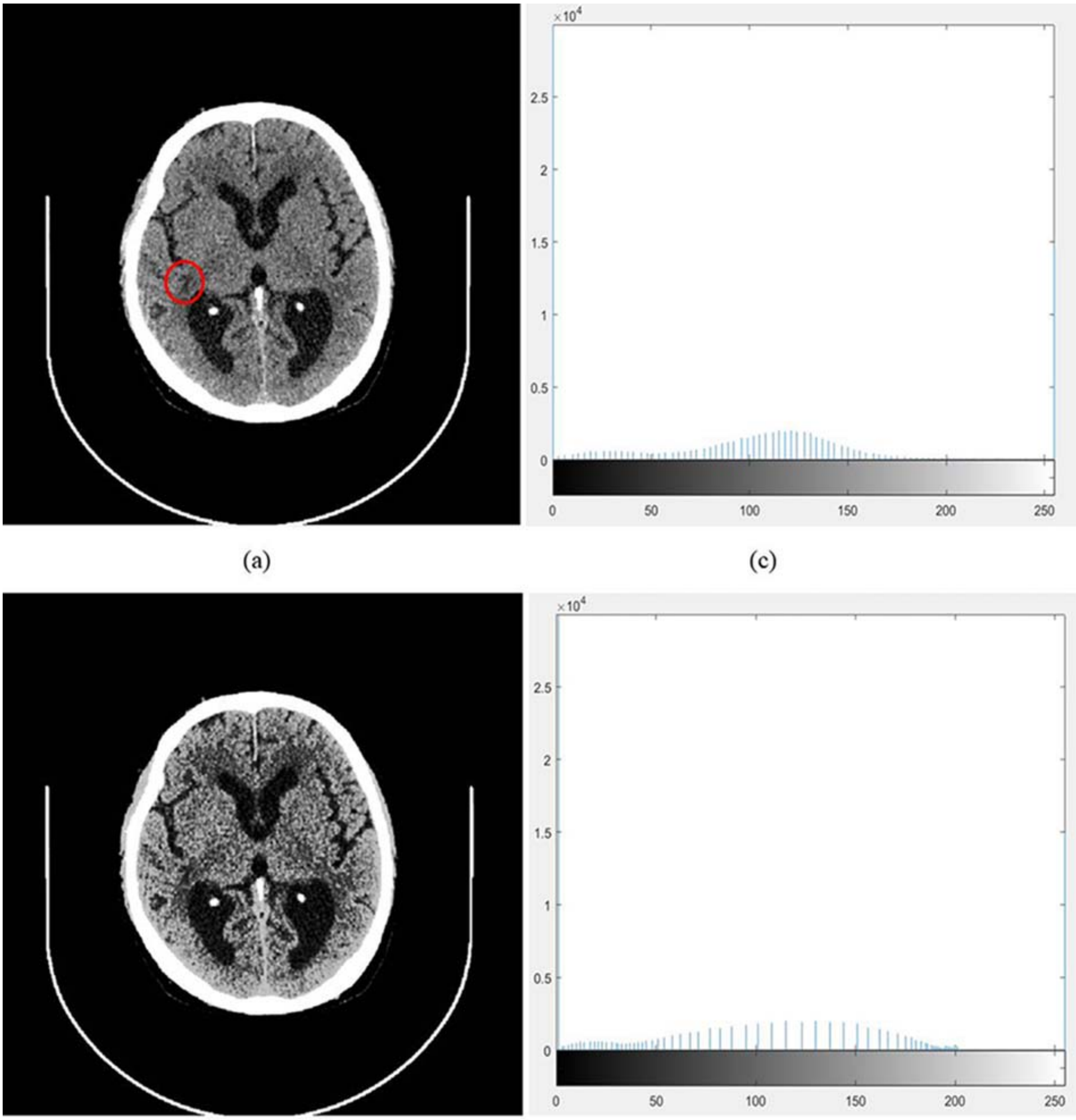
Since the dynamic range of an image is always normalized into the range of [0,1], the transform function for an output image, Z in Equation 4 can be simplified to Equation 5.

$$Z = TF(f) = cdf(f_t) \qquad (5)$$

Nevertheless, there are some drawbacks from HE technique. HE may over enhance some area and reduce the accuracy on ischemic stroke detection. This is due to noise has also been introduced to the CT brain images while HE is implemented. HE will also affect the mean brightness of the original image.

Contrast Enhancement Using Brightness Preserving Bi-Histogram Equalization

In order to preserve the mean brightness of the original image, brightness preserving bi-histogram equalization (BBHE) technique is proposed (Kim, '97). BBHE separates the original image histogram into two sub-images as shown in Figure 1.



(b) (d)

Fig 3. CT brain image (a) original image (b) image after dualistic sub-image histogram equalization (c) histogram of original image (d) histogram of image after dualistic sub-image histogram equalization.

Basically, BBHE is done by dividing the image histogram based on mean gray level. In another word, it is separated based on the mean intensity value of all pixels among the original image. The first sub-image histogram has the range of 0 to f_t, whereas the second sub-image histogram has the range of f_{t+1} to f_{T-1}. Hence, the mean brightness of the output image will be between the input mean and the middle gray level. For CT brain image, the overall performance of BBHE can be affected due to the two extreme-levels which contribute more than half of the total pixel values. As the disadvantage of BBHE technique is very dependent to the difference of gray level distribution, the CT brain image may not be proper enhanced. Example of the BBHE technique on CT brain image is shown in Figure 2.

From Figure 2, due to the mean calculation of BBHE technique, it can be seen that the background of the CT brain image after implementation of BBHE tends to be slightly brighter as compared to the original image.

