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Image Contrast Enhancement using Tri-histogram Equalization based on Minimum and Maximum Intensity Occurrence

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Abstract — This paper proposes an image enhancement technique using Tri-histogram equalization defined in terms of minimum and maximum intensity. Traditionally for image contrast enhancement, histogram equalization technique is used extensively. However, histogram equalization tends to change the mean brightness of any image to the middle gray level of the dynamic range, which often results in over or under enhancement and introduce some annoying artifacts. To overcome such problems, several bi-histogram based techniques and one tri-histogram based technique has been proposed. While bi-histogram based techniques divides the histogram of any image into two sub-histograms and equalize them independently, tri-histogram based technique divides the histogram into three sub histograms. This paper presents a novel tri-histogram based enhancement approach where two intensity values which are used to divide the histogram into three parts can be found by computing the minimum and maximum pixels per intensity count. After dividing the histogram into three parts, each of the parts are equalized individually and then combined together to produce the final enhanced image. The simulation results show that the proposed method outperforms other conventional bi-histogram and tri-histogram based techniques in terms of brightness preservation, structural similarity and PSNR.

Keyword — Brightness Preservation, Digital Image Processing, Image Enhancement, Intensity, Tri-histogram Equalization

1. Introduction

Most of the consumer graded image sensing device capture images that are significantly flat. Thereby, contrast enhancement plays a major role in the improvement of visual quality in computer vision, pattern recognition and in the processing of digital images. Among many other techniques for contrast enhancement, Global Histogram Equalization (GHE) was the most extensively utilized one. The target of global histogram equalization is to achieve uniform distribution of intensities for any image, which is done by flattening the probability distribution of that image and stretching the dynamic range of gray levels. In theory, the mean brightness of the histogram equalized image is always the middle gray level regardless of the input mean, which in practice, makes this method less ideal for consumer electronic appliances where brightness preservation is a necessary aim [2].

Several algorithms have been proposed by many researchers over the recent years to solve the aforementioned problem of GHE. One of the earliest attempts was Brightness Preserving Bi-histogram equalization (BBHE) which divides the input image histogram into two parts based on the input mean brightness and equalize both parts individually to obtain the final image [4]. Later, [8] proposes a new method namely equal area Dualistic Sub-Image Histogram Equalization (DSIHE) in which the authors claimed to outperform BBHE in terms of brightness preservation and image content (entropy) preservation. In DSIHE, instead of using mean brightness to divide the histogram as in BBHE, median value was chosen.

Nevertheless, in cases where higher degree of brightness preservation is the requirement, it has been found that, both BBHE and DSIHE could not perform well. This leads to a number of other methods including Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) [2], Recursive Mean-Separate Histogram Equalization (RMSHE) [1], Recursive Sub-Image Histogram Equalization (RSIHE) [6], Recursively Separated and Weighted Histogram Equalization (RSWHE) [3], etc. MMBEBHE provides a novel extension of bi-histogram equalization method where the histogram is divided into two parts by a threshold value which yields minimum difference between input mean and output mean. While other techniques like RMSHE, RSIHE and RSWHE divide the input histogram recursively. RMSHE uses mean brightness to divide the histogram while RSIHE uses median value instead. RSWHE is similar to RMSHE and RSIHE with an addition of a weighting process using normalized power law function.

Among some of the recent techniques, Exposure based Sub Image Histogram Equalization (ESIHE) [7] tries to separate the input histogram into two by finding an exposure threshold value and then clipping the histogram using clipping threshold, finally equalizing both of the clipped histogram separated by the exposure threshold individually. Another technique known as Statistic Separate Tri-Histogram Equalization (SSTHE) [5] was the first instance of the tri-histogram based separation technique which couldn't outperform any of the aforementioned bi-histogram based equalization methods.

Although various techniques are available to solve a broad range of enhancement problems, very little effort has been made on tri-histogram based contrast enhancement. In this paper, we present a new tri-histogram equalization algorithm refers to Minimum and Maximum Intensity based Tri-Histogram Equalization (MMITHE). Study shows that, the proposed method performs better in brightness preservation and contrast enhancement for low contrast and under-exposed images.

The rest of the paper is organized as follows: Section 2 presents the new tri-histogram based separation technique using minimum and maximum intensity as division points. Section 3 describes about absolute mean brightness error measurement feature used to measure enhanced images brightness preservation and quality. Section 4 gives experimental results with section 5 concluding the paper.

