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CONTRAST ENHANCEMENT BRAIN INFARCTION IMAGES USING SIGMOIDAL ELIMINATING EXTREME LEVEL WEIGHT DISTRIBUTED HISTOGRAM EQUALIZATION

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Abstract. *In modern days, Non-Contrast Computed Tomography (NCCT) is one of the imaging modalities. It performs well in detecting bleeding and tumors in brain images, but less effective in brain infarction diagnosis. Therefore, a contrast enhancement technique known as Sigmoidal Eliminating Extreme Level Weight Distributed Histogram Equalization (SigEELWDHE) is introduced in this paper. It is to improve the contrast of NCCT brain images for better infarction diagnosis. The SigEELWDHE starts to enhance NCCT brain images by sigmoidal filtering function through point processing. Then, the filtered image is then enhanced with Eliminating Extreme Level Weight Distributed Histogram Equalization (EELWDHE) to produce final enhanced image. This method helps to eliminate the maximum and minimum grey level of the image. It modifies histogram of the image using weighting distribution function. 300 NCCT brain images with infarctions are used to evaluate the results of SigEELWDHE through visualization evaluation and Image Quality Assessments (IQA) models. In addition, the performance of the SigEELWDHE is also compared with Brightness preserving Bi-Histogram Equalization (BBHE), Dualistic Sub-Image Histogram Equalization (DSIHE), Recursive Sub-Image Histogram Equalization (RSIHE), Adaptive Gamma Correction with Weighting Distribution (AGCWD), and Extreme-Level-Eliminating Histogram Equalization (ELEHE). The results show that the SigEELWDHE produces better contrast and visualization quality than existing methods.*

Keywords: Contrast enhancement, Histogram weighting distribution, Brain infarction, Histogram equalization, Sigmoidal filtering, Extreme level elimination, Non-contrast computed tomography

1. **Introduction.** Brain infarction is one of the brain lesions which can cause stroke. It is usually caused by blood clots from other parts of the body. Most of evaluations on brain infarction depend on medical imaging modalities. In modern days, Non-Contrast Computed Tomography (NCCT) is one of the best known methods for initial brain infarction evaluation. This is due to its wide availability, low cost, short scan time, and high reliability [1,2]. At the same time, NCCT is sensitive in differentiating types of strokes. Thus, it is able to identify bleeding and tumor in brain clearly [3]. However, the performance of infarction detection is still less effective, especially early infarction. Therefore, this paper introduces a new contrast enhancement method to enhance NCCT brain images and improve the performance. Figure 1 shows that brain infarctions in an NCCT brain image are marked by arrows. Infarcts in NCCT brain image have lower pixel value or appeared darker than normal healthy brain soft tissue.

An NCCT image is stored as a 16-bit greyscale image in the format of Digital Imaging and Communications in Medicine (DICOM) [4,5]. 4-bit of DICOM image is used to store

FIGURE 1. A Non-Contrast Computed Tomography (NCCT) brain image with infarcts shown by the red colored arrows

all related medical information in textual form and the rest 12-bit stores image data [6]. Hounsfield Unit (HU) is introduced by a researcher named Hounsfield in 1992 [7]. This unit is mainly used for electronic medical images to visualize and determine the different parts of human body in quantitative values and also their range. Equation (1) shows the conversion between pixel value and HU unit of an NCCT brain image [8,9]. The selected NCCT brain image is the input image (IM) in Equations (1) and (2).

$$P(i,j) = \frac{IM(i,j) - RI}{RS} \tag{1}$$

where $P(i,j)$ is the pixel value of selected NCCT image at position of (i,j); $IM(i,j)$ is the HU value of selected NCCT brain image at position of (i,j); RS is the rescale slope; RI is the rescale intercept. Both of them are constant values [10].

According to Hsieh [11] and Romans [12], there are 2 important parameters in windowing setting and they are Window Center (WC), and Window Width (WW). WC value determines the displayed structure on the greyscale images, while WW controls the contrast of greyscale images [13]. Equation (2) shows the windowing formula to convert an NCCT brain image into a greyscale image (G), based on the values of WC and WW.

$$G(i,j) = \begin{cases} G_{\min}, & IM(i,j) < W_{\min} \\ \dfrac{IM(i,j) - W_{\min}}{WW}, & W_{\min} < IM(i,j) < W_{\max} \\ G_{\max}, & IM(i,j) > W_{\max} \end{cases} \tag{2}$$

where $IM(i,j)$ is the HU value of selected NCCT brain image at position of (i,j); $G(i,j)$ is the greyscale level of selected NCCT brain image after windowing technique is applied; $W_{\max}$ is the maximum window value in HU as shown in Equation (3); $W_{\min}$ is the minimum window value in HU as shown in (4); $G_{\min}$ is the minimum greyscale level of selected NCCT brain image; $G_{\max}$ is the maximum greyscale level of selected NCCT brain image.

$$W_{\max} = WC + \frac{WW}{2} \tag{3}$$

$$W_{\min} = WC - \frac{WW}{2} \tag{4}$$

However, even after using windowing method, the contrast of infarcts in the greyscale NCCT brain image is enhanced insufficiently. This is due to non-linear characteristics of NCCT brain image. Therefore, post-processing on the image is required and contrast enhancement method is implemented. Most of prior contrast enhancement methods are used for normal greyscale images, such as Brightness preserving Bi-Histogram Equalization (BBHE), Dualistic Sub-Image Histogram Equalization (DSIHE), Recursive Sub-Image Histogram Equalization (RSIHE), and Adaptive Gamma Correction with Weighting Distribution (AGCWD) approaches. Currently, there are only a few contrast enhancement techniques developed specifically for NCCT brain images in infarction diagnosis. Extreme-Level-Eliminating Histogram Equalization (ELEHE) is one of the best known contrast enhancement techniques specifically designed to enhance NCCT images.

