IMAGE CONTRAST ENHANCEMENT USING TRIPLE CLIPPED DYNAMIC HISTOGRAM EQUALISATION BASED ON STANDARD DEVIATION

Ansari Md. Saad, Swarnava Bag, Saraf Parth Vikrant

Advisor: Prof. Debdoot Sheet

ABSTRACT

Contrast enhancement is one of the quintessential tasks in image processing. Here, we propose a robust enhancement algorithm, called Triple Clipped Dynamic Histogram equalisation based on Standard Deviation (TCDHE-SD). In this method, there are four main steps: (i) Partitioning the histogram into three parts with approximately the same number of pixels, based on the standard deviation, (ii) Performing histogram clipping on each sub-histogram, (iii) Mapping each sub-histogram to its new dynamic range, and (iv) Performing histogram equalisation on each sub-histogram independently. This method achieves a better average information content score (entropy) over other contemporary non-adaptive histogram equalisation methods, while reasonably preserving mean brightness, and achieving contrast enhancement.

***Index Terms*—** Image Processing, Contrast Enhancement, Histogram equalisation, Standard Deviation

1. INTRODUCTION

The quality of an image can be judged by its contrast. If the image has a low contrast, then a lot of the perceptual information is lost in the concentrated intensity levels. Many algorithms exist for contrast enhancement. Some examples include brightness adjustment, global contrast adjustment, logarithmic transformations, and so on. The most common method of contrast enhancement is Global Histogram Equalisation (GHE). It is used for almost all types of images, as it applies a uniform equalisation over the full histogram of the image. However, it is inefficient on images that contain too dark or too bright regions. Some combination of histogram-based and non-linear techniques are used to compensate for shadows and bright spots.

Global Histogram Equalisation (GHE) is the most popular method for contrast enhancement. It performs fairly well on many types of images, while being a fairly simple algorithm itself. In the GHE method, we take the grayscale histogram of the input image and remap them according to the cumulative (probability) density function (CDF). The GHE method has many limitations, primarily because it performs a linear equalisation on the full histogram of the input image, which leads to creation of artifacts and noise amplification in the output, and might also result in a significant shift in the mean brightness of the image, due to the equalisation being performed on the full histogram of the input image.

Many other histogram-based algorithms have been proposed to overcome the limitations of the Global Histogram Equalisation (GHE) algorithm, such as the Bi-histogram equalisation (BHE), which partitions the histogram into two sub-histograms based on the mean of intensity values. Then, the equalisation process takes place independently on both of the sub-histograms independently. The main advantage of the BHE algorithm is its mean brightness preservation. As the input image histogram is partitioned around the mean intensity value, the mean brightness before and after the equalisation process remains the same. But in some cases, the BHE algorithm has an intensity saturation problem, or it does not enhance much contrast.

Another algorithm, Dynamic Histogram Equalisation (DHE) has also been proposed, which takes into account the maxima (extremity points) of the frequency values in the histogram of the input image, and then partitions and equalises the histogram accordingly. In the DHE algorithm, the image histogram is divided into many sub-histograms based on the maxima values in the image histogram. If there are a large number of peaks in the image histogram, the image is partitioned into a large number of sub-histograms. This may cause insignificant enhancement in some sub-histograms.

Each of the above methods are proposed to solve a specific problem in the field of contrast enhancement. Our method creates a reasonable and balanced relationship between contrast enhancement, preserving the mean brightness and preserving average information content.

2. TRIPLE-CLIPPED DYNAMIC HISTOGRAM EQUALISATION BASED ON STANDARD DEVIATION

The proposed method, called TCDHE-SD, consists of the following four sections:

1. Triple-partitioning of the histogram
2. Histogram clipping

3. Mapping each partition of the histogram to a new dynamic range
4. Performing Histogram equalisation on each sub-histogram independently