2. Minimum and Maximum Intensity Based Tri-histogram Equalization

In contrast to all of the bi-histogram equalization methods described in the previous section, tri-histogram based equalization methods chooses two intensity values to divide the histogram of the input image into three parts and then equalize each part individually.

Suppose $X = \{X(i,j)\}$ denotes an input image composed of L discrete gray levels, denoted by $\{X_0, X_1, ..., X_{L-1}\}$ and X_{min} and X_{max} denotes intensity values with minimum and maximum pixel per intensity count respectively, such that, $X_{\min} \in \{X_0, X_1, ..., X_{L-1}\}$ and $X_{\max} \in \{X_0, X_1, ..., X_{L-1}\}$. These two intensity values can be used to divide the input image into three sub-images X_l, X_m and X_u such that,

$$X = X_l \cup X_m \cup X_u \tag{1}$$

where

$$X_l = \{X(i,j) \mid X(i,j) \le X_{\min}, \forall X(i,j) \in X\} \tag{2}$$

$$X_m = \{X(i,j) \mid X_{\min} < X(i,j) \le X_{\max}, \forall X(i,j) \in X\} \tag{3}$$

and

$$X_u = \{X(i,j) \mid X(i,j) > X_{\max}, \forall X(i,j) \in X\} \tag{4}$$

This means, sub-image X_l consist of all pixels with intensity values in the range $\{X_0, X_1, ..., X_{\min}\}$, X_m consist of all pixels with intensity values in the range $\{X_{\min+1}, X_{\min+2}, ..., X_{\max}\}$ and X_u consist of all pixels with intensity values in the range $\{X_{\max+1}, X_{\max+2}, ..., X_{L-1}\}$.

Now, the probability density function (PDF) of the sub-images X_l, X_m, X_u can be defined as

$$PDF_l(X_k) = \frac{n_k}{n_l} \tag{5}$$

where $k = 0, 1, ..., min$, and

$$PDF_m(X_k) = \frac{n_k}{n_m} \tag{6}$$

where $k = min+1, min+2, ..., max$, and

$$PDF_u(X_k) = \frac{n_k}{n_u} \tag{7}$$

where $k = max+1, max+2, ..., L\text{-}1$. Here, $n_l = \sum_{k=0}^{\min} n_k$, $n_m = \sum_{k=\min+1}^{\max} n_k$ and $n_u = \sum_{k=\max+1}^{L-1} n_k$ represents the total number of pixels in the sub-image X_l, X_m and X_u respectively. Note that, the total number of pixels in the image is $N = n_l + n_m + n_u$, by definition. From the above definition of the probability density function, cumulative density function (CDF) can be defined as

$$CDF_l(X_k) = \sum_{j=0}^{\min} PDF_l(X_j) \tag{8}$$

where $k = 0, 1, ..., min$, and

$$CDF_m(X_k) = \sum_{j=\min+1}^{\max} PDF_m(X_j) \tag{9}$$

where $k = min+1, min+2, ..., max$, and

$$CDF_u(X_k) = \sum_{j=\max+1}^{L-1} PDF_u(X_j) \tag{10}$$

where $k = max+1, max+2, ..., L\text{-}1$. Note that, by definition, $CDF_l(X_k) = CDF_m(X_k) = CDF_u(X_k) = 1$.

We can define the transformation function $f_l(X_k)$, $f_m(X_k)$ and $f_u(X_k)$ exploiting the cumulative density functions obtained from Eqs. (8), (9) and (10) as

$$f_l(X_k) = X_0 + (X_{\min} - X_0) CDF_l(X_k) \tag{11}$$

$$f_m(X_k) = X_{\min+1} + (X_{\max} - X_{\min+1}) CDF_m(X_k) \tag{12}$$

and

$$f_u(X_k) = X_{\max+1} + (X_{L-1} - X_{\max+1}) CDF_u(X_k) \tag{13}$$

Based on these transform functions, the decomposed sub-images are equalized independently and the union of these equalized sub-images form the final output image. Mathematically we can state this as, Y is the output image found by

$$Y = \{Y(i,j)\} = f_l(X_k) \cup f_m(X_k) \cup f_u(X_k) \tag{14}$$

As (11), (12) and (13) suggest, $f_l(X_k)$ equalizes the input image over the range (X_0, X_{min}), $f_m(X_k)$ equalizes it over the range (X_{min+1}, X_{max}) and $f_u(X_k)$ equalizes it over the range (X_{max+1}, X_{L-1}). As a consequence, (14) equalizes the input image X over the entire dynamic range (X_0, X_{L-1}), which is expected to result in better brightness preservation than the global histogram equalization.