However, according to the performances of these existing contrast enhancement techniques as mentioned, it is found that these approaches are yet to be improved. Therefore, a novel contrast enhancement technique, known as Sigmoidal Eliminating Extreme Level Weight Distributed Histogram Equalization (SigEELWDHE) technique is proposed. The proposed technique aims to generate better contrast enhanced output image in terms of entropy, PSNR and SSIM values as well as the visual assessment. The performance of the SigEELWDHE is evaluated on 300 NCCT brain images and benchmarked with existing approaches. All summary descriptions about existing approaches will be further discussed in the next section.

2. **Problem Statement and Preliminaries.** In this paper, there are 5 prior approaches that are used for comparison with the SigEELWDHE in performance evaluations. These 5 prior approaches are Brightness preserving Bi-Histogram Equalization (BBHE), Dualistic Sub-Image Histogram Equalization (DSIHE), Recursive Sub-Image Histogram Equalization (RSIHE), Extreme-Level-Eliminating Histogram Equalization (ELEHE), and Adaptive Gamma Correction with Weighting Distribution (AGCWD).

Kim proposed Brightness preserving Bi-Histogram Equalization (BBHE) method to enhance greyscale images. The results show that it preserves more brightness of greyscale images than normal histogram equalization method [14]. In Figure 2, it shows that BBHE technique separates the image into 2 sub-images. The sub-images are separated according to the grayscale intensity. In order to find the threshold value separating the two sub-images, this method determines the threshold value by using the mean of greyscale values

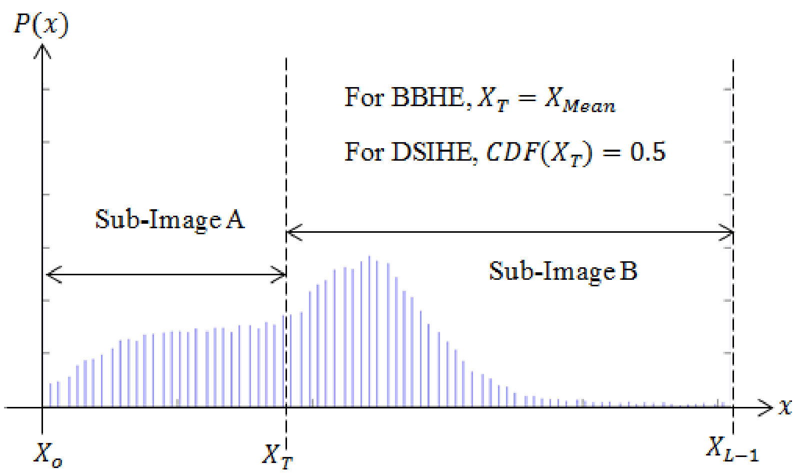

FIGURE 2. An illustration showing how threshold values are calculated for the BBHE and DSIHE techniques separating an image into two sub-images based shown on a greyscale intensity histogram

of the input image. Thus, in Figure 2, the threshold value is equal to the mean value, $X_T = X_{Mean}$. Then, both sub-images are enhanced with histogram equalization method independently before they are combined again as an output image.

The algorithm of Dualistic Sub-Image Histogram Equalization (DSIHE) method is similar to BBHE method. As shown in Figure 2, the DSIHE method also separates the original image into 2 sub-images according to the grayscale intensity. The only difference is the formula used to determine the threshold value. This threshold value can be gained by calculating the greyscale level that produces maximum entropy value of Shannon, which is 0.5 [15]. The formula is shown in Figure 2, where the threshold value $CDF(X_T)$ is 0.5. Results show that it enhances the contrast of a greyscale image and performs better than BBHE method. Figure 2 shows the summarization of the algorithms of these 2 methods using an image histogram, given that the image has x greyscale level, with the range of $[X_0, X_1, \ldots, X_{L-1}]$, and X_T, is the threshold value that is used to segment 2 sub-images. Each x greyscale level has pixel counts of $P(x)$.

Recursive Sub-Image Histogram Equalization (RSIHE) method enhances greyscale image by segmenting the input greyscale image into multiple sub-images through maximum entropy separation recursively [16]. The number of sub-images is based on the sequence of 2^r, where r is the iteration numbers. Figure 3 shows the algorithm of RSIHE method with iterations of $r = 2$ using an image histogram. This figure assumes that r is equal to 2, and then 4 sub-images will be produced, with 2 iterations of maximum entropy separation. First iteration is done by segmenting the input greyscale image into 2 sub-images: image A, and image B with threshold value, and X_T is then calculated from maximum entropy calculation of input greyscale image. This step is similar to the DSIHE method. Then, in the next iteration, each sub-image is further segmented into 2 sub-images with threshold value that is computed from maximum entropy calculation of each sub-image.