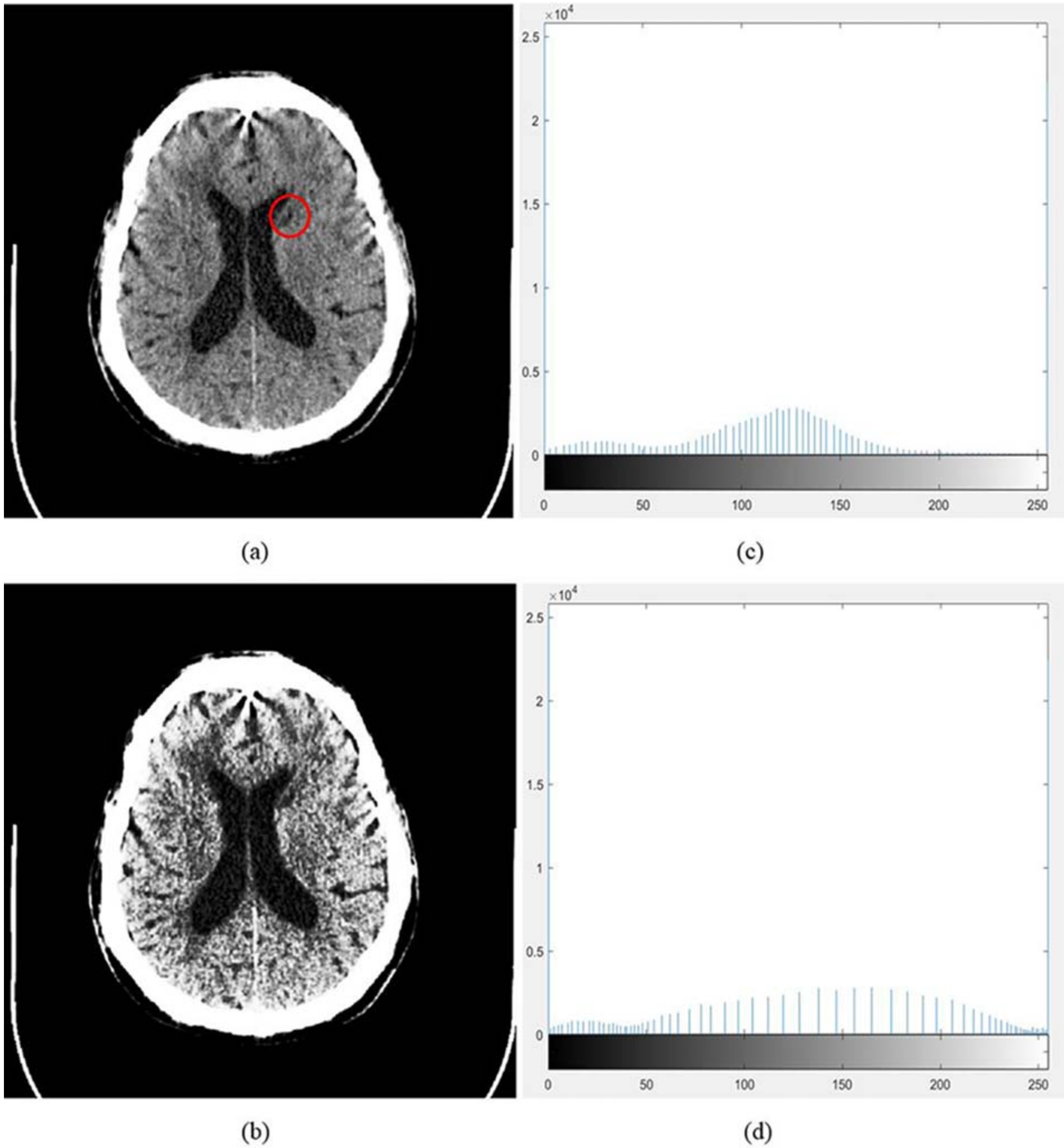


Fig 4. CT brain image (a) original image (b) image after extreme-level eliminating histogram equalization (c) histogram of original image (d) histogram of image after extreme-level eliminating histogram equalization.

Contrast Enhancement Using Dualistic Sub-Image Histogram Equalization

Dualistic sub-image histogram equalization (DSIHE) has exactly the same concept as BBHE by dividing the input image into two sub-images as shown in Figure 1. The only contra is DSIHE separated the images by targeting at the highest Shannon's entropy value of the output image instead of the mean gray levels (Wang *et al.*, '99). In short, DSIHE separates the input image into two sub-images with one dark and one bright. DSIHE technique may not cause a clear difference as compared to the original brightness of the input image, particularly when there are wide region with almost the similar intensity value.

Thus, DSIHE may not perform well in the CT brain images, since the window setting sets majority of the pixels to both of the extreme levels within the 8-bit grayscale range which are 0 and 255. In some CT brain images, BBHE and DSIHE technique tend to intensify the normal brain tissue as close to the hypodense area. This might cause wrong interpretation on the CT brain

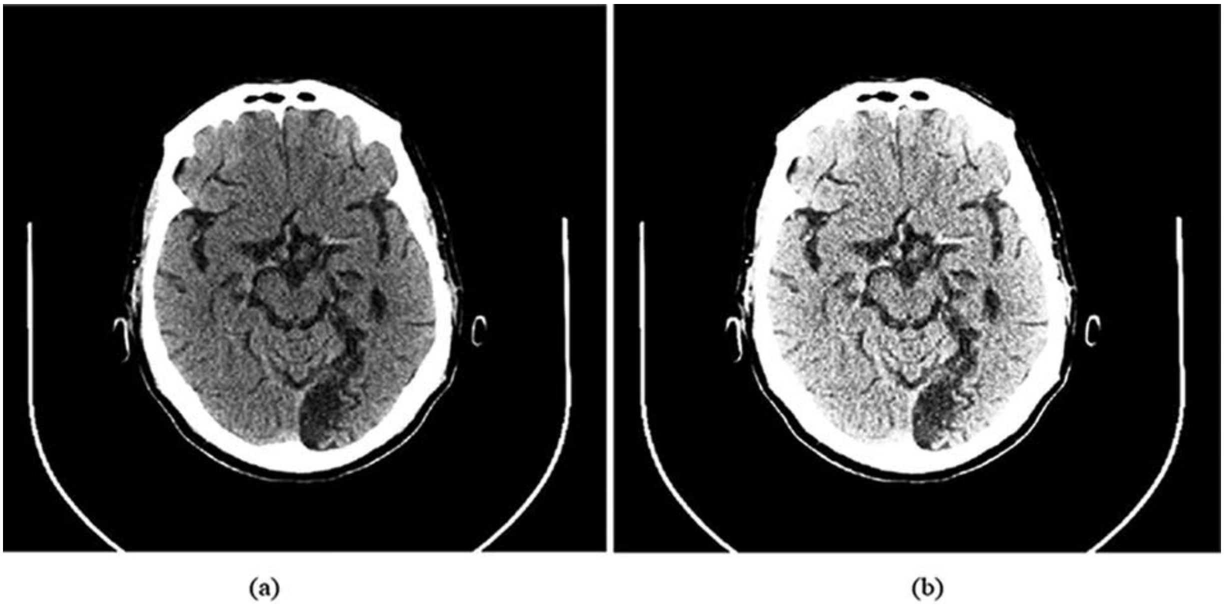


Fig 5. Washed-out effect on CT brain image (a) original image (b) image after adaptive gamma correction with weighting distribution.

images while the process of examination and analyzation is carried out. Example of DSIHE technique is shown in Figure 3.