2.1 Analysis on the Brightness Change by MMITHE

It is well known that, the enhancement result of GHE produces an image with uniform gray level, i.e.

$$PDF(X) = \frac{1}{X_{L-1} - X_0} \tag{15}$$

for $X_0 \le X \le X_{L-1}$. This PDF can be used to derive statistically expected output mean, *E(.)* of the GHE method, which is

$$E(Y) = \sum_{X_0}^{X_{L-1}} xPDF(x)dx$$
$$= \sum_{X_0}^{X_{L-1}} \frac{x}{X_{L-1} - X_0} dx \tag{16}$$
$$= \frac{X_{L-1} + X_0}{2}$$

The derivation above is evident on one principle drawback of the GHE method which is, GHE produces the enhanced image where mean of that image always resides in the middle gray region, regardless of the property of the input image. This means, whether we provide a dark or light image, low contrast or high contrast image, GHEs output mean will always be the middle gray level.

This property is not desired in consumer graded applications. On the other hand, if we analyze our proposed MMITHE method, we find that, the mean brightness of the output image can be expressed as

$$\begin{aligned} E(Y) &= E(Y \mid X \le X_{\min})PDF(X \le X_{\min}) \\ &+ E(Y \mid X_{\min} < X \le X_{\max})PDF(X_{\min} < X \le X_{\max}) \\ &+ E(Y \mid X > X_{\max})PDF(X > X_{\max}) \\ &= (\frac{X_0 + X_{\min}}{2})PDF(X \le X_{\min}) \\ &+ (\frac{X_{\min+1} + X_{\max}}{2})PDF(X_{\min} < X \le X_{\max}) \\ &+ (\frac{X_{\max+1} + X_{L-1}}{2})PDF(X > X_{\max}) \end{aligned} \tag{17}$$

For ease of calculation, let the input image is equally distributed over the two dividing points X_{min} and X_{max}, which, in turn makes

$$\begin{aligned} PDF(X \le X_{\min}) &= PDF(X_{\min} < X \le X_{\max}) \\ &= PDF(X > X_{\max}) = 1/3 \end{aligned} \tag{18}$$

From equation (17), we now have

$$\begin{aligned} E(Y) &= \frac{1}{3}(\frac{X_0 + X_{\min}}{2}) + \frac{1}{3}(\frac{X_{\min} + 1 + X_{\max}}{2}) \\ &+ \frac{1}{3}(\frac{X_{\max} + 1 + X_{L-1}}{2}) \\ &= \frac{1}{3}(\frac{X_0 + X_{L-1} + 2X_{\min} + 2X_{\max} + 2}{2}) \\ &= \frac{1}{3}(X_G + X_{\min} + X_{\max} + 1) \end{aligned} \tag{19}$$

Where $X_G=(X_0+X_{L-1})/2$. Above equation is evident that, the expected output mean brightness of the equalized image can be found by averaging the middle gray level of the dynamic range with the chosen two division points which are the minimum and maximum intensity occurrences in the proposed method.

2.2 Algorithm of MMITHE

Step 1: Compute the histogram, *h(k)* of the input image.

Step 2: From the histogram, find intensities with minimum and maximum pixel per intensity count.

Step 3: Divide the input image into three sub-images using minimum and maximum intensity values obtained in step 2.

Step 4: Apply histogram equalization on the sub-images obtained in step 3.

Step 5: Combine the equalized images obtained in step 4 into one output enhanced image

3. Measurement Feature to Asses Image Quality

In this section, we provide definition to the most extensively used image quality assessment feature to analyze the brightness preservation of an enhancement method, known as absolute mean brightness error (AMBE), which we used to analyze our test images.

3.1 Absolute Mean Brightness Error (AMBE)

Absolute mean brightness error is a measurement feature used to measure how close the mean brightness of the enhanced image is to the input image. Hence, it's a measure to prove the enhanced image's brightness preservation. AMBE is defined as

$$AMBE(X,Y) = |X_m - Y_m| \tag{20}$$

where X_m is the mean of the input image X={X(i,j)} and Y_m is the mean of the output enhanced image Y={Y(i,j)}. Both of the mean brightness can be obtained by

$$X_m = \frac{\sum_{K=1}^{L-1} K.PDF(K)}{\sum_{K=1}^{L-1} PDF(K)} \tag{21}$$

For a particular image, the smaller the value of AMBE, the better its brightness preservation is obtained.