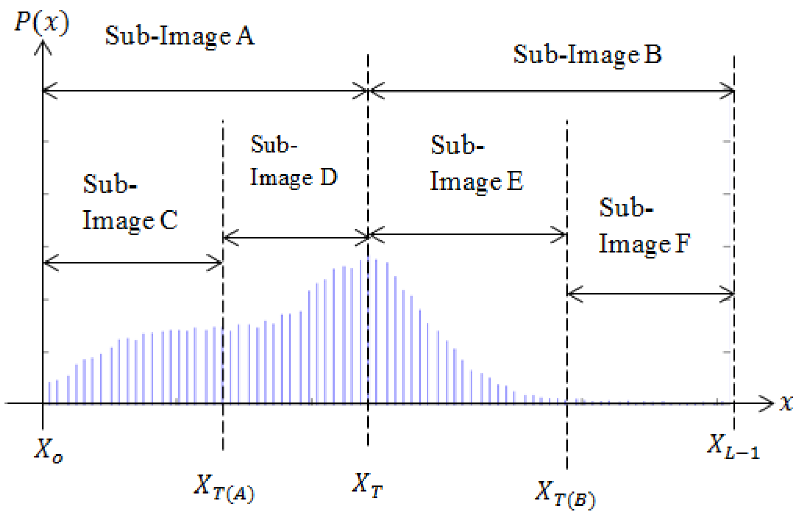

FIGURE 3. Summary of RSIHE method using an image histogram with iterations of $r = 2$

Tan et al. proposed Extreme-Level-Eliminating Histogram Equalization (ELEHE) method to enhance the visibility of infarctions of selected NCCT brain image [17]. Assuming that the image is preprocessed with windowing method and the generated greyscale image has x greyscale level, $[X_0, X_1, \ldots, X_{L-1}]$. ELEHE method eliminates the extreme greyscale level of input windowed greyscale image, by assuming that probability density functions of input image at greyscale level of X_0 and X_{L-1} are equal to 0. Next, cumulative distribution function of this new probability density function is calculated. The last step is to enhance the input image using the histogram equalization function and reallocate the greyscale level of input image to produce the output image.

The last prior contrast enhancement method is AGCWD method, which was introduced by Huang et al. in 2013 [18]. This method enhances input greyscale image through 3 main steps. First step is to analyze the histogram in terms of statistical and probability terms. Next step is to reduce or avoid generation of artifacts. Huang et al. suggest redistributing greyscale level of input greyscale image, using weighting distribution function. The last step is to enhance the contrast of input greyscale image through gamma correction function, instead of histogram equalization function. This is due to capability of gamma correction to produce smooth curve of cumulative distribution function graph.

3. **Control Design.** The algorithm of Sigmoidal Eliminating Extreme Level Weight Distributed Histogram Equalization (SigEELWDHE) technique is shown in Figure 4. The algorithm starts with selection of an NCCT brain image and then applies windowing method to producing a respective greyscale image of brain structure with soft tissue using Equations (2) to (4) [19,20]. It is then based on the values of WW and WC to be stored in textual information of selected NCCT brain image. After that, the brain structure is cropped out from generated greyscale image. One of the reasons is to reduce background pixel values to be processed since brain structure with soft tissue is the Return of Interest (ROI) in this paper. Another reason is histogram of cropped greyscale image. It helps to provide better visualization and observations. Figure 5 shows the visualization and respective histograms of selected NCCT brain image, greyscale image after windowing, and cropped greyscale image.

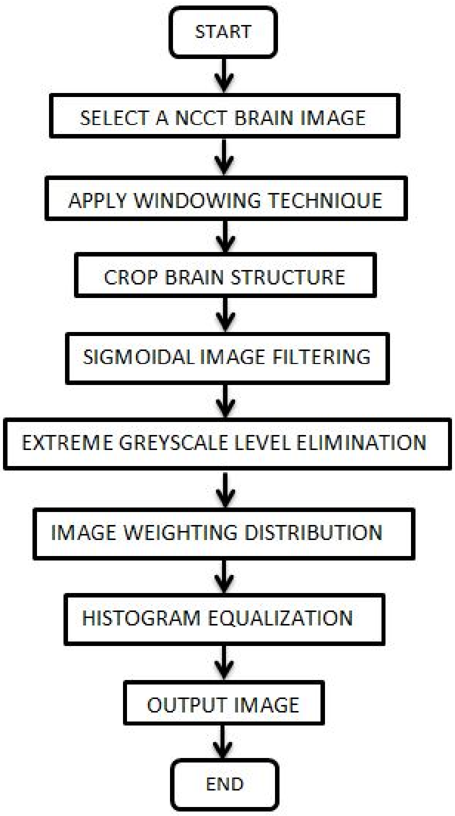

FIGURE 4. Algorithm of sigmoidal eliminating extreme level weight distributed histogram equalization