Contrast Enhancement Using Extreme-Level Eliminating Histogram Equalization

By considering the extreme-levels with intensity 0 (dark region) and 255 (bright region) within the CT brain images which are occupied more than half of the total image pixels, another contrast enhancement technique for brain image namely extreme-level eliminating histogram equalization (ELEHE) is proposed. This is to ensure that there will not be any huge difference on the gray level distribution among the input image histogram.

Other than this, Tan *et al*. (2012a) proposed that the enhancement of the two extreme-levels is unnecessary as the two extreme-levels are already at the boundary of the grayscale range. In short, raising the minimum component at intensity 0 and reducing the maximum component at intensity 255 are not significant. Based on Equations 2 and 3, the cumulative density function (CDF) of ELEHE technique is simplified to Equation 6.

$$cdf(f_t) = \sum_{a=1}^{t-1} pdf(f_a), \qquad (6)$$

where probability density function (PDF) of intensity $f_0 = 0$, and $f_{T-1} = 0$ since the two extreme-levels are eliminated.

This is to ensure that the two extreme-levels are maintained, while stretching the other gray levels as much as possible, since the density difference on the other gray levels are smaller as compared to the boundary of the grayscale range on CT brain images. Nevertheless, this ELEHE technique is also able to make the diagnosis process to be harder as the intensity on the area of normal brain tissue also becomes darker as shown in Figure 4.

Contrast Enhancement Using Adaptive Gamma Correction With Weighting Distribution

Another recently proposed method is the adaptive gamma correction with weighting distribution (AGCWD) technique, which has slightly different way of enhancing image. This AGCWD is almost similar to the histogram equalization technique, but instead of using the normal transform function of HE, it implements a different changing parameter (γ) which is based on gamma correction technique. The most general

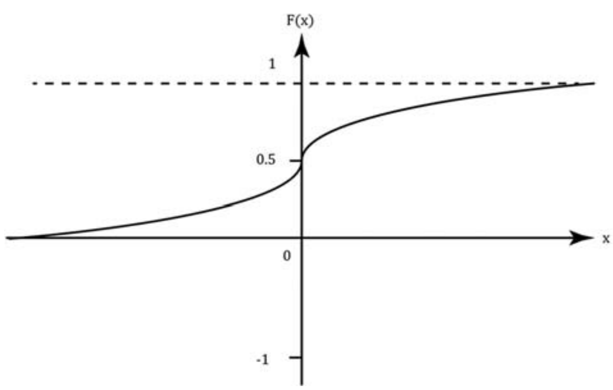


Fig 6. Sigmoid function represented by a “S” shape curve.

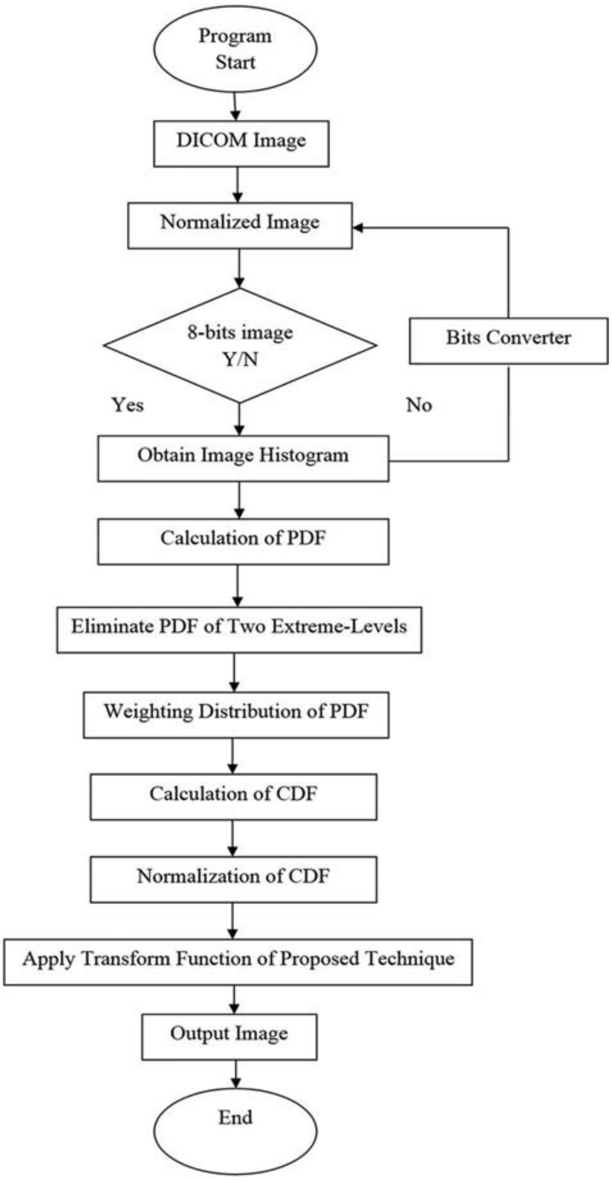


Fig 7. Algorithm flow chart for gamma correction extreme-level eliminating with weighting distribution technique.

form of the transform-based gamma correction technique (Huang *et al*., 2013) is shown in Equation 7.

$$T(f_t) = f_{T-1}\left(\frac{f_t}{f_{T-1}}\right)^{\gamma}, \quad (7)$$

where f_{T-1} is the maximum intensity of the 8-bit grayscale range, 255.

From Equation 7, it can be seen that the lower the gamma parameter (γ), the higher the changes on the contrast. Thus, calculation of cumulative density function (CDF) is included to prevent such cases and provide better and much more uniform contrast. Transform function of adaptive gamma correction (AGC) is shown in Equation 8.

$$T(f_t) = f_{T-1}\left(\frac{f_t}{f_{T-1}}\right)^{1-cdf(f_t)} \quad (8)$$

The advantage of this AGC function is that it can prevent from sudden changes on the high intensity value while continuously increased on the low intensity. Moreover, AGCWD technique also implements the use of weighting distribution function as to smoothen enhancement. Area within an image with high probability density function (PDF) will not get over enhanced, whereas the area with low PDF will not be less enhanced. The weighting distribution function (WDF) can be calculated as Equation 9.

$$pdf_{WDF}(f_t) = pdf_{\max}\left(\frac{pdf(f_t) - pdf_{\min}}{pdf_{\max} - pdf_{\min}}\right)^{\alpha}, \quad (9)$$

where α is the tuned parameter, $pdf_{\max}$ is the highest PDF value of the image histogram, and $pdf_{\min}$ is the lowest PDF value of image histogram.