4. Results and Discussions

To demonstrate the performance of the proposed method, in this section, the simulation results are compared with the global histogram equalization method (GHE), along with some other bi-histogram and tri-histogram equalization techniques such as BBHE, DSIHE, MMBEBHE, ESIHE and SSTHE. Eight different test images such as: *Mount Teide, Fish, Wheel, House, Snow Hill, Cameraman, Restaurant and Sandwick* are compared between the proposed and other existing methods, while first three of which are presented for visual quality analysis.

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Table 1 shows a matrix of AMBE measurements between test images where rows correspond to the test images and columns correspond to enhancement methods. As can be seen from table 1, compared to other methods, MMITHE provides significantly better brightness preservation for a broad range of images as evident from the minimum value of AMBE. MMBEBHE is also very good in terms of brightness preservation, while other bi-histogram based methods such as BBHE, DSIHE, ESIHE, along with the existing tri-histogram based method SSTHE performs poorly in the tested cases.

Table 1. AMBE measurement between test images

File	GHE	Bi-HE Methods				Tri-HE Methods	
		BBHE	DSIHE	MMBEBHE	ESIHE	SSTHE	MMITHE
Mount Teide	81.0916	27.8927	22.622	12.7794	56.5199	27.1936	**11.8317**
Fish	42.5636	26.1404	25.0187	10.6076	18.8043	23.6254	**4.2324**
Wheel	41.3501	10.3941	15.4912	1.3053	5.9665	16.9197	**1.036**
House	52.658	16.4289	17.9424	14.7611	24.3205	15.1204	**12.7702**
Snow Hill	3.3994	2.2087	2.2087	1.4095	10.8823	9.0521	**1.119**
Cameraman	10.4783	24.2581	17.9147	1.1832	17.3724	21.091	**0.68476**
Restaurant	20.561	10.0057	10.2009	1.2093	3.3959	11.1965	**0.12589**
Stanwick	5.1929	5.3568	0.16319	9.8087	8.9367	14.0288	**0.053192**

Qualitative measures are equally important along with quantitative measures, since contrast enhancement can only be appreciated if the resultant image gives a pleasing appearance. To test the robustness of the proposed method, a range of low to high contrast images are used. All these images are analyzed using the existing bi-histogram and tri-histogram based methods.

The concrete result of contrast enhancement is clearly observed in Figure 1 to 3. If we closely observe the background of the *Mount Teide* image in Figure 1, we find that, GHE, BBHE, ESIHE, SSTHE significantly degrade the quality of that region by over-enhancement, while DSIHE, MMBEBHE and the proposed method provides better control for over-enhancement.