2.1. Triple-partitioning of the histogram

The histogram of the input image is partitioned into three sub-histograms based on the standard deviation of the intensity values at each pixel of the image. First, we estimate a Gaussian distribution of the intensity values of the input image, using its mean and standard deviation. Each pixel of the image can be considered as a random variable. According to the Central Limit Theorem, the sum of a sequence of random variables tends towards the Gaussian distribution. Thus, using the estimated distribution, the image histogram can be partitioned into three sub-histograms with approximately the same number of pixels.
The mean intensity of an image is calculated as,

$$\mu = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} X(i,j)$$

where $X(i,j)$ is the intensity at row i, column j, μ is the mean intensity of the image, and M, N are the dimensions of the imput image. Using μ, we can calculate the standard deviation of the image as,

$$\sigma = \sqrt{\frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left(X(i,j) - \mu\right)^2}$$

where σ is the standard deviation of the intensity values of the image. Now that we have μ and σ, We can partition the histogram into three equal partitions such that,

$$\begin{aligned} &P(0 < X < \mu - a\sigma) \approx 0.33 \\ &P(\mu - a\sigma < X < \mu + a\sigma) \approx 0.33 \\ &P(\mu + a\sigma < X < L - 1) \approx 0.33 \end{aligned}$$

As the gaussian distribution is symmetric about the mean μ, find a such that,

$$\begin{aligned} &P(\mu - a\sigma < X < \mu + a\sigma) \approx 0.33 \\ &P(-a < \tfrac{X-\mu}{\sigma} < a) \approx 0.33 \end{aligned}$$

Given that μ is the mean of the random variable X, and σ its standard deviation, let $Z = \frac{X-\mu}{\sigma}$ be another random variable. Now, $Z \sim N(0,1)$. Thus,

$$\begin{aligned} &P(-a < Z < a) \approx 0.33 \\ &\implies \Phi(a) - (1 - \Phi(a)) \approx 0.33 \\ &\implies \Phi(a) = 0.665 \end{aligned}$$

From the table of standard deviation, the value of a is found to be $a \approx 0.43$. We can then proceed to find the partitioning points m_1 and m_2 as,

$$\begin{aligned} m_1 &= \mu - 0.43\sigma \\ m_2 &= \mu + 0.43\sigma \end{aligned}$$

If the input image has the intensity range $[m_0 : m_3]$, the histogram of the image, W, is partitioned into three histograms W_L, W_M, W_U, with intensity ranges $[m_0 : m_1 - 1]$, $[m_1 : m_2 - 1]$, $[m_2 : m_3]$ respectively.

2.2. Histogram Clipping

To control the enhancement ratio in the histogram equalisation process, and to prevent intensity saturation and excessive enhancement in the output image, we perform histogram clipping. The shape of the input histogram is changed based on a specified threshold level before proceeding with the equalisation process. The mean of the intensity at each sub-histogram is considered to be the histogram clipping threshold. Thresholds T_1, T_2, T_3 for the three sub-histograms are calculated as follows:

$$\begin{aligned} T_1 &= \frac{1}{m_1 - m_0} \sum_{k=m_0}^{m_1-1} h(k) \\ T_2 &= \frac{1}{m_2 - m_1} \sum_{k=m_1}^{m_2-1} h(k) \\ T_3 &= \frac{1}{m_3 - m_2 + 1} \sum_{k=m_2}^{m_3} h(k) \end{aligned}$$

where $h(k)$ is the histogram of the input image. The bars of any sub-histogram with a greater level than the threshold are limited by the threshold level. The clipped histogram is obtained using the following equations,

$$h_c(k) = \left\{ \begin{array}{ll} h(k), & h(k) < T_1 \\ T_1, & h(k) \geq T_1 \end{array} \right\} \quad m_0 \leq k < m_1$$

$$h_c(k) = \left\{ \begin{array}{ll} h(k), & h(k) < T_2 \\ T_2, & h(k) \geq T_2 \end{array} \right\} \quad m_1 \leq k < m_2$$

$$h_c(k) = \left\{ \begin{array}{ll} h(k), & h(k) < T_3 \\ T_3, & h(k) \geq T_3 \end{array} \right\} \quad m_2 \leq k \leq m_3$$