The new cumulative density function (CDF) after the process of WDF is formulated as Equation 10.

$$cdf_{WDF}(f_t) = \sum_{t=0}^{t_{\max}} pdf_{WDF}(f_t) \quad (10)$$

Next, this CDF is normalized to the range of intensity 0–1. In another word, the purpose of normalization process is to standardize the gray level range. The new CDF equation is shown in Equation 11.

$$cdf_{\text{normalized}}(f_t) = \frac{cdf_{WDF}(f_t)}{\Sigma pdf_{WDF}(f_t)} \quad (11)$$

Based on Equation 8 and the WDF, the new gamma parameter (γ) is given in Equation 12.

$$\gamma = 1 - cdf_{\text{normalized}}(f_t) \quad (12)$$

Thus, the transform function of AGCWD technique can be calculated as Equation 13.

$$TF_{AGCWD}(f_t) = f_{T-1}\left(\frac{f_t}{f_{T-1}}\right)^{1-cdf_{\text{normalized}}(f_t)}, \quad (13)$$

where f_t represents normalized intensity value and f_{T-1} is the maximum normalized intensity value.

In overall, although AGCWD performs better in enhancing the normal grayscale and color images compared to HE technique, it still produces some artifact on CT brain images. Part of the image will be washed-out on the CT brain images due to the two extreme-levels. Example of the implementation of AGCWD technique is shown in Figure 5.

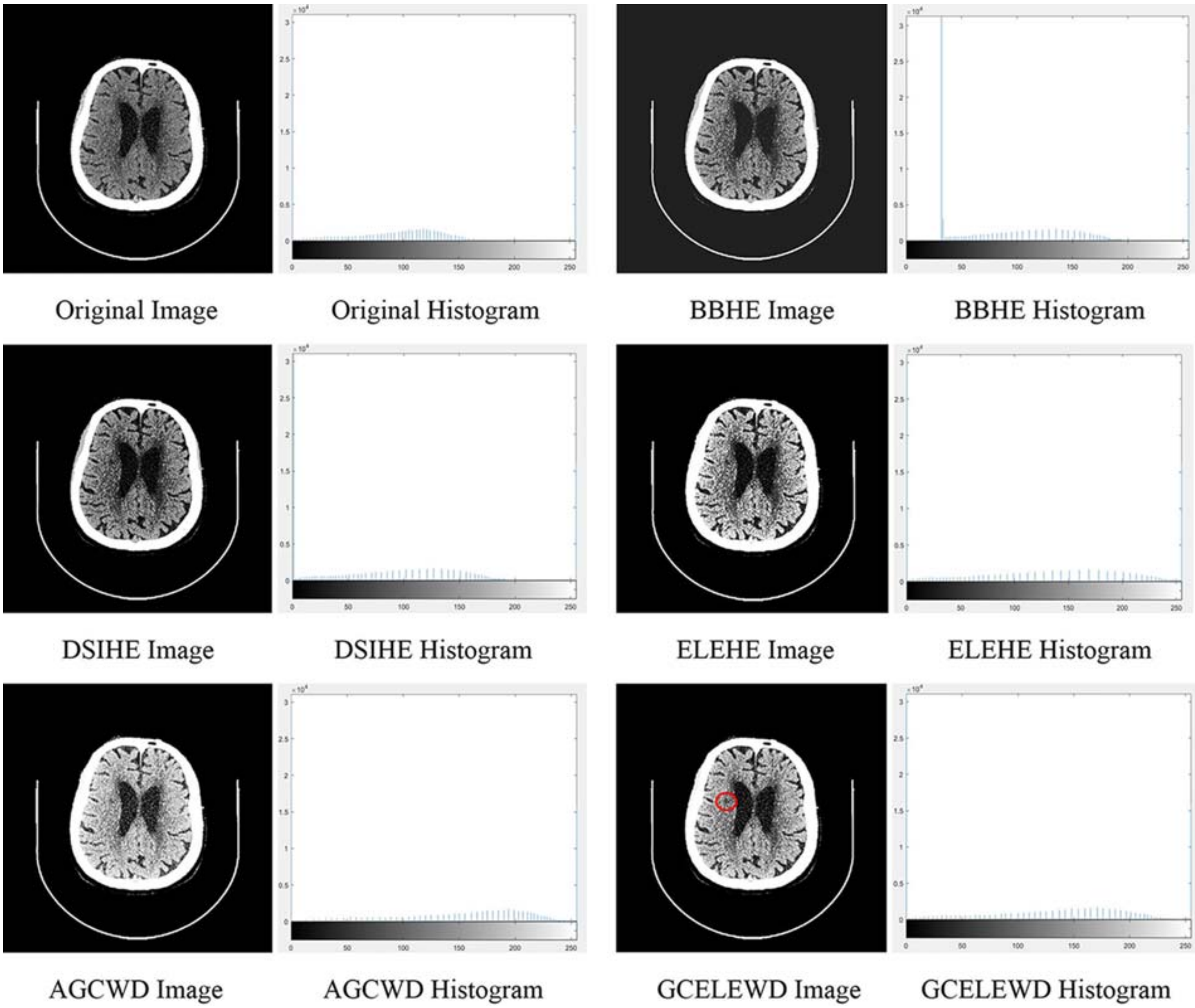


Fig 8. The implementation of various contrast enhancement techniques on CT brain image A with the image at left and respective histogram at right.

Contrast Enhancement Using Gamma Correction Extreme-Level Eliminating With Weighting Distribution

In this section, a new contrast enhancement method based on the details of extreme-level eliminating histogram equalization and adaptive gamma correction with weighting distribution is formulated. Basically, this is done by considering the drawbacks of both of the technique on enhancing the CT brain images. The new proposed gamma correction extreme-level eliminating with weighting distribution (GCELEWD) aims to help doctor and hospitalist with better detection of ischemic stroke and shorten the time taken for diagnosis process on CT brain image.

The details of the GCELEWD technique are derived as follows. Consider an original image i with K gray discrete levels, and the PDF, $pdf(i_K)$ is shown in Equation 14.

$$pdf(i_k) = \frac{n_k}{n}, \tag{14}$$

where $k = 0,1,2,\ldots,K-1$, n_t represents the total amount of pixels value at gray level i_k and $i_k \in \{i_0, i_1, i_2, \ldots, i_{K-1}\}$.

