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A Comparative Study of Contrast Enhancement using Image Fusion

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Abstract: *Image enhancement is used to improve the visual quality of an image. In this paper a different approach on image fusion has been described for image enhancement. The two main algorithms involved in this approach are Recursive Mean Separate Histogram Equalization and Linear Image Fusion. To get the fused image in this approach the input images are the original image and the Recursive Mean Separate Histogram Equalised image of the original image. The quality of an image has been judged by the parameters of Average Gradient and Standard Deviation and the result is compared with the image obtained after Linear Image Fusion.*

Keywords: *Histogram equalization, linear image fusion, recursive mean separate histogram equalization, average gradient, standard deviation.*

I. Introduction

The goal of image enhancement is to improve the visual quality of the input image. Numerous techniques are available for image enhancement in the literature. Histogram equalization is a very popular technique for enhancing the contrast of an image. Histogram equalization can be applied in various fields such as medical image processing and radar image processing. However, histogram equalization is not commonly used in consumer electronics because it may significantly change the brightness of an input image and cause undesirable artifacts. To overcome this problem the mean preserving Bi-histogram equalization (BBHE) has been proposed. But there are still cases that are not handled well by BBHE. But Mean-Separate Histogram Equalization provides not only better but also scalable brightness preservation to avoid annoying artifacts.

Image fusion is used to combine two or more images. By fusing the original image and the mean preserved By-histogram equalized image we can retain the best features of the two images. Section 2, 3, 4, 5 contains the related background information. Section 6 outlines the algorithm and section 7 shows the simulation results. Finally, section 8 concludes this work.

II. Histogram Equalization

The histogram of an image represents the frequency of occurrences of all the gray levels in an image. If n(k) is the frequency of k^{th} intensity level and n is the total number of pixels in the gray-level image then the normalized histogram is represented by the equation

$$P(k) = n(k) / n \tag{1}$$

The conventional histogram equalization is based on cumulative frequency distribution which is given by the equation

$$C(k) = \sum_{j=0}^{k} p(j) \tag{2}$$

In conventional histogram equalization the original brightness of the image cannot be preserved. Various brightness preserving

III. Image Fusion

Image fusion is the process by which two or more images can be combined. For example lower resolution multispectral images can be fused with higher resolution panchromatic images to get high resolution images with more information.

Image fusion can be divided into signal level fusion, pixel level fusion, feature level fusion and decision level fusion [7]. We use pixel level image fusion for our experiment.

For image fusion we need two source images where one can be the original image and the other can be the histogram equalized image. We take the following expression [2] to obtain the fused image If of two images I1 and I2.

$$If = \alpha * I1 + (1-\alpha) * I2 \tag{3}$$

where $0 \leq \alpha \leq 1$. When $\alpha = 1$ then the fused image would be identical to the original image I1. When $\alpha = 0$ then the fused image would be identical to the histogram equalized image I2.

Generally the overall visual quality of the original image is better than the equalized image. We do the experiment for the values of $\alpha=0.5$, $\alpha=0.6$ and $\alpha=0.7$, because of the better visual quality of the original image. According to [2] for $\alpha=0.7$ it gives better result in most of the cases.

IV. Image Statistics

4.1 Standard Deviation

Standard deviation shows how much deviation from the average or mean exists. It represents the dynamic range of values present in an image about the mean. If we get greater value of standard deviation then greater is the contrast of the fused image. If m is the mean of the image, then the standard deviation about the mean is given by:

$$STD = \sqrt{\frac{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (I(x, y) - m)2}{MN}} \quad (4)$$

Here I(x, y) is the intensity of the pixel, M is the number of rows and N is the number of columns.

4.2 Average Gradient

Average gradient is used for measuring the clarity of the image. More the average gradient value means more clarity of the image. It is represented by the formula:

$$AG = \frac{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} g(x, y)}{MN} \quad (5)$$

V. Recursive Mean Separate Histogram Equalization

In Recursive Mean Separate Histogram Equalization the brightness preservation can be achieved by mean separation.

The output mean E(Y) of typical HE is given by:

$$E(Y) = (X0 + XL-1) / 2 = XG \quad (6)$$

Where (X0, XL-1) is the entire dynamic range of intensity levels. In the equation (6) the output mean is always equal to the middle gray level XG . This HE is equivalent to RMSHE with recursion level, r = 0.

The output mean E(Y) after BBHE is as follows:

$$E(Y) = (Xm + XG) / 2 \quad (7)$$

BBHE is equivalent to RMSHE with recursion level r = 1.

