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Image Enhancement using Recursive Separate Standard Intensity Deviation Based Clipped Sub Image Histogram Equalization

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***Abstract:** To improve image contrast, this paper introduces a recursive separate standard intensity deviation based clipped sub image histogram equalization method. This is an extension of standard intensity deviation value based sub image histogram equalization algorithm, in terms of histogram separation and equalization. In existing equalization methods do not effectively utilizes the information from different region in equalization process. In this scheme, the image histogram is bisected based on standard intensity deviation value. The further separation is carried out based on the specific region threshold value and the resulting four sub histograms are equalized individually. This is an effective method for enhancing, low exposure, medical and mammogram images and for addressing the over-enhancement problem. The performance evaluation of the proposed method is presented with the help of average information and visual quality assessment and the proposed algorithm outperforms existing recursive algorithms based on histogram equalization.*

***Keywords:** Histogram equalization, Clipped histogram, standard intensity deviation value, low contrast enhancement, entropy value.*

I. INTRODUCTION

The contrast enhancement of an image is one of key factor in the process of an image enhancement [1]. The histogram equalization (HE) is one of the standard method that is used to improve image contrast effectively, by stretching image intensity. This method is widely applies in various field due to its easiness of implementation. The limitation of HE is that, it doesn't preserve brightness of the image and produces undesirable effects [2]. In addressing these problems, different brightness preserving methods were proposed to enhance image contrast [3].

The brightness preserving bi-HE (BBHE) [4] and dualistic sub image HE (DSIHE) [5] methods, use image subdivision based on mean and median value of image respectively to create sub images. The minimum mean brightness error bi-HE [MMBEBHE] was developed [6] to improve brightness. It is a continuation of BBHE and uses threshold value for histogram separation.

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However, these methods fail to focus on over enhancement.

Meanwhile multi-histogram equalization methods like recursive mean separate HE [RMSHE] have been developed [7], which uses mean value to bisect histogram only once. Further division of histogram is based on respective mean value of sub histograms and is done recursively. It also equalizes the sub histograms individually. In recursive sub image HE [RSIHE], the multiple histogram division is based on median value [8]. In these methods, the iterations number is a critical choice as increase in number of iterations may create over-enhancement. To limit, over-enhancement rate, 'histogram clipping approach' was used which optimizes the over enhancement by restricting high-frequency bins [9][10][11].

By incorporating clipped histogram approach, median-mean based sub image clipped HE (MMSICHE) [12] was proposed and it uses, clipped histogram instead of original histogram of the image. Here, histogram subdivision is mainly using median and individual mean intensity into four such subdivision. Then, each sub image is subjected to histogram equalization. However, multi histogram method faces, difficulties in finding subdivision threshold value. Another method, non-parametric modified HE (NMHE) [13], uses spatial transformation of grey scale of histogram to yield acceptable quality. Recently, the exposure-based sub image HE [ESIHE], enhances image by exposure parameter in determining threshold value for image subdivision [14]. This work has been extended further as recursive and recursive separate, approaches. The recursive ESIHE [R_ESIHE] iteratively performs ESIHE until the threshold value is reached, whereas recursive separate ESIHE [RS_ESIHE] splits the modified histogram into sub-images based on separate exposure threshold [15]. However, these methods fail to retain maximum image information.

The new approach, standard intensity deviation based clipped SIHE (SIDCSIHE) [16] method uses a new optimized value to split the clipped image histogram. It enhances image contrast by altering the pixel intensity and also controls the over-enhancement. This paper is an extension of SIDCSIHE, called recursive separate SIDCSIHE (RS_SIDCSIHE). The proposed method first divides the clipped histogram into sub histograms based on the optimized threshold value and later does HE of the sub histograms individually. Histogram clipping is also done to avoid excessive enhancement. This method aims to improve average information contents of the feeding image. The performance is analyzed by enhancing low exposure images such as medical and mammogram.

The structure of this manuscript is presented as follows; section 2 explains the proposed method piecewise. Section 3 deals with experimental results and its discussion. Later, the conclusion is outlined in section 4.

II. PROPOSED METHOD

The proposed algorithm includes, calculation of standard intensity deviation, histogram clipping, and calculation of individual threshold, histogram subdivision, and equalization. The following subsections contain the detail description of each step, presented in the paper.