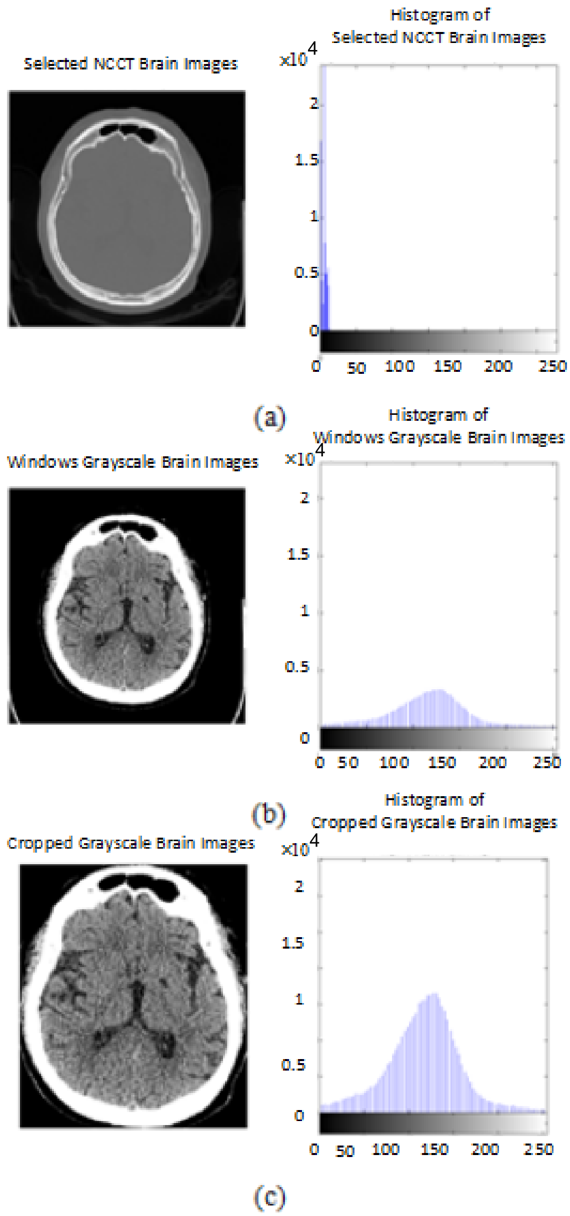

Figure 5. Image and respective histogram: (a) selected NCCT brain image, (b) windowed greyscale image, and (c) cropped greyscale image

Then, the cropped greyscale image is enhanced with sigmoidal filtering method. The input image (I) is the cropped greyscale image. Sigmoidal filtering method normalizes and then filters the non-linear input image through point processing. Every greyscale level at every pixel position of (i, j) is enhanced with sigmoidal filtering function. This non-linear filtering method converts 2-dimensional input image with greyscale range from 0 to 255, into a sigmoidal filtered image (Sig_f) with desired greyscale range from 0 to 255.

First step is to calculate the sigmoidal values for input image. The sigmoidal values are calculated by using equation shown in Equation (8). According to Equation (8), if the threshold value is more than 0, it involves two different formulae in order to calculate the sigmoidal values of the image. Thus, different threshold values cause variations in the output sigmoidal filtered image. Since the greyscale level of input image is always greater than or equal to 0, in our approach, threshold value for input image is set to 0 in order to simplify the calculation.

$$Sig_N(i,j) = (J_{\max} - J_{\min}) \times Sig(i,j) + J_{\min} \tag{5}$$

$$J_{\max} = \frac{\max\{Sig_f\}}{\max\{I\}} \tag{6}$$

$$J_{\min} = \begin{cases} \dfrac{\min\{Sig_f\}}{\min\{I\}}, & \min\{I\} \neq 0 \\ 0, & \min\{I\} = 0 \end{cases} \tag{7}$$

$$Sig(i,j) = \begin{cases} \dfrac{1}{1 + e^{-\left(\frac{I(i,j) - Th}{\max\{I\}}\right)}}, & I(i,j) \geq Th \\ \dfrac{1}{1 + e^{-\left(\frac{Th - I(i,j)}{\max\{I\}}\right)}}, & I(i,j) < Th \end{cases} \tag{8}$$

where $Sig(i,j)$ is sigmoidal values of input image at position of (i,j); $Sig_n(i,j)$ is sigmoidal normalized values of input image at position of (i,j); $J_{\max}$ is the ratio of maximum greyscale level of desired sigmoidal filtered image with input image as shown in (6); $J_{\min}$ is the ratio of minimum greyscale level of desired sigmoidal filtered image with input image as shown in (7); $\max\{I\}$ is the maximum greyscale level of input image; $\min\{I\}$ is the minimum greyscale level of input image. $\max\{Sig_f\}$ is the maximum greyscale level of desired sigmoidal filtered image; $\min\{Sig_f\}$ is the minimum greyscale level of desired sigmoidal filtered image; Th is the threshold value for input image.

Then, the values are normalized by using Equation (5) before filtering the input image. According to the threshold value of 0, Equations (4) and (8) are further simplified as shown in Equations (9) and (10) respectively.

$$Sig(i,j) = \frac{1}{1 + e^{-\left(\frac{I(i,j) - Th}{\max\{I\}}\right)}} = \frac{1}{1 + e^{-\left(\frac{I(i,j) - 0}{255}\right)}} = \frac{1}{1 + e^{-\left(\frac{I(i,j)}{255}\right)}} \tag{9}$$

$$Sig_N(i,j) = (J_{\max} - J_{\min}) \times Sig(i,j) + J_{\min} = (J_{\max} - J_{\min}) \times \frac{1}{1 + e^{-\left(\frac{I(i,j)}{255}\right)}} + J_{\min} \tag{10}$$

Sigmoidal normalization function is then further simplified into Equation (10). After that, the last step is to produce sigmoidal filtered image (Sig_f) by enhancing or changing the contrast or greyscale level of input image as shown in Equations (12) and (13). It is based on sigmoidal normalized values and a contrast factor (q) which controls and normalizes the final contrast of sigmoidal filtered image. The respective formula is shown in Equation (11). Figure 6 shows the input image with respective histogram, and sigmoidal filtered image with respective histogram.

$$q = -\frac{1}{\max\{Sig_f\}} \tag{11}$$

$$Sig_f(i,j) = I(i,j) + (q \times Sig_N(i,j)) \tag{12}$$

$$Sig_f(i,j) = \begin{cases} Sig_f(i,j), & Sig_f(i,j) \geq 0 \\ 0, & Sig_f(i,j) < 0 \end{cases} \tag{13}$$

where $I(i,j)$ is the greyscale level at position (i,j) of input image; $Sig_f(i,j)$ is greyscale level of sigmoidal filtered image; q is a constant contrast factor which controls and normalizes the final contrast; $Sig_N(i,j)$ is sigmoid normalized values provided by (10) and determines amount of normalized contrast or greyscale level to be adjusted to input image for every position (i,j).