2.3. Mapping each partition to a new dynamic range

Each sub-histogram has a specific intensity range. In case of an equalisation process for each sub-histogram independently, the domain of the sub-histogram does not expand beyond the specified range. On the other hand, in a sub-histogram with a large range, the problem of over-expansion is created. This may cause loss of image detail and saturation of intensity in the output image. To combat this, we map the sub-histograms to a new set of dynamic ranges, given by,

$$
\begin{aligned}
n_0 &= 0 \\
n_1 &= n_0 + (L-1)\frac{m_1 - m_0}{m_3 - m_0 + 1} \\
n_2 &= n_1 + (L-1)\frac{m_2 - m_1}{m_3 - m_0 + 1} \\
n_3 &= n_2 + (L-1)\frac{m_3 - m_2 + 1}{m_3 - m_0 + 1} = (L-1)
\end{aligned}
$$

where $L-1$ is the highest pixel intensity possible in the n-bit image. Therefore, after performing the mapping process, the new dynamic ranges of the lower, middle, and higher sub-histograms are $[n_0 : n_1 - 1]$, $[n_1 : n_2 - 1]$, $[n_2 : n_3]$, respectively.

2.4. Equalising each partition independently

After determining the new dynamic range of each sub-histogram, we proceed to independently equalise each sub-histogram. For this, we first need to find the probability distribution function (PDF) for each sub-histogram. We can find the PDF using the following equations,

$$
\begin{aligned}
\mathrm{PDF}_L(k) &= \frac{hc(k)}{N_L}, \quad m_0 \le k < m_1 \\
\mathrm{PDF}_M(k) &= \frac{hc(k)}{N_M}, \quad m_1 \le k < m_2 \\
\mathrm{PDF}_U(k) &= \frac{hc(k)}{N_U}, \quad m_2 \le k \le m_3
\end{aligned}
$$

In the above equations, N_L, N_M, and N_U are the number of pixels in the clipped sub-histogram. After we determine the PDF, we calculate the cumulative density function (CDF) of each sub-histogram using the corresponding PDF,

$$\mathrm{CDF}_L(k) = \sum_{i=m_0}^{k} \mathrm{PDF}_L(i)$$

$$\mathrm{CDF}_M(k) = \sum_{i=m_1}^{k} \mathrm{PDF}_M(i)$$

$$\mathrm{CDF}_U(k) = \sum_{i=m_2}^{k} \mathrm{PDF}_U(i)$$

After finding the CDF of each sub-histogram, we can then determine the transfer function, according to the following equations,

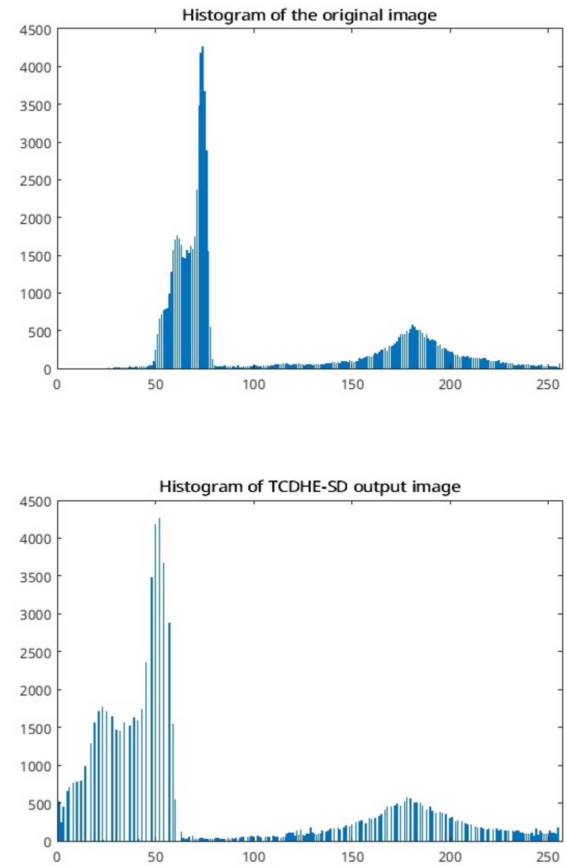

Fig. 1.

$$
\begin{aligned}
F_L &= n_0 + (n_1 - 1) \cdot \mathrm{CDF}_L \\
F_M &= n_1 + (n_2 - 1 - n_1) \cdot \mathrm{CDF}_M \\
F_U &= n_2 + (n_3 - n_2) \cdot \mathrm{CDF}_U
\end{aligned}
$$

Using the above transfer functions, each partition is equalised independently. Then, we integrate all three transfer functions to create one single transfer function. Then, the output image of the TCDHE-SD method is produced by applying the transfer function to the input image.