A. SID value calculation

The standard deviation (SD) function, σ, is calculates the variance of corresponding image intensity and mean value of the input image histogram [17].

$$\sigma = \left(\frac{\sum_{i=1}^{L}(i-H_{\mu})^2 x H(i)}{\sum_{i=1}^{L} H(i)}\right)^{1/2} \quad (1)$$

The mean value is defined as

$$H_{\mu} = \frac{\sum_{i=1}^{L} H(i)\, i}{\sum_{i=1}^{L} H(i)} \quad (2)$$

where (Hi) , is image histogram, i and L its intensity and total gray levels respectively. The normalized value of SD with range [0 1] is expressed as

$$\sigma_{norm} = \left(1 - \left({}^{\sigma}/_{L}\right)\right) \quad (3)$$

Another parameter X_{SID} is defined using equation 3 and total number of grey level. This value is used to make image histogram partition for modification.

$$X_{SID} = L * \sigma_{norm} \quad (4)$$

B. Histogram Clipping

The threshold value T_c is the mean of histogram, which clips the image histogram above T_c .

$$T_c = mean\ (H(i)) \quad (5)$$
$$H_c(i) = T_c \ \ for\ H(i) \geq T_c \quad (6)$$

Where (i) and $H_c(i)$ are the input and clipped histograms respectively. The histogram clipping is efficient by its less number of computations [14]. The histogram clipping processes are as shown in fig 1a.

C. Calculation of individual standard intensity deviation value

Here, 2^r sub histograms are generated based on recursion level *r* (in this case *r*=2). The SID value divides the clipped histogram into two sub-images. The further decomposition of sub-images individually is directed by threshold values X_{lSID} and X_{uSID}. The calculations of these values based on X_{SID} is as shown in fig 1b. The X_{lSID} and X_{uSID} are lower and upper standard intensity deviation values of individual sub-images [15] and are, respectively, given by

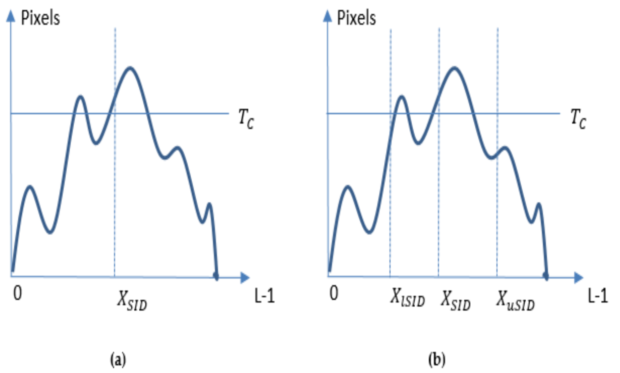

Fig. 1: The Subdivision process (a) Histogram subdivision and clipping; (b) Recursive separated histogram subdivision and clipping.

$$X_{lSID} = L\left[\frac{X_{SID}}{L} - \frac{\sum_{0}^{X_{SID}-1} * H(i) * i}{L\sum_{0}^{X_{SID}-1} H(i)}\right], \quad (7)$$

$$X_{uSID} = L\left[1 - \frac{\sum_{X_{SID}}^{L-1} H(i) * i}{L\sum_{X_{SID}}^{L-1} H(i)} + \frac{X_{SID}}{L}\right], \quad (8)$$

D. Histogram Sub deviation and Equalization.

The original histogram is divided into two sub histograms with ranges from $0\ to\ X_{SID}$ and $X_{SID+1}\ to\ L-1$ based on X_{SID} value. These sub histograms are further divided into two smaller sub histograms by using separate threshold values X_{lSID} and X_{uSID}, thus creating sub-images, with gray level ranging from $0\ to\ X_{lSID-1}$, $X_{lSID}\ to\ X_{SID-1}$, $X_{SID}\ to\ X_{uSID-1}$ and $X_{uSID}\ to\ L-1$.