The output mean for RMSHE recursion level r = n can be represented as follows:

$$E(Y) = Xm + [(XG - Xm)/2n] \quad (7)$$

If n grows larger then E(Y) will eventually converge to the input mean.

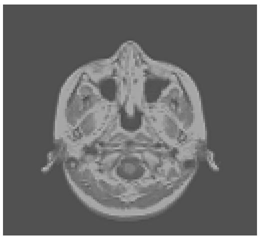
VI. Algorithm

Standard deviation and average gradient of an image can judge the brightness and clarity of the image. Using these two parameters in RMSHE we can get the recursion level where for a particular value of E(Y) we can get an image with good brightness and good contrast.

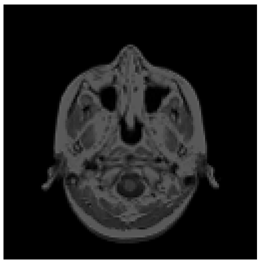
- Let the input image is I1.
- Start computing the recursive mean separate bi-histogram equalized image with recursion level starting from r = 0.
- Compute the standard deviation and average gradient of the image at each recursion level if the values are increasing at each level. If any one of the parameter will decrease, stop computing at that level and take image of the previous level.
- Do image fusion using equation number (3) with the original image and the recursive mean separate histogram equalized image for three different values of α. If we set the value of α greater than 0.5 then the fused image will take more portion from the original image. According to [2] generally the visual quality of the original image is better than the equalized image and α=0.7 works well so the experiment will be done for three consecutive values of α that is 0.5, 0.6 and 0.7.

VII. Simulation Results

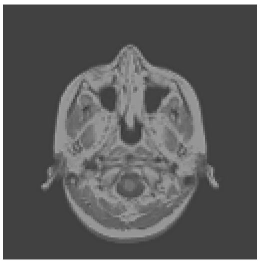
In this section, the proposed approach is verified by examples. In the simulation MRI images of skull are given as examples. The parameter α in the proposed approach is set to 0.5, 0.6 and 0.7 respectively. The original image, normal histogram equalized image and the images generated by the proposed approach are given in the following figures. Here we used the standard deviation and average gradient for comparing the performance. The results are given in the following tables.



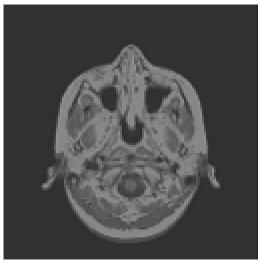
(a)



(b)

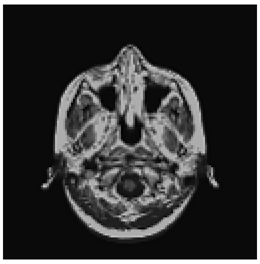


(c)

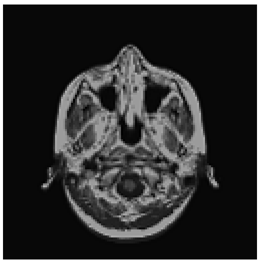


(d)

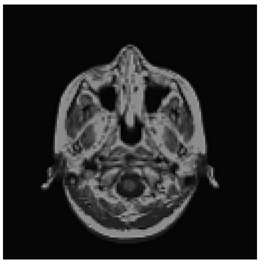
Fig 1. (a) Original Image (b) Image after applying LIF with α=0.5 (c) Image after applying LIF with α=0.6 (d) Image after applying LIF with α=0.7



(a)



(b)



(c)

Fig 2. (a) Fused image according to the proposed algorithm with α=0.5 (b) α=0.6 and (d) α=0.7 respectively

Image	Value of parameter α	Standard deviation of fused image applying LIF	Standard deviation of fused image applying Proposed algorithm
MRI of skull	0.5	30.8760	54.2403
	0.6	31.1035	49.6948
	0.7	31.6698	45.5534

Table1: Comparison between LIF and the proposed algorithm using standard deviation

Image	Value of parameter α	Average gradient of fused image applying LIF	Average gradient of fused image applying Proposed algorithm
MRI of skull	0.5	4.4190	9.7346
	0.6	4.3690	8.6428
	0.7	4.7346	7.5846

Table1: Comparison between LIF and the proposed algorithm using average gradient

VIII. Conclusion

Comparing the simulation results in the above figures and the Table one can easily recognize that the proposed algorithm enhances the quality of the fused image. In terms of standard deviation and average gradient the proposed algorithm gives better results as shown in the tables. It means the proposed algorithm increases the contrast of the fused image and also the clarity (sharpness) enhances.

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