In order to eliminate the two extreme-levels on 8-bits CT brain images which occupied more than half of the image pixel, the PDF value of GCELEWD on the minimum intensity 0 and maximum intensity 255 is summarized as Equation 15.

$$pdf(i_0) = 0 \text{ and } pdf(i_{K-1}) = 0 \tag{15}$$

After the process of eliminating the extreme-levels, weighting distribution function (WDF) is used to smoothen the overall enhancement. Thus, the new PDF with WDF after eliminated the two extreme-levels is derived as Equation 16.

$$pdf_{WDF}(i_k) = pdf_{\max}\left(\frac{pdf(i_k) - pdf_{\min}}{pdf_{\max} - pdf_{\min}}\right)^{\propto} \tag{16}$$

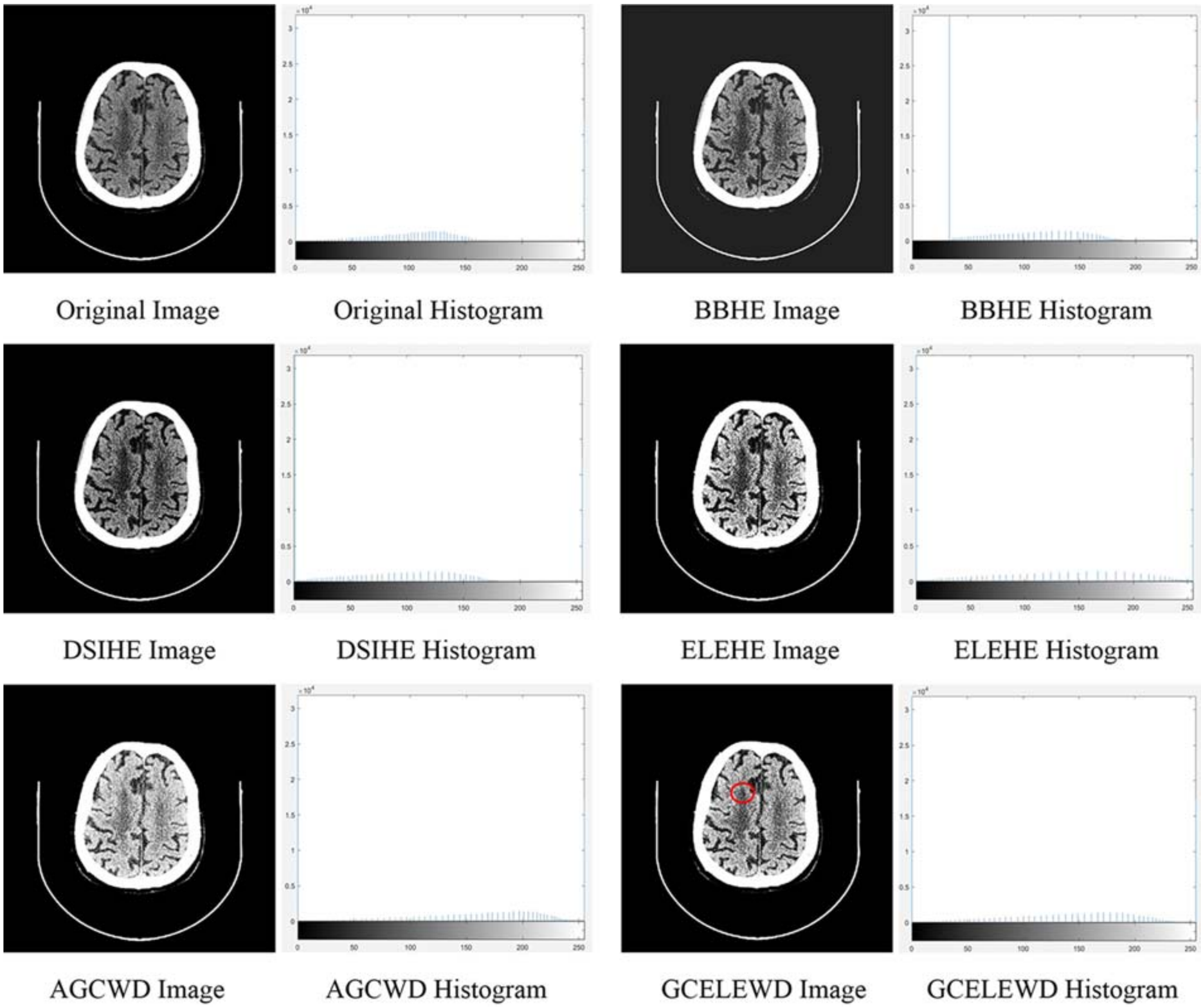


Fig 9. The implementation of various contrast enhancement techniques on CT brain image B with the image at left and respective histogram at right.

Besides that, in order to normalize the non-linear function of weighting distribution probability density function in Equation 16, the parameter alpha (α) is obtained from the derivation of sigmoid function. Sigmoid function is normally represented by a continuous nonlinear activation function (Saruchi, 2012) as shown in Figure 6.

It is also used to ensure that the PDF can be normalized accordingly with a smooth continuous function. The parameter alpha (α) can be defined as Equation 17.

$$\alpha = \max\left\{\frac{1}{\left(1 + e^{-pdf(i_k)}\right)}\right\} = 0.50 \tag{17}$$

Thus, the parameter alpha, α is set to 0.50 for all cases according to the sigmoid function in Equation 17.

The cumulative density function (CDF) of this new proposed technique can be simplified as shown in Equation 18.

$$cdf_{WDF}(i_k) = \sum_{k=1}^{k-1} pdf_{WDF}(i_k) \tag{18}$$

The new CDF in Equation 18 can be normalized from intensity level of 0–255 to the range of intensity level of 0–1 and it is given in Equation 19.

$$cdf_{\text{norm}}(i_k) = \frac{cdf_{WDF}(i_k)}{\Sigma pdf_{WDF}(i_k)} \tag{19}$$

Considering the pros and cons with the transform function of histogram equalization and the gamma correction on various CT brain images with ischemic stroke cases, GCELEWD technique is proposed. GCELEWD technique could eliminate the artifact such as noise around the skull and wash-out effect on the brain area. It is also used to prevent from normal brain tissues on the CT brain image being intensified as this could make the process to detect on ischemic stroke to be harder and more confusing. The new proposed