The cumulative distribution function (CDF) of all sub-image are expressed as

$$C_{lowL} = \sum_{i=0}^{X_{lSID}-1} \frac{H_c(i)}{N_{lowL}} \quad for\ 0 \leq i \leq X_{lSID} - 1 \quad (9)$$
$$C_{lowU} = \sum_{i=X_{lSID}}^{X_{SID}-1} \frac{H_c(i)}{N_{lowU}} \quad for\ X_{lSID} \leq i \leq X_{SID} - 1 \quad (10)$$
$$C_{upL} = \sum_{i=X_{SID}}^{X_{uSID}-1} \frac{H_c(i)}{N_{upL}} \quad for\ X_{SID} \leq i \leq X_{uSID} - 1 \quad (11)$$
$$C_{upU} = \sum_{i=X_{uSID}}^{L-1} \frac{H_c(i)}{N_{upU}} \quad for\ X_{uSID} \leq i \leq L - 1 \quad (12)$$

where N_{lowL} ,N_{lowU} , $N_{upL}$and N_{upU} are the total number of pixels in the individual sub images, respectively. The output image transfer function $F(i)$ is obtained by combining all individual equalized sub histograms as shown below

$$F(i) = \begin{cases} X_{lSID} * C_{lowL} \\ (X_{lSID}+1) + (X_{SID} - X_{lSID} + 1) * C_{lowU} \\ (X_{SID}+1) + (X_{uSID} - X_{SID} + 1) * C_{upL} \\ (X_{uSID}+1) + (L - X_{uSID} + 1) * C_{upU} \end{cases} \quad (13)$$

E. Algorithm of RS-SIDCSIHE

- Compute $H(i)$, X_{SID}, and $H_c(i)$.

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- The further division of two sub histogram from clipped histogram by using X_{SID}.
- Compute X_{lSID} and X_{uSID}, then distribute the sub histogram into further four sub histograms.
- Final image is obtained by combining all equalized individual sub histograms.

III. EXPERIMENTAL RESULTS

The proposed method undergoes both objective and subjective assessment and is compared with previous HE, RMSHE, RISHE, MMSICHE, NMHE and RSESIHE methods. The visual quality of the image is analyzed in subjective assessment with low exposure, medical, and mammogram images. The objective assessment is analyzed by using entropy value. The detailed study is as follows.

A. Subjective assessment

Subjective assessment is a direct approach to analyses the quality of the proposed image the through direct visual observation. To prove proposed method strength and flexibility, the different standard images are taken from various fields, like, low exposure images (fish, field, plane), medical images (Brain_MRI, MRI) and mammogram image (mdb209) as shown in fig2-7.

Fig 2a is an underwater fish image. Fig 2b, d, f, g are processed by HE, RSIHE, NMHE, and RSESIHE methods, these images look too bright and features are not clearly distinguishable. Especially dark and bright pebbles look same in color. Fig 2c, e, are the images of RMSHE and MMSICHE methods, appear too dark. Fig 2h, i, show the results of SIDSICHE, RS_SIDSICHE, these methods enhance in a balanced way, not only in scales of fish or pebbles or rock surface but also in surrounding dark areas of the image. They are looking more natural with improved visual quality and objects are easily distinguishable in comparison to other methods.

Fig 3a is an input low exposure field image and fig 3b, c, d are processed by HE, RMSHE and RSIHE methods. These images show over-enhancement and soil portion like a white spot, the roof of the vehicles are so bright and shrubs are too dark. Figure 3e is the result of MMSICHE method has a black spot all over. Fig 3f, g, h are the visuals of NMHE, RSESIHE, and SIDCSIHE. In these methods some of the information, is not so clear, which are highlighted in red boxes. The vehicle's side and shadow are darker, shrubs branches are merged, soil portion and shrubs are not distinguishable. The supremacy of the proposed method can be seen in fig 3i, which has balanced enhancement in every feature of image and is obvious from the visuals of images that one can distinguish soil, plants, and vehicles clearly.

Fig 4a is a brain_MRI image. Fig 4b, c, d, g are the result of HE, RMSHE, RSIHE and RSESIHE methods, here noise is amplified and leads to over enhancement. The dark image obtained by MMSICHE method is shown in fig 4e. Fig 4h, i, processed by applying SIDCSIHE and RS_SIDCSIHE has pleasant effect due to the contrast-enhancement of the image as compared to all other methods.