Final step is to apply indirect contrast enhancement technique, known as Eliminating Extreme Level Weight Distributed Histogram Equalization (EELWDHE) technique in

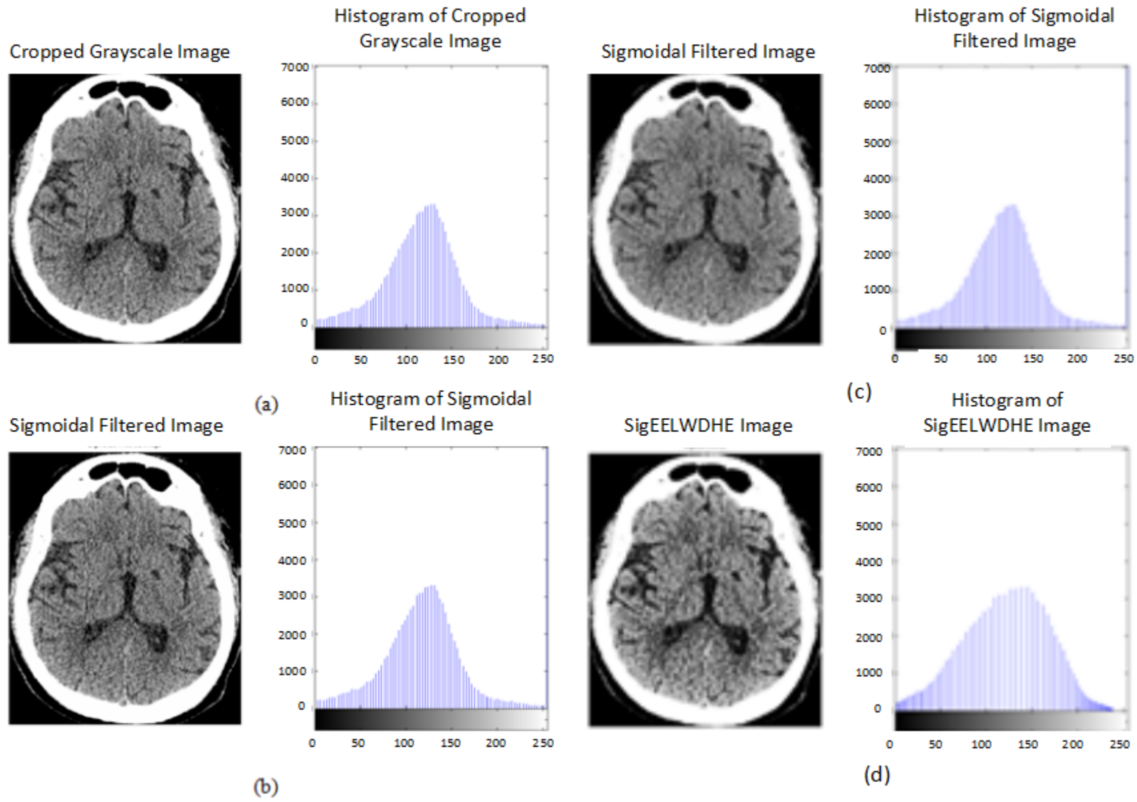

Figure 6. (a) Cropped greyscale image and respective histogram, (b) sigmoidal filtered image and respective histogram, (c) sigmoidal filtered image and respective histogram, and (d) output image and respective histogram produced by proposed method, SigEELWDHE

order to further enhance sigmoidal filtered image to generating output image. Sigmoidal filtered image (Sig_f) is the output image of previous sigmoid filtering section. In this section, sigmoidal filtered image (Sig_f) is used as the input image (F_{in}). The input image (F_{in}) is enhanced with the implementation of Eliminating Extreme Level Weight Distributed Histogram Equalization (EELWDHE) method.

This method starts with eliminating pixel counts of extreme greyscale level input image (F_{in}) with Equation (14). Given that the input image contains K greyscale level with the range of $[0, 1, 2, \ldots, K-1]$, extreme level elimination is done by assuming that pixel counts of extreme greyscale levels of input image are equal to 0. This step reduces computation time without enhancing the background pixels.

$$\sum_{k=0}^{K-1} n_{ELE}(k) = \begin{cases} \sum_{k=1}^{K-2} n(k), & 0 < k < K-1 \\ 0, & k = 0, K-1 \end{cases} \tag{14}$$

where n_{ELE} stores number of pixel counts that eliminates the extreme greyscale level of the input image (F_{in}); $n(k)$ is the number of pixel counts that contains kth greyscale level.

Next step is to calculate the probability density function value of input image (F_{in}) with Equation (15).

$$\sum_{k=0}^{K-1} PDF_{ELE}(k) = \sum_{k=0}^{K-1} \frac{n_{ELE}(k)}{N_{ELE}} \tag{15}$$

where $PDF_{ELE}(k)$ is the extreme greyscale level eliminated probability density function value at kth greyscale level; $n_{ELE}(k)$ is the extreme greyscale level eliminated pixel counts that contains kth greyscale level; $N_{ELE} = \sum_{k=0}^{K-1} n_{ELE}(k)$ is the sum of extreme greyscale level eliminated pixels counts of every kth greyscale level.