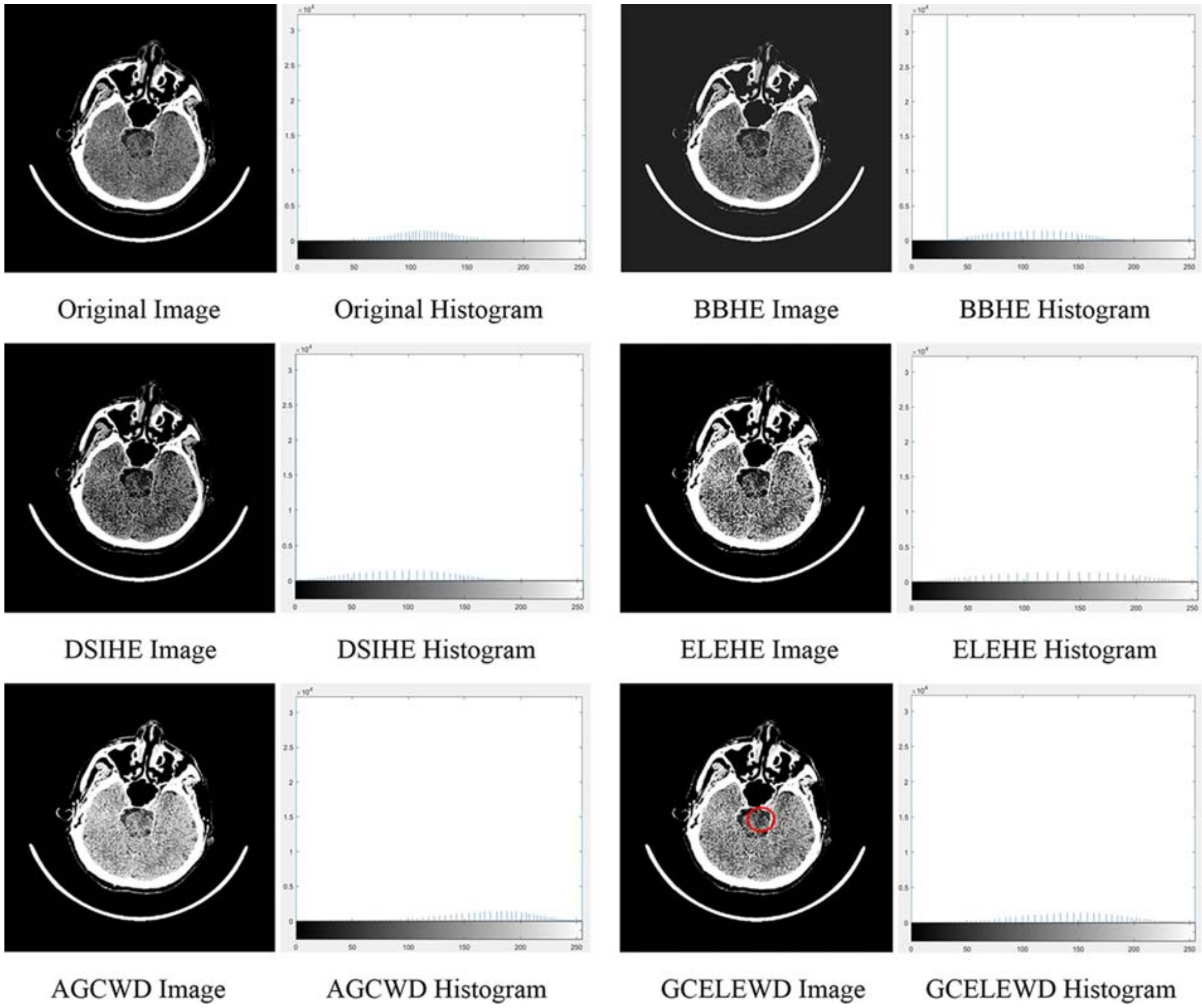


Fig 10. The implementation of various contrast enhancement techniques on CT brain image C with the image at left and respective histogram at right.

transform function derived from transform function of histogram equalization and gamma correction is defined from Equations 20 to 24. In ELEHE technique, the cumulative density function (CDF) is directly applied to the transform function of histogram equalization, whereas for this new proposed GCELEWD, CDF with WDF is implemented.

$$TF_{HE}(i_k) = [(i_{K-1} - i_0)cdf_{\text{norm}}(i_k)] + i_0 \tag{20}$$

$$TF_{GC}(i_k) = i_{K-1}\left(\frac{i_k}{i_{K-1}}\right)^{1-cdf_{\text{norm}}(i_k)} \tag{21}$$

$$STF(i_k) = TF_{HE}(i_k) + TF_{GC}(i_k) \tag{22}$$

$$= i_{K-1}\left[cdf_{\text{norm}}(i_k) + \left(\frac{i_k}{i_{K-1}}\right)^{1-cdf_{\text{norm}}(i_k)}\right] + i_0[1 - cdf_{\text{norm}}(i_k)]$$

$$TF_{GCELEWD}(i_k) = \frac{STF(i_k)}{2} \tag{23}$$

$$TF_{GCELEWD}(i_k) = \frac{i_{K-1}\left[cdf_{\text{norm}}(i_k) + \left(\frac{i_k}{i_{K-1}}\right)^{1-cdf_{\text{norm}}(i_k)}\right] + i_0[1 - cdf_{\text{norm}}(i_k)]}{2}, \tag{24}$$

where i_k is the normalized intensity level, i_0 is the minimum normalized intensity which is 0 and i_{K-1} is the maximum normalized intensity which is equivalent to 1.

Thus, a new general transform function of contrast enhancement using GCELEWD technique can be simplified to Equation 25. This transform function can be applied to map the gray levels in the original image with its respective new gray level in the output image. GCELEWD technique is applicable for detection on any ischemic stroke cases in CT brain images.

$$TF_{GCELEWD}(i_k) = \frac{cdf_{\text{norm}}(i_k) + {i_k}^{1-cdf_{\text{norm}}(i_k)}}{2}, \tag{25}$$