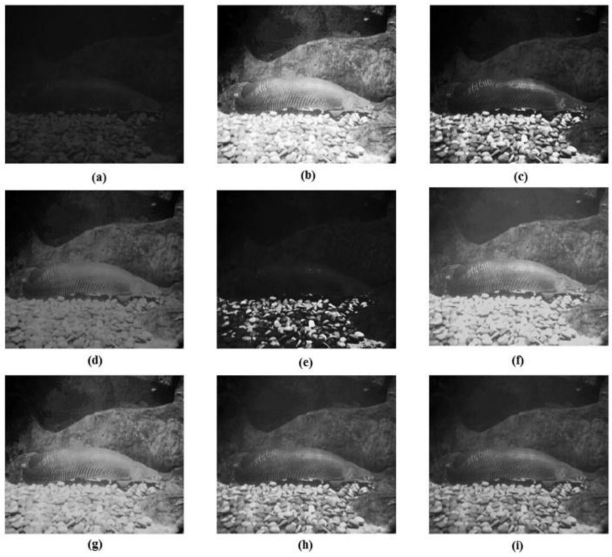

Fig 2. a) Input image of low exposure fish image and resultant images obtained by (b) HE; (c) RMSHE; (d) RSIHE; (e) MMSICHE ;(f) NMHE; (g) RSESIHE; (h) SIDCSIHE; (i) RS_SIDCSIHE.

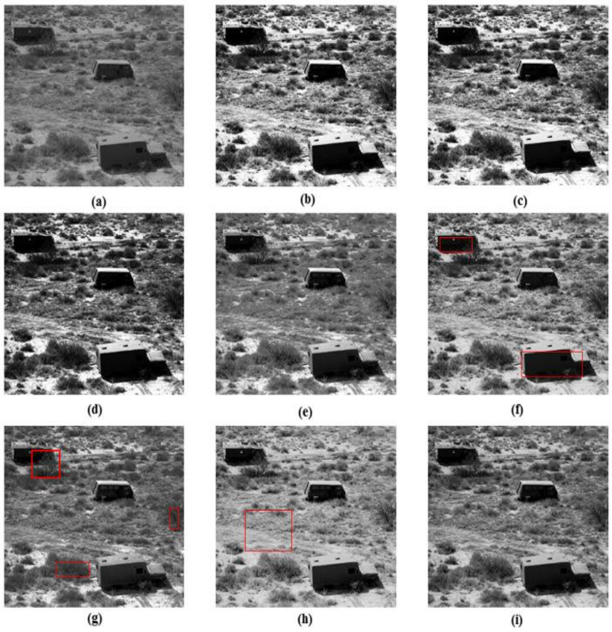

Fig 3. Input image of low exposure field image and resultant images obtained by (b) HE; (c) RMSHE; (d) RSIHE; (e) MMSICHE; (f) NMHE; (g) RSESIHE; (h) SIDCSIHE; (i) RS_SIDCSIHE.

The original MRI image is shown fig 5a. Fig 5b, d, g, are the results of HE, RSIHE, and RSESIHE methods, all these images leads to over enhancement. The image obtained by MMSICHE, RMSHE methods is shown in fig 5e and 4c are dark in nature. The fig 5h,i are the results of SIDCSIHE and proposed method yield better contrast-enhanced image.

The low exposure plane (Berkeley dataset) image is shown in fig 6a and the fig 6b-6e, g are the results of HE, RMSHE, MMSICHE, NMHE, and RSESIHE methods. In these images, the plane looks dark, and the neighboring raincloud region is unclear and have hostile visual artifacts and over-enhancement.

The fig 6f obtain by NMHE has a flawless look but not meet the visual effect of 6h, i , the results of SIDCSIHE and proposed the methods, respectively. The proposed method output image has natural and look due to preservation of maximum information.