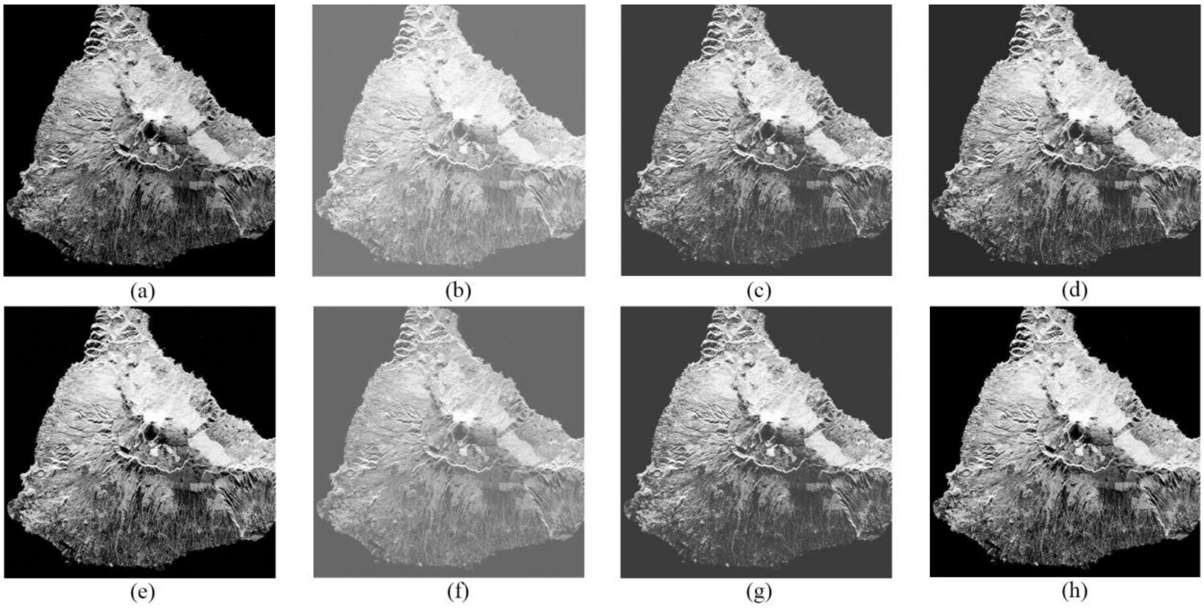

Fig. 1. Enhancement results of Mount Teide image: (a) Original, (b) GHE, (c) BBHE, (d) DSIHE, (e) MMBEBHE, (f) ESIHE, (g) SSTHE, (h) MMITHE

The background of Figure 2 of the fish image is similarly over enhanced by GHE, BBHE, DSIHE, ESIHE and SSTHE methods. Only MMBEBHE and the proposed method provide better overall enhancement. Again, Figure 3 shows that the jacket of the observer is blown out by GHE, BBHE, DSIHE and SSTHE, while rest of the methods performs quite well. Enhancement results for many other images also suggest that the proposed method provides most pleasing visual quality in most of the cases.

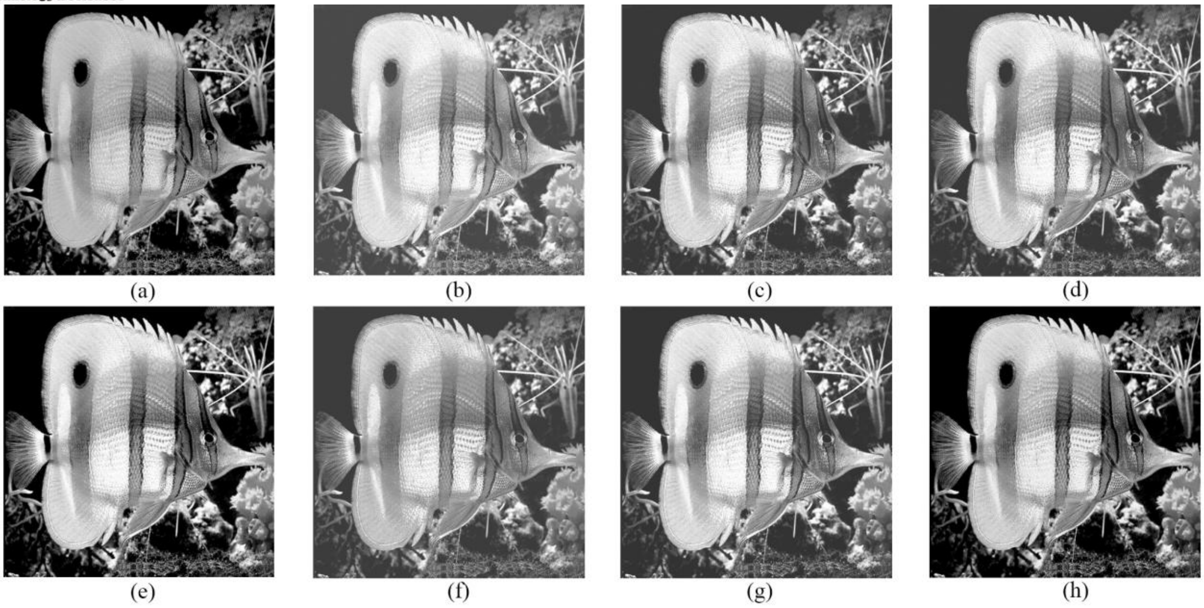

Fig. 2. Enhancement results of Fish image: (a) Original, (b) GHE, (c) BBHE, (d) DSIHE, (e) MMBEBHE, (f) ESIHE, (g) SSTHE, (h) MMITHE