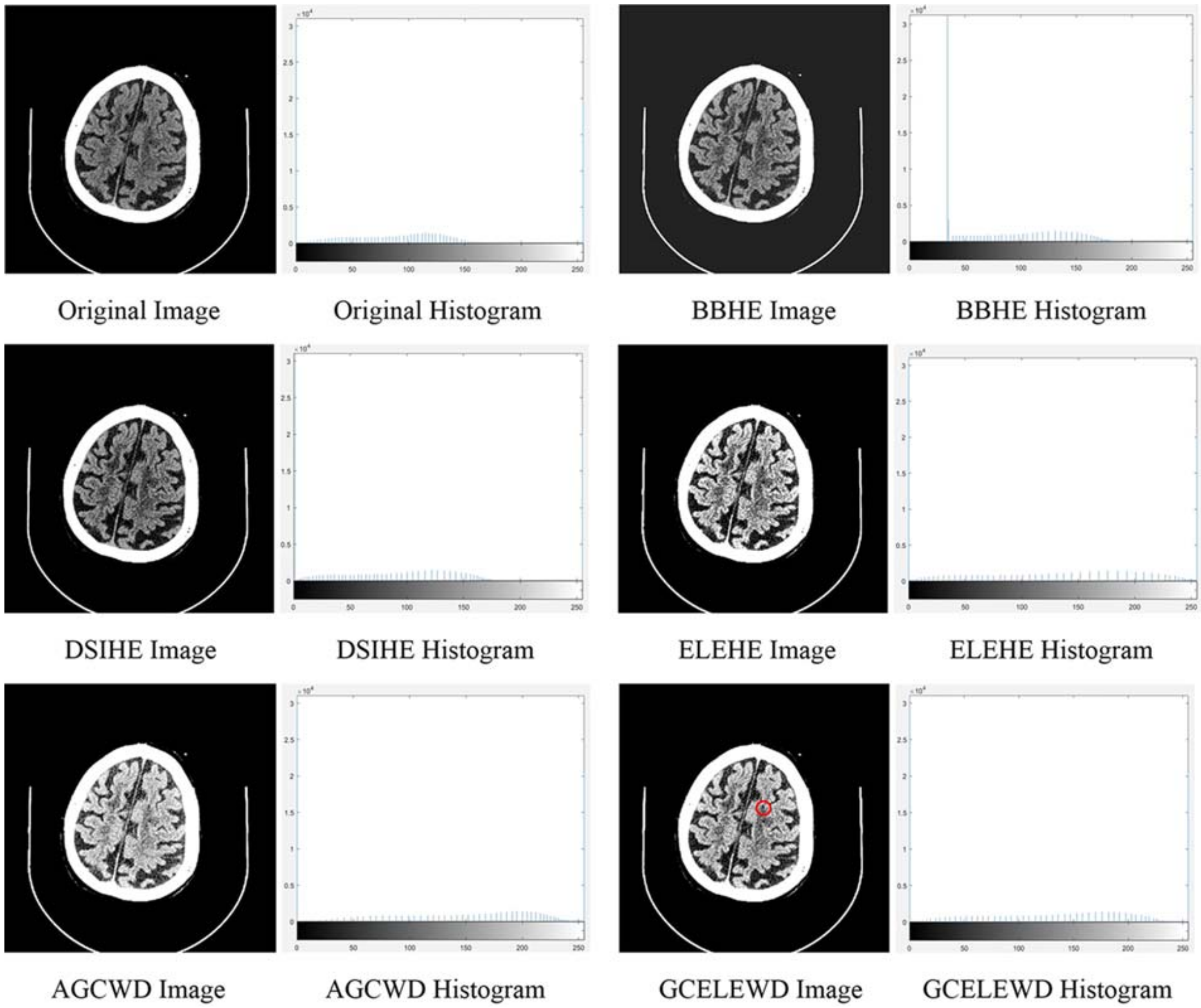


Fig 11. The implementation of various contrast enhancement techniques on CT brain image D with the image at left and respective histogram at right.

where $k = 0,1,2,\ldots,K-1$, i_k is the normalized intensity level and cdf_{norm} is the normalized cumulative density function of original image.

Block Diagram of the New Formulated Method: GCELEWD

Figure 7 shows the block diagram of the new formulated method.

Results and Discussions

To evaluate the proposed contrast enhancement GCELEWD technique, various CT brain images with different cases have been tested. The sizes of the CT brain images are all in the dimension of 512×512. The gamma extreme-level eliminating with weighting distribution (GCELEWD) technique, brightness preserving bi-histogram equalization (BBHE) technique, dualistic sub-image histogram equalization (DSIHE) technique, extreme-level eliminating histogram equalization (ELEHE) technique, and adaptive gamma correction with weighting distribution (AGCWD) technique are implemented with some generated results. Figures 8–12 show some of the CT brain images with different size and location of lesion.

It is very challenging for hospitalists to diagnose on ischemic stroke on some CT brain images especially when the hypodense area is hardly seen. Thus, in order to conquer the image contrast issue, various image contrast enhancement methods is used to apply on the CT brain images. From Figures 8 to 12, it can be seen that the intensity of normal brain tissue around the lesion for BBHE, DSIHE, and ELEHE become darker and closer to the intensity of hypodense area. Thus, it is very difficult for ischemic stroke detection. In addition, AGCWD technique tends to cause some noise, over enhancement, and little bit of washed-out effect. The new proposed GCELEWD technique outperforms the four existing techniques in terms of ischemic stroke detection, as the hypodense area could be intensified