Then, histogram weighting distribution function in Equation (16) is implemented to reduce generated adverse effects and modify image histogram slightly [21]. α is a constant power parameter and the value is defined with Equation (17).

$$\sum_{k=0}^{K-1} PDF_w(k) = \sum_{k=0}^{K-1} \left(PDF_{\max} \times \left(\frac{PDF_{ELE}(k) - PDF_{\min}}{PDF_{\max} - PDF_{\min}} \right) \right) \tag{16}$$

$$\alpha = \max \left\{ \sum_{k=0}^{K-1} \left(\frac{1}{1 + e^{-PDF_{ELE}(k)}} \right) \right\} \tag{17}$$

where PDF_w is values of extreme level eliminated probability density function of input image that redistributes with weighting distribution function; $PDF_{\min} = \min \left\{ \sum_{k=0}^{K-1} PDF_{ELE}(k) \right\}$ is the minimum value of extreme level eliminated probability density function value of input image; $PDF_{\max} = \max \left\{ \sum_{k=0}^{K-1} PDF_{ELE}(k) \right\}$ is the maximum value of extreme level eliminated probability density function value of input image; α is a constant value gained from maximum value of sigmoidal enhanced of extreme level eliminated probability density function value of input image.

$$\sum_{k=0}^{K-1} CDF_w(k) = \begin{cases} \sum\limits_{k=1}^{K-1} (PDF_w(k) + PDF_w(k-1)), & k > 0 \\ PDF_w(0), & k = 0 \end{cases} \tag{18}$$

$$\sum_{k=0}^{K-1} HE(k) = \sum_{k=0}^{K-1} ((K_{\max} - K_{\min}) \times CDF_w(k) + K_{\min}) \tag{19}$$

After that, cumulative distribution function values of input image (CDF_w) is calculated with Equation (18). Equation (19) is then used to calculate normalized cumulative distribution function values of input image where CDF_w stores the values of cumulative distribution function of input image.

After that, the histogram equalization is implemented as shown in Equation (19) where $K_{\max}$ is the ratio of maximum greyscale level of desired output image (F_o) with input image (F_{in}) as shown in Equation (20); $K_{\min}$ is the ratio of minimum greyscale level of desired output image (F_o) image with input image (F_{in}) as shown in Equation (21); HE is the histogram equalization function.

$$K_{\max} = \frac{\max\{F_o\}}{\max\{F_{in}\}} \tag{20}$$

$$K_{\min} = \begin{cases} \dfrac{\min\{F_o\}}{\min\{F_{in}\}}, & \min\{F_{in}\} \neq 0 \\ 0, & \min\{F_{in}\} = 0 \end{cases} \tag{21}$$

The last step is to implement Equation (22) to reallocate the input greyscale level of input image (F_{in}) to produce the final output image (F_o).

$$F_o = \left\{ \sum_{k=0}^{K-1} HE(k) \right\} \tag{22}$$

Thus, Figure 7 shows input image (F_{in}) and output image (F_o) with respective histograms. The output image is the final output image produced by the SigEELWDHE method. Then, NCCT brain images are applied with the proposed SigEELWDHE and the existing methods as mentioned in Section 2. The outcome is assessed in Section 4 by comparing the performance of SigEELWDHE with other existing methods.

4. **Main Results.** In this section, the performance of the SigEELWDHE is measured and discussed. There are 300 NCCT brain images with infarctions that are enhanced with the SigEELWDHE. The respective output images are measured and compared with 2 evaluation assessments. They are visualization assessment and quantitative assessments. At the same time, the SigEELWDHE is further compared with existing methods in both assessments. These prior methods include Brightness preserving Bi-Histogram Equalization (BBHE), Dualistic Sub-Image Histogram Equalization (DSIHE), Recursive Sub-Image Histogram Equalization (RSIHE), Extreme-Level-Eliminating Histogram Equalization (ELEHE), and Adaptive Gamma Correction with Weighting Distribution (AGCWD). These NCCT brain images are in the size of 512×512.

In this assessment, quality of visualization produced by selected input image, prior methods and the SigEELWDHE are analyzed. There are 2 NCCT brain images with different types of infarctions: images A and B. They are randomly chosen from 300 NCCT brain images to be enhanced with the SigEELWDHE and prior methods as shown in following figures: Figure 7, and Figure 8.

These figures showed that AGCWD method over enhanced the most when compared with other methods. It washes out not only the contrast of normal brain soft tissue, but also infarctions, which may cause diagnosis to miss some part of infarctions. BBHE method and ELEHE method enhance the infarctions area to become darker, similar to AGCWD method, they brighten the contrast of normal brain tissue. However, at the

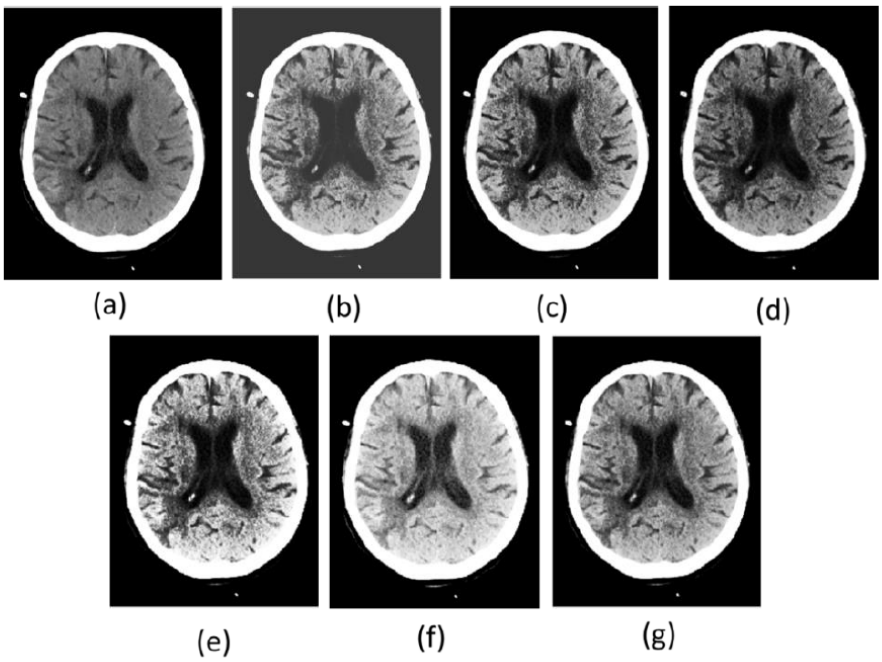

Figure 7. (a) Selected NCCT brain image A (F_{in}), output image A enhanced by (b) BBHE method, (c) DSIHE method, (d) RSIHE method, (e) ELEHE method, (f) AGCWD method, and (g) proposed method, SigEELWDHE (F_o)

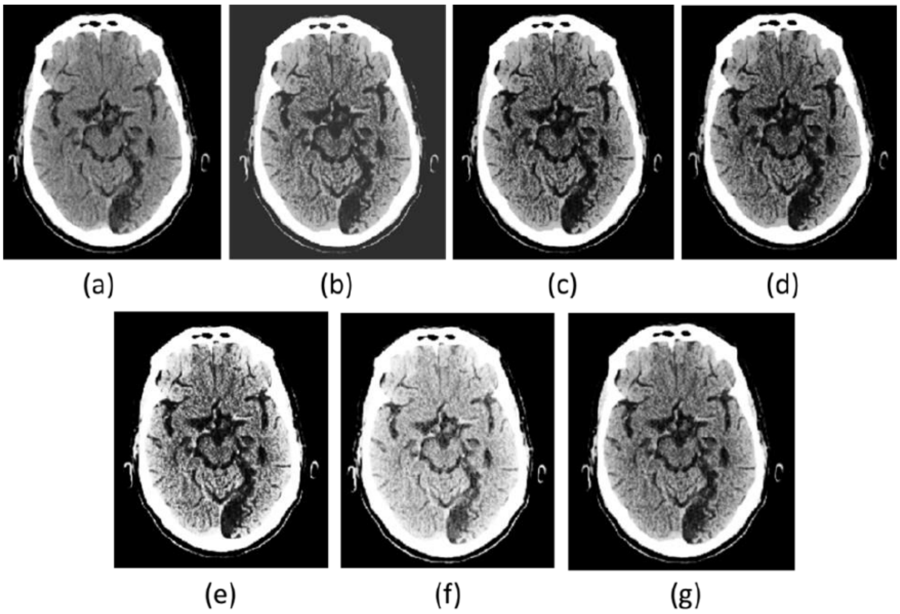

FIGURE 8. Image of (a) selected NCCT brain image B, output image B enhanced by (b) BBHE method, (c) DSIHE method, (d) RSIHE method, (e) ELEHE method, (f) AGCWD method, and (g) proposed method, SigEELWDHE

same time, both of them introduce some dark artifacts that may cause misinterpretation in infarction diagnosis, by assuming that artifacts are infarctions. When comparing these 2 methods, ELEHE provides better contrast of infarctions but over enhancement problem on normal brain tissue and artifacts are more serious than BBHE method.

For DSIHE approach and RSIHE approach, both methods intensify contrast of infarctions and slightly brighten the normal brain tissue. It can reduce the amount of unwanted artifacts produced. However, these two methods introduce blurring effect to the selected NCCT brain image. RSIHE approach has less blurring effect than DSIHE approach.

While for the SigEELWDHE, the results from the figures show that it enhances visibility of infarction area and slightly enhances the normal brain soft tissue. At the same time, it does not produce blurring effect or unwanted artifacts compared with prior methods. Therefore, the conclusion is that SigEELWDHE provides better contrast of NCCT brain image for infarction diagnosis, when compared with other existing approaches.

In order to measure the performance of the SigEELWDHE in quantitative, Image Quality Assessments (IQA) models are implemented. There are 3 IQA models that are implemented: entropy assessment model, Peak Signal to Noise Ratio (PSNR) assessment, and Structural Similarity (SSIM) assessment model [22]. Entropy measures the statistical average of information of an image [23,24]. PSNR is the ratio of peak pixel value of output image to output image noise [25]. SSIM calculates the similarities of structural information between input image and output image [26]. Table 1 shows the result of entropy for 10 selected input images and respective output images produced by prior approaches and the SigEELWDHE. Table 2 and Table 3 show the result of PSNR, and SSIM for 10 output images produced by prior approaches and the SigEELWDHE.

Table 1 shows that all entropies of output images produced by prior methods are reduced, when compared with entropy of input image. Table 1 also shows that among prior approaches, RSIHE method reduces the entropy of input image at the most, and the reduction rate is about 1.88%. About 1.82% of input image entropy had been reduced with

Table 1. The entropy measurement on selected 10 NCCT brain images enhanced with BBHE, DSIHE, RSIHE, ELEHE, AGCWD, and proposed method

Image	Input Image	BBHE	DSIHE	RSIHE	ELEHE	AGCWD	SigEELWDHE
1	4.7106	4.6591	4.6444	4.6234	4.6662	4.6877	4.7106
2	4.7096	4.6605	4.6370	4.6409	4.6598	4.6930	4.7075
3	4.7985	4.7581	4.7301	4.7518	4.7555	4.7793	4.7985
4	4.7409	4.6934	4.6478	4.6709	4.6984	4.7234	4.7392
5	4.7842	4.7372	4.7012	4.7233	4.7404	4.7517	4.7842
6	4.4705	4.4222	4.3997	4.3820	4.4242	4.4523	4.4695
7	3.6290	3.6248	3.5270	3.5013	3.6181	3.6066	3.6290
8	3.6830	3.6777	3.5937	3.5590	3.6720	3.6594	3.6830
9	4.7547	4.7017	4.6620	4.6707	4.7021	4.7323	4.7537
10	4.2943	4.2803	4.2225	4.2141	4.2712	4.2650	4.2943

Table 2. The PSNR measurement on selected 10 NCCT brain images enhanced with BBHE, DSIHE, RSIHE, ELEHE, AGCWD, and proposed method

Image	BBHE	DSIHE	RSIHE	ELEHE	AGCWD	SigEELWDHE
1	20.2253	19.5503	21.4891	18.4904	15.9549	25.6103
2	17.8835	19.6781	22.0673	16.5888	14.9166	22.0759
3	18.9172	22.2439	22.3398	17.492	15.4776	23.6573
4	19.1272	18.9319	21.8817	17.5686	15.3939	23.7745
5	20.1337	17.9709	22.0108	18.3919	15.9155	25.3147
6	21.014	19.5309	19.6874	18.9395	16.9004	24.9742
7	22.3127	14.0973	26.8577	25.8737	19.4212	34.9253
8	22.4461	14.6514	26.7752	25.427	19.2067	35.0871
9	19.9591	20.5656	20.5767	18.1232	15.9393	24.8767
10	22.3854	16.0141	23.9059	21.3301	17.3354	29.8279

Table 3. The SSIM measurement on selected 10 NCCT brain images enhanced with BBHE, DSIHE, RSIHE, ELEHE, AGCWD, and proposed method

Image	BBHE	DSIHE	RSIHE	ELEHE	AGCWD	SigEELWDHE
1	0.7071	0.7561	0.7648	0.7936	0.8922	0.9324
2	0.6807	0.7324	0.7555	0.7678	0.8697	0.9124
3	0.7871	0.8434	0.8345	0.8292	0.8803	0.9419
4	0.6928	0.7485	0.7812	0.7824	0.877	0.9198
5	0.6609	0.7079	0.7443	0.7723	0.8841	0.9206
6	0.7257	0.7935	0.7829	0.7948	0.9141	0.9257
7	0.674	0.5731	0.6995	0.9589	0.9398	0.9907
8	0.7465	0.6454	0.7766	0.9632	0.938	0.9931
9	0.729	0.7997	0.8092	0.7784	0.8853	0.9213
10	0.716	0.6864	0.731	0.8836	0.9092	0.9717

implementation of DSIHE. Next method that reduces the most of input image entropy is ELEHE method, with 0.82%, followed by BBHE method with 0.81% entropy average reduction rate, and AGCWD with entropy average reduction rate of 0.5%. While for the SigEELWDHE, it has the lowest entropy average reduction rate compared with prior methods, which is about 0.01%. This means that the SigEELWDHE has the least loss of image information when compared with prior approaches.

The SigEELWDHE also has the best performance in Table 2. It has the highest value of average PSNR value of 27.0123. In terms of PSNR, AGCWD performs the worst with average PSNR value of 16.6462. DSIHE method performs better than AGCWD method. The average PSNR value is 18.3432. The average PSNR value of 19.8225 had been achieved by ELEHE method, followed by 20.4404 for BBHE method, while RSIHE achieves average PSNR value of 22.7592. Therefore, in terms of PSNR, the SigEELWDHE is always the best choice for contrast enhancement on NCCT brain images compared with prior approaches.

In Table 3, the result shows that SigEELWDHE performs the best when compared with existing methods. This is due to the fact that it always has the highest value of SSIM, range from 91.24% to 99.31%. Based on Table 3, the SigEELWDHE suffers from the least average loss of structural information of input image. It is about 5.7%. Among prior methods, AGCWD method performs the best about 10.1% average loss of structural information. The worst method that has the highest average loss of input image structural information about 28.8% is BBHE method. Then, for the sequence of performance of the rest existing methods, in terms of average loss of input image structural information, the DSIHE method is about 27.14%, 23.21% for RSIHE method, and 16.76% for ELEHE.

Based on all tables tabulated, they show that the SigEELWDHE is more suitable and better contrast enhancement method for NCCT brain images for infarction diagnosis. This is because it has the closest entropy value to the input image, highest PSNR values and the highest Structural Similarity (SSIM) with input images.

5. **Conclusions.** A novel contrast enhancement method is developed to improve NCCT brain image with infarctions. According to the performance measured in entropy, PSNR and SSIM values as well as the visual assessment, the SigEELWDHE generates better contrast enhanced output image than other 5 prior methods in both visualization and Image Quality Assessments (IQA). Thus, the SigEELWDHE shows the ability to produce an effective reference for medical radiologists whether they are professional or junior in infarction diagnosis. In conclusion, the implementation of the SigEELWDHE is able to improve the process of infarction diagnosis.

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