**Journal of Telematics and Informatics (JTI)**
Vol.8, No.1, June 2020, pp. 9-17
ISSN: 2303-3703


# Improvement of Enhanced Image Using Mean and Standard Deviation Increment Method Based on Visual Representation Statistics

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***Abstract***

*Processes of image quality enhancement often leave deficiencies in the image result. These deficiencies in the form of loss of local contrast and loss of detail in some parts of the image. These deficiencies resulted in some important information on the image become unreadable. The deficiency that caused from processes of image enhancement can be minimized by taking information back from the original image. Taking this information can be done by combining the original image with the image of the improvements. Before the fusion of image, the means of average value and standard deviation value from the result on image should be improved first enhancement, so that fusion of image can be maximum. From the tested of 500 (five hundred) images that consist of image lacks brightness, image lacks contrast, and image lacks brightness and contrast, there were 74 (seventy four) image that can not be full repaired by using the proposed method. But for the image of the other experiments, the proposed method could improve image deficiencies. In this success level from method which is proposed reaches 85 %.*

***Key Word* :** *image improvement, mean increament, standard deviation increament.*

## 1. Introduction

Designing an improvement (improvement) in image quality must be the goal to make the original image better for certain applications or objects. In addition, improving image quality also has the purpose of improving the interpretation and perception of information contained in images by the human eye, or to provide better input for techniques that support other images.

Many methods have been approved to improve the image on the spatial domain, some are based on modifications, some are based on local contrast resolution and edge information. These methods are more effective at improving the perception and information of images in the human eye, but some methods still lack, such as reversing local contrast and detail, including Gamma Correction, Multi Scale Retinex (MSR), and Gradient Domain Method[1].

Qiang Chen solved this problem by using a fusion method that uses free sigmoidal merging weights based on local contrast measurements[8]. This method can correct deficiencies in the quality improvement results by improving the contrast that is lost on the results of quality improvements taken from the original image. However, this method depends on the quality of the input image. The lower the quality of the input image, the lower the quality of the image produced, and vice versa.

On the other hand, Daniel J. Jobson found a relationship between statistical characteristics and good visual representation. Jobson stated the facts about imagery can be measured using an average value (μ), and image contrast can be assessed using standard deviation (σ). The work states that the ideal image has an average of μ of 100-200 or 0.3921-0.7843 for normalized images, and the average σ is 40-80 or 0.1568-0.3137 for normalized images[2].

Meanwhile in an effort to improve image quality, Hadiq in his research conducted a histogram evaluation first[6]. The histogram evaluation process begins with making an image grayscale potato, nk is the number of pixels at the ash level to k, and n is the total number of pixels in the image, histogram evaluation checks every nk / n. If nk / n has an accumulation of 0.5% -3%, then the pixels at the gray level to k are combined with pixels at the gray level to k + 1[3]. The image of the evaluation results is then optimized for the average value and default deviation, so that it can be accessed at the request of an ideal image for Daniel J. Jobson's research. This method can correct deficiencies in the quality improvement results by improving the contrast that is lost on the results of quality improvements taken from the original image. But this Hadiq method cannot be applied to images that have very low contrast and conversion rates

## 2. Research Method

### 2.1. Visual Representation Statistics

Daniel J. Jobson conducted a study of the relationship between statistical characteristics of images with good visual representation. In the study, Jobson suggested that image brightness can be measured using an average value (μ), and image contrast can be measured using standard deviation (σ)[2].

To measure regional parameters, Jobson divides the image into several sub-images that do not overlap with the size of each block of 50 x 50. In each sub-image, the calculation of the values μ and σ[3].

Calculation of μ sub image values is done by the following equation :

$$I_f(i,j) = \frac{1}{(2P+1)(2Q+1)} \sum_{m=i-P}^{i+P} \sum_{n=j-Q}^{j+Q} f(m,n)$$

While the calculation of σ sub imagery with the following equation :

$$\sigma_f = \frac{1}{(2P+1)(2Q+1)} \sum_{m=i-P}^{i+P} \sum_{n=j-Q}^{j+Q} [f(m,n) - I_f(i,j)]^2$$

where *(2P + 1) (2Q + 1)* is the width of the sub-image analyzed.

In the study Jobson found that everything that looks good visually has convergent statistical characteristics.