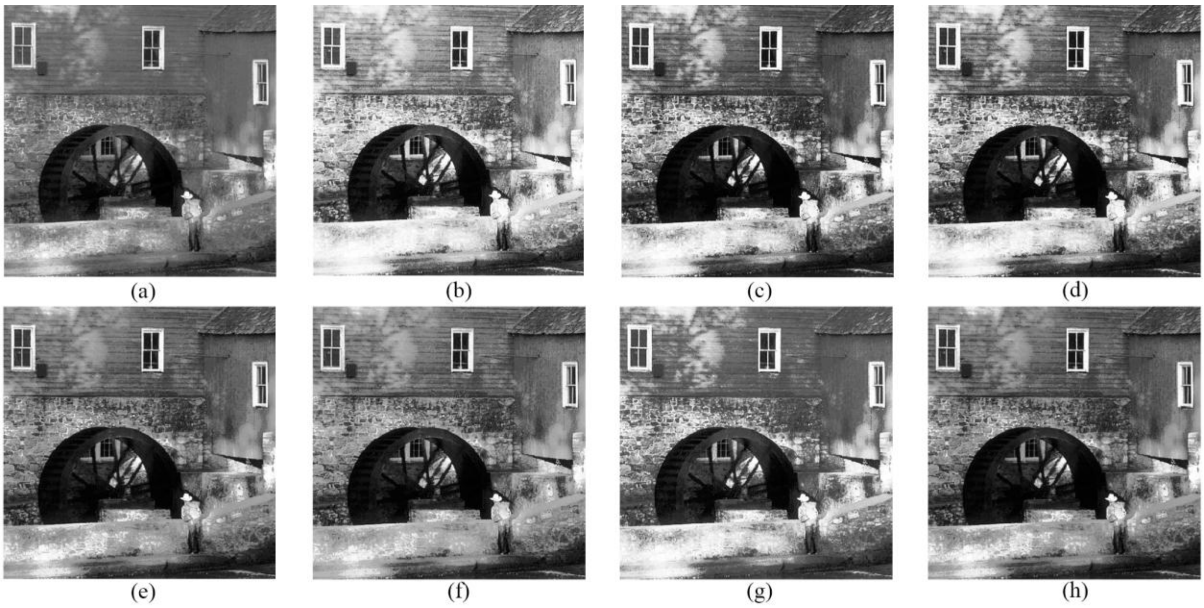

Fig 3. Enhancement results of Wheel image: (a) Original, (b) GHE, (c) BBHE, (d) DSIHE, (e) MMBEBHE, (f) ESIHE, (g) SSTHE, (h) MMITHE

5. Conclusion

In this paper, we proposed a novel contrast enhancement technique based on tri-histogram equalization. The proposed tri-histogram based enhancement technique is very much effective in terms of brightness preservation. The algorithm is also easy to implement in real-time processing. Also the enhanced images has a promising visual quality for display purpose in consumer graded electronic devices. Thus the proposed technique can be a good selection for image contrast enhancement.

Reference

[1] Chen, S.D., Ramli, A.R., “Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation”, IEEE Trans. on Consumer Electronics, vol. 49, no. 4, 2003, pp. 1301–1309.

[2] Chen, S.D., Ramli, A.R., “Minimum mean brightness error bi-histogram equalization in contrast enhancement”, IEEE Trans. Consumer Electron, vol. 49, no. 4, 2003, pp. 1310–1319.

[3] Kim, M., Chung, M.G., “Recursively separated and weighted histogram equalization for brightness preservation and contrast enhancement”, IEEE

Trans. Consumer Electron, vol. 54, no. 3, 2008, pp. 1389–1397.

[4] Kim, Y.T., “Contrast enhancement using brightness preserving bi-histogram equalization”, IEEE Trans. on Consumer Electronics, vol. 43, no. 1, 1997, pp. 1–8.

[5] Lin, P.H., Lin, C.C., Yen, H.C., “Tri-Histogram Equalization Based on First Order Statistics”, IEEE 13th International Symposium on Consumer Electronics, Kyoto, 2009, pp. 387-391.

[6] Sim, K.S., Tso, C.P., Tan, Y.Y., “Recursive sub-image histogram equalization applied to gray scale images”, Pattern Recogn. Lett, vol. 28, no. 10, 2007, pp. 1209–1221.

[7] Singh, K., Kapoor, R., “Image enhancement using Exposure based Sub Image Histogram Equalization”, Pattern Recogn. Lett, vol. 36, 2014, pp. 10-14.

[8] Wan, Y., Chen, Q., Zhang, B.M., “Image enhancement based on equal area dualistic sub-image histogram equalization method”, IEEE Trans. Consumer Electron, vol. 45, no. 1, 1999, pp. 68–75.