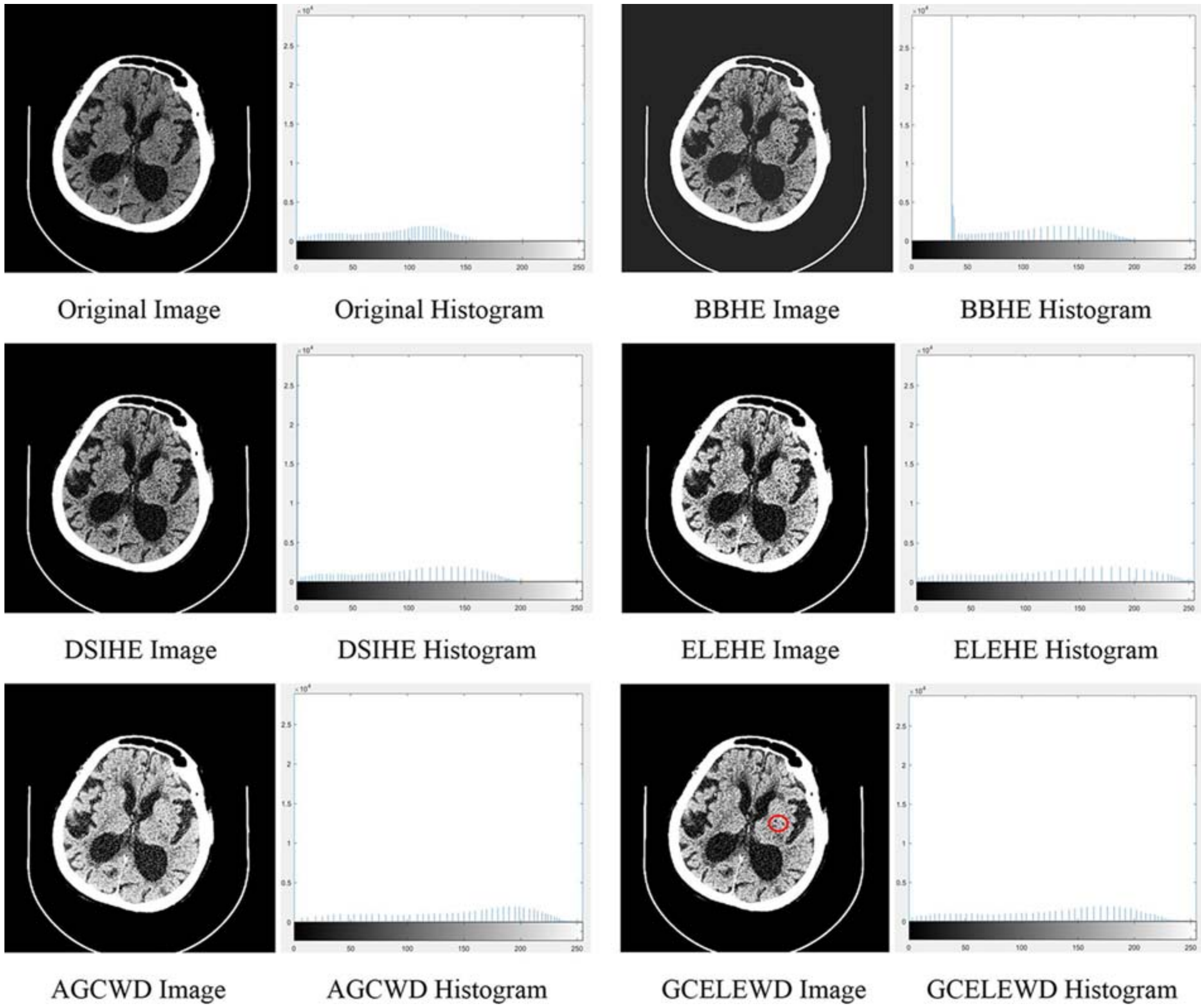


Fig 12. The implementation of various contrast enhancement techniques on CT brain image E with the image at left and respective histogram at right.

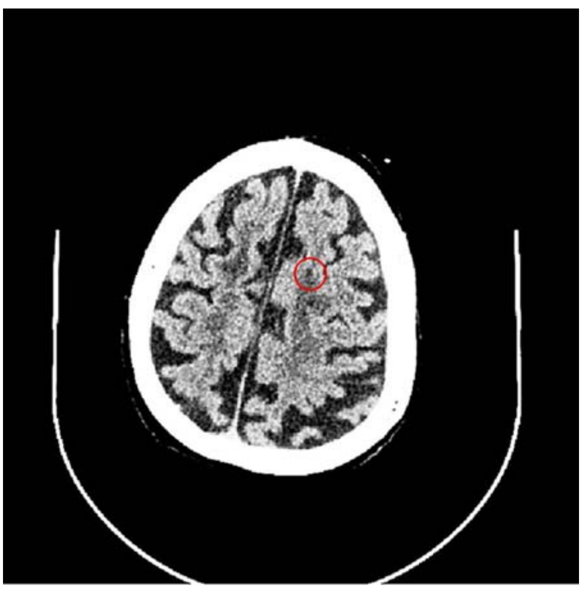


Fig 13. GCELEWD enhanced of CT brain image D.

TABLE I Comparison on peak signal to noise ratio and structure similarity index of various contrast enhancement techniques for CT brain image A, CT brain image B, CT brain image C, CT brain image D, and CT brain image E

CT brain image	A	B	C	D	E
BBHE					
PSNR	18.9714	18.7252	18.9014	18.5434	18.0535
SSIM	0.2514	0.2404	0.2371	0.2611	0.2953
DSIHE					
PSNR	31.4089	30.3474	28.3189	33.89	28.9832
SSIM	0.8852	0.8823	0.8753	0.8939	0.8953
ELEHE					
PSNR	22.6235	23.3871	24.4515	21.6888	20.4074
SSIM	0.9571	0.9587	0.9539	0.9598	0.9481
AGCWD					
PSNR	19.5288	20.0266	20.6279	19.4839	18.4181
SSIM	0.9617	0.9673	0.9637	0.9615	0.9435
GCELEWD					
PSNR	22.857	23.5218	25.1517	22.091	20.9231
SSIM	0.9722	0.9754	0.9779	0.9697	0.9605

TABLE II Comparison on measure of enhancement by entropy of various contrast enhancement techniques for CT brain image A, CT brain image B, CT brain image C, CT brain image D, and CT brain image E

	EMEE					
CT brain image	Original	BBHE	DSIHE	ELEHE	AGCWD	GCELEWD
A	4.1086	0.1609	0.6124	4.1288	2.7671	4.126
B	4.001	0.1538	0.5967	4.029	2.7001	4.0267
C	3.7955	0.1461	0.5606	2.5512	2.5582	2.5532
D	3.9043	0.147	0.5812	3.9284	2.6319	3.9254
E	4.4806	0.1609	0.6654	4.5228	3.0318	4.5192

(highlighted), and the whole image is greatly enhanced. Figure 13 shows the results of CT brain image D after enhancement by GCELEWD technique.

Furthermore, image quality assessment (IQA) modules such as peak signal to noise ratio (PSNR), structure similarity index (SSIM), and measure of enhancement by entropy (EMEE) are also used to test on the performance of BBHE, DSIHE, ELEHE, AGCWD, and the proposed GCELEWD technique. The results are tabulated in Tables I and II, respectively.

From Table I, DSIHE shows the highest peak signal to noise ratio (PSNR) value for all the CT brain images, followed by the GCELEWD technique, ELEHE technique, AGCWD technique, and BBHE technique. Nevertheless, in terms of visualization and detection of ischemic stroke on CT brain image, it will be helpful if it could stress out the abnormal region on the image. Hence, the image produced by DSIHE is too dark and may not able to highlight the exact location of lesion. In addition, the background of BBHE enhanced image also tends to be brighter. Moreover, GCELEWD technique yields the highest structure similarity index (SSIM) value compared to the four existing techniques. In another word, GCELEWD technique provides better luminance and contrast.

From Table II, it can be clearly seen that ELEHE has the highest measure of enhancement by entropy (EMEE) value for most of the CT brain images except CT brain image C. High EMEE value normally means high level of enhancement obtained. Nonetheless, too much of enhancement in ELEHE also may cause the intensity on the area of normal brain tissue become darker, which is unwanted in actual stroke diagnosis process. On the other hand, original image has the highest EMEE value for CT brain image C, followed by AGCWD, GCELEWD, ELEHE, DSIHE, and BBHE technique. Besides that there are only small difference of EMEE value between the ELEHE and GCELEWD technique for most of the CT brain images.

Conclusion

Contrast in CT brain image is very important to highlight the hypodense area particularly for ischemic stroke detection. In this paper, a new proposed contrast enhancement technique namely gamma correction extreme-level eliminating with weighting distribution (GCELEWD) for CT brain image is developed. This new technique is capable to intensify the hypodense area and greatly enhance the contrast of the whole CT brain image. GCELEWD technique outperforms the rest of the four existing techniques in terms of visualization of ischemic stroke detection and image quality assessment (IQA) module. Additionally, GCELEWD technique provides clear visualization for ischemic stroke detection and it can be used to aid doctor for faster diagnosis process.

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