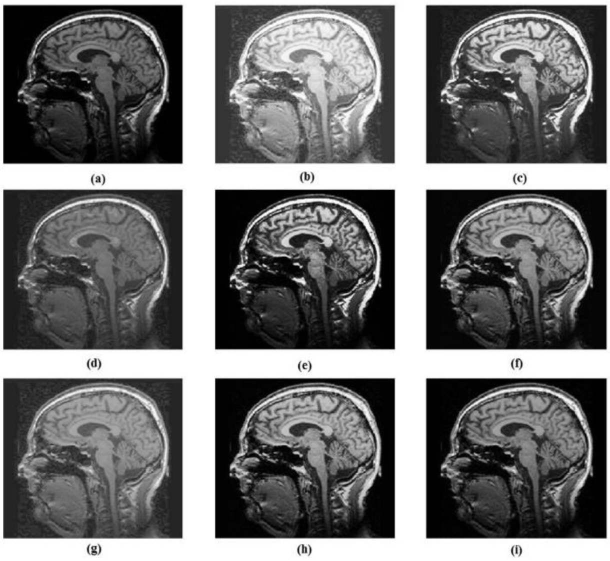

Fig 4. Input image of Brain_MRI and resultant images obtained by (b) HE; (c) RMSHE; (d) RSIHE; (e) MMSICHE; (f) NMHE; (g) RSESIHE; (h) SIDCSIHE; (i) RS_SIDCSIHE.

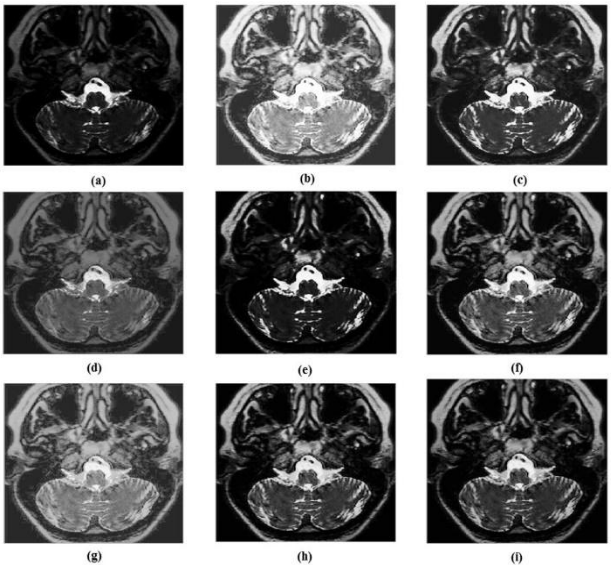

Fig 5. Input image of MRI and resultant images obtained by (b) HE; (c) RMSHE; (d) RSIHE; (e) MMSICHE; (f) NMHE; (g) RSESIHE; (h) SIDCSIHE; (i) RS_SIDCSIHE.

The original mammogram image (mdb209) is shown in fig 7a. Fig 7b-g are the results of HE, RMSHE, RSIHE, MMSICHE, NMHE, and RSESIHE. These images fail to show detail information like normal fatty tissue, dense breast tissue and infected area clearly. Especially fig 7e, f, fail to distinguish the outer surface of the breast and surrounding dark area. Fig 7h, i, are the results of the SIDCSIHE and proposed methods, show the outer surface clearly and highlights the deep abnormal area. The proposed method output image has accepted look with maximum information content.

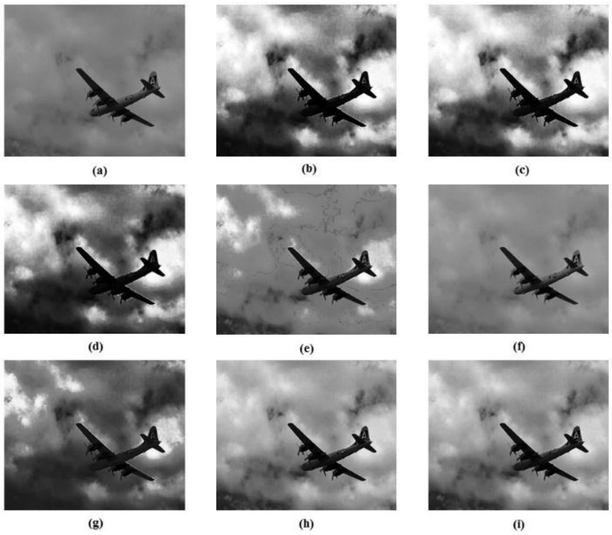

Fig 6. Input image of plane and resultant images obtained by (b) HE; (c) RMSHE; (d) RSIHE; (e) MMSICHE; (f) NMHE; (g) RSESIHE; (h) SIDCSIHE; (i) RS_SIDCSIHE.