3. RESULTS AND DISCUSSIONS

In order to evaluate and compare the existing methods, 4 images are chosen namely, cycle, office, and the standard images like the ”coins.png” and ”cameraman.tif” from the MATLAB library. The simulation results of the proposed TCDHE-SD algorithm are compared with different methods like GHE, BHE, DHE, BPDFHE and CLAHE on all 4 images, which can be observed in Figs. 2-5

Contrast enhancement involves changing the original values so that more of the available range is used, thereby increasing the contrast between targets and their backgrounds. Contrast enhancement processes adjust the relative brightness and darkness of objects in the scene to improve their visibility. Among the contrast enhancement methods, the most appropriate would be the one that can display all the input image information, while enhancing the natural contrast simultaneously. The main purpose of histogram clipping is gaining control of the enhancement ratio. It also prevents creating intensity saturation and excessive enhancement. In order to extract information from the image, the average information content (entropy) is used as the quantitative evaluation. Entropy measures the amount of richness of the image details (usually measured in bits). The larger entropy value indicates that more information is available from the image.

$$E(PDF) = -\sum_{k=0}^{L-1} \mathrm{PDF}(k) \cdot log_2(\mathrm{PDF}(k))$$

where PDF(k) is the probability density function from an image at the intensity level k and L–1 is the highest pixel intensity in the image.

The proposed algorithm improves the visual quality of an image via contrast enhancement. For optimal performance, the entropy should be as close to the original image as possible so that the actual image information is preserved. The proposed TCDHE-SD algorithm produces an image of higher entropy as compared to other methods, hence its entropy is closer to the entropy of the original image. So, it can be said that most of the information in the original image is preserved in the TCDHE-SD image too which leads to optimal enhancement. Our method excels at the three following tasks simultaneously:

1. Contrast Enhancement
2. Mean Brightness Preservation
3. Preservation of average information content

Contrast enhancement is achieved by spreading out the most frequent intensity values, i.e. stretching out the intensity range of the image. In this proposed algorithm, mapping the partitions into a new dynamic range and histogram equalization of each partition enhances the contrast optimally. It is observed that the proposed TCDHE-SD algorithm image has some white spaces in between the intensity levels in the histogram. This is due to the contrast enhancement which essentially spreads out the histogram to its new dynamic range.

But from the observed results, it can be inferred that the image produced by CLAHE algorithm has an entropy greater than the original image. MATLAB has an inbuilt function for Contrast-Limited Adaptive Histogram Equalisation (CLAHE), called "adapthisteq()". This method operates on tiles over the input image, finding the best output pixel value for each image based on the intensity values of the pixels in its neighbourhood. This means that based on their neighbourhoods, pixels with the same intensity value may have different values in the output image. This subsequently means that the transfer function is a one-to-many function, as opposed to the one-to-one function that is generated by many contemporary non-adaptive histogram equalisation techniques. This is in line with the experimental observation that the entropy of the image enhanced by the CLAHE algorithm is greater than the original image, as the uncertainty increases due to the mapping in the CLAHE algorithm being one-to-many. This proves that our proposed TCDHE-SD method works best for contrast enhancement, mean brightness preservation, and preservation of average information content.

4. REFERENCES

[1] Majid Zarie, Ali Parsayan, and Hassan Hajghassem, "Image contrast enhancement using triple clipped dynamic histogram equalisation based on standard deviation," *IET Image Processing*, vol. 13, no. 7, pp. 1081–1089, 2019.

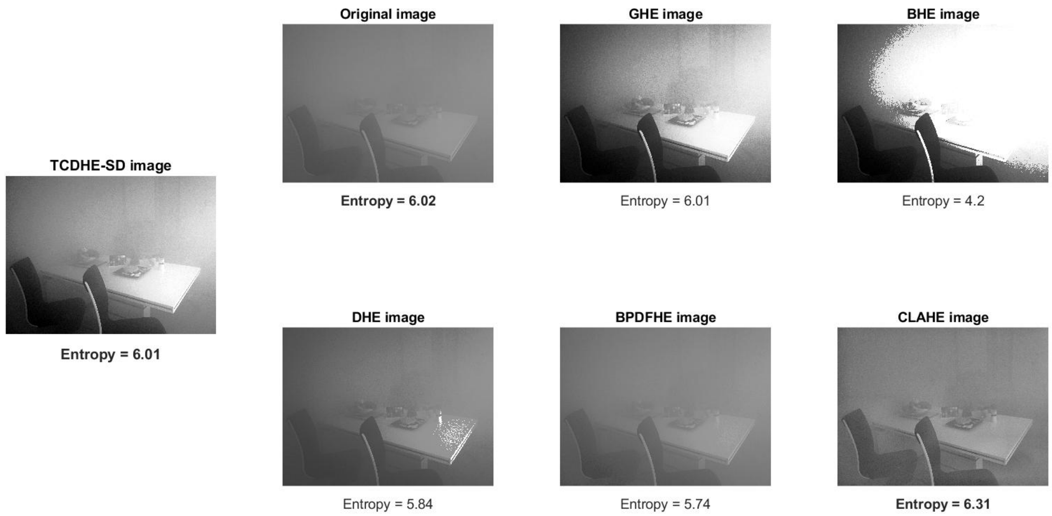

Fig. 2. Office

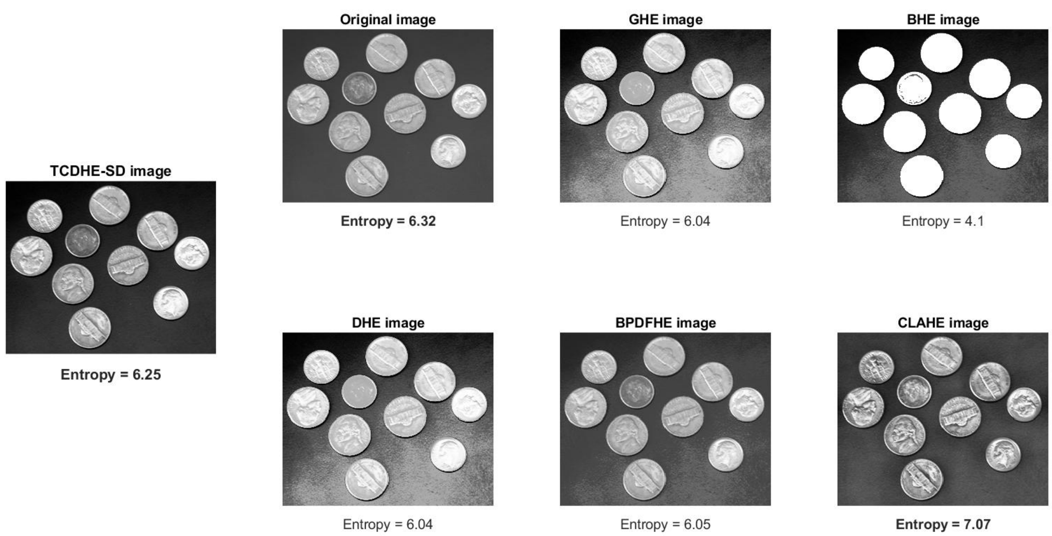

Fig. 3. Coins.png

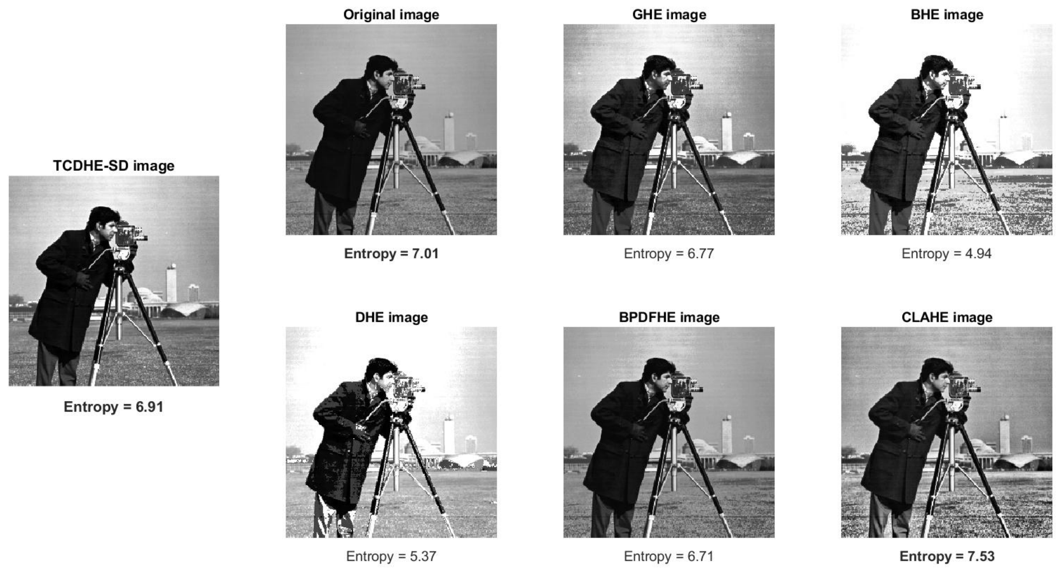

Fig. 4. Cameraman.tif

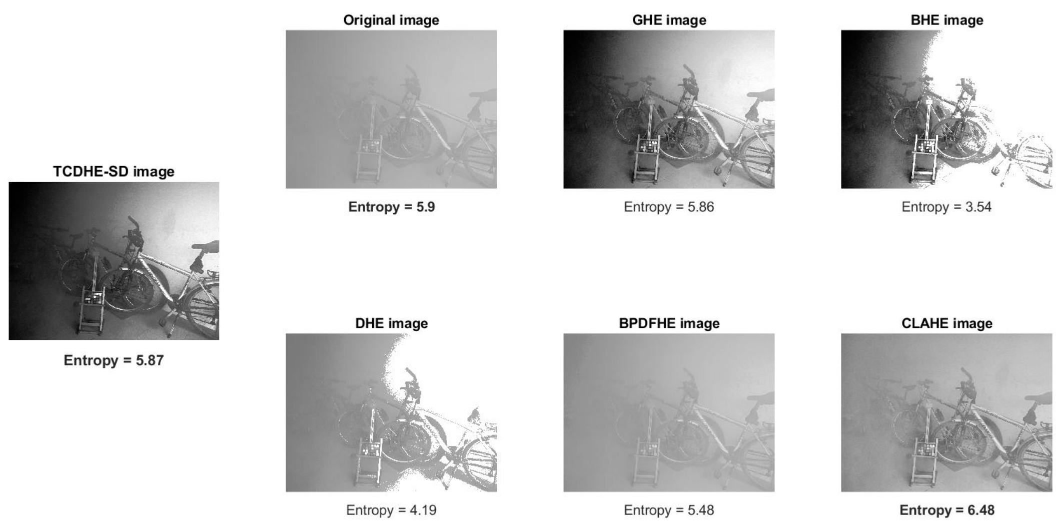

Fig. 5. Cycle

	Coins		Cycle		Cameraman		Office	
Equalization Technique	Entropy	Entropy Deviation	Entropy2	Entropy Deviation2	Entropy3	Entropy Deviation3	Entropy4	Entropy Deviation4
Original Image	6.32		5.9		7.01		6.02	
GHE	6.04	0.28	5.86	0.04	6.77	0.24	6.01	0.01
BHE	4.1	2.22	3.54	2.36	4.94	2.07	4.2	1.82
DHE	6.04	0.28	4.19	1.71	5.37	1.64	5.84	0.18
BPDFHE	6.05	0.27	5.48	0.42	6.71	0.3	5.74	0.28
CLAHE	7.07	0.75	6.48	0.58	7.53	0.52	6.31	0.29
TCDHE-SD	6.25	0.07	5.87	0.03	6.91	0.1	6.01	0.01

Fig. 6. Entropy measures on different algorithms[1]