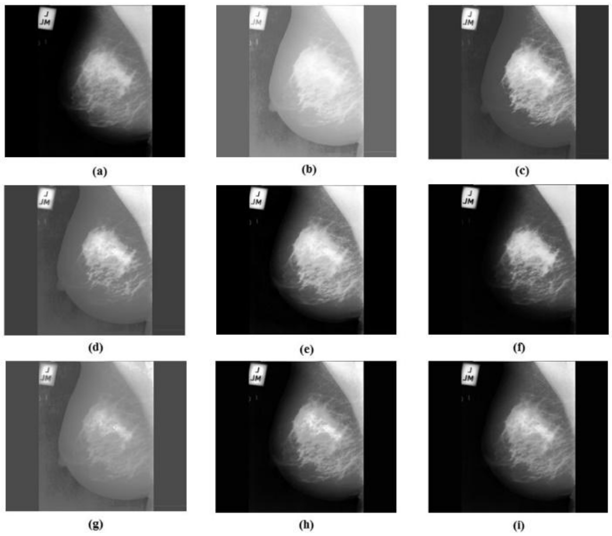

Fig 7. Input image of mammogram (mdb209) and resultant images obtained by (b) HE; (c) RMSHE; (d) RSIHE; (e) MMSICHE; (f) NMHE; (g) RSESIHE; (h) SIDCSIHE; (i) RS_SIDCSIHE.

B. Objective assessment

In addition to subjective assessment, the objective assessment is conducted and compared with other previous methods in terms of entropy value. It evaluates the capability of the proposed method for extracting details of the image. A higher entropy value specifies the image of better quality and more information content. The entropy is defined as

$$Entropy(p) = -\sum_{k=0}^{L-1} p(k) \log p(k) \quad (14)$$

where $p(k)$, is PDF at the intensity level k and L is the total number of gray levels of the image.

The objective assessment by the entropy value provides the quantitative information of various methods are recorded in table I. The different type of low exposure and medical test images are used for the study. The table I, shows that the proposed (RS_SIDCSIHE) method has the improved entropy value in most of the cases as compared to other methods.

In addition, to assess the strength of the objective assessment of proposed algorithm, all the methods are applied on Berkeley dataset of 100 images [18] and 100 mammogram images [19]. The measured entropy values are presented in table II. From table I and II, proposed method with its better entropy value have better enhancement effect than other methods.

Table- I. Average entropy values of comparisons methods

Input Image	Input entropy	HE	RMSHE	RSIHE	MMSICHE	NMHE	RSESIHE	SIDCSIHE	Proposed
fish	5.051	4.880	5.010	5.027	4.947	4.761	5.038	5.050	**5.050**
fish2	4.491	4.426	4.377	4.474	4.376	4.469	4.484	4.489	**4.489**
field	6.563	5.956	6.431	6.429	6.537	6.345	6.452	6.548	6.541
mosque	6.263	5.826	6.102	6.179	6.206	6.216	6.223	6.258	6.255
jet	6.678	5.710	6.552	6.442	6.569	6.442	6.482	6.514	**6.600**
brain MRI	6.254	5.021	5.768	5.890	6.110	6.209	5.970	6.161	6.175
Face MRI	6.379	4.991	6.010	6.099	6.298	6.336	6.070	6.285	6.284
Spine MRI	5.904	5.045	5.497	5.612	5.736	5.846	5.671	5.823	5.828
chest XRAY	7.273	5.976	7.126	7.180	7.215	7.214	7.164	7.220	7.215
average	6.095	5.315	5.875	5.926	5.999	5.982	5.950	6.039	**6.048**

Table II. Average entropy values of the proposed methods for Berkeley dataset and mammogram images

Methods	Berkeley dataset (100 images)	100 Mammogram images
Input entropy	7.182	4.460
HE	5.848	3.337
RMSHE	6.996	4.153
RSIHE	6.992	4.102
MMSICHE	7.094	4.368
NMHE	7.063	4.219
RSESIHE	6.985	4.066
SIDSICHE	7.100	4.363
RS_SIDCSIHE(Proposed)	**7.115**	**4.373**

IV. CONCLUSION

The effective recursive separate histogram equalization method is proposed for enhancing low exposure images, medical image, and mammogram images. The decomposition of histogram into sub histograms and further decomposition of each of these sub histograms, based on individual threshold value provides effective method for contrast enhancement. This approach is bringing out more information content of the images. The supremacy this method shows in the entropy value objectively and visual quality subjectively as compared to other methods with wide variety of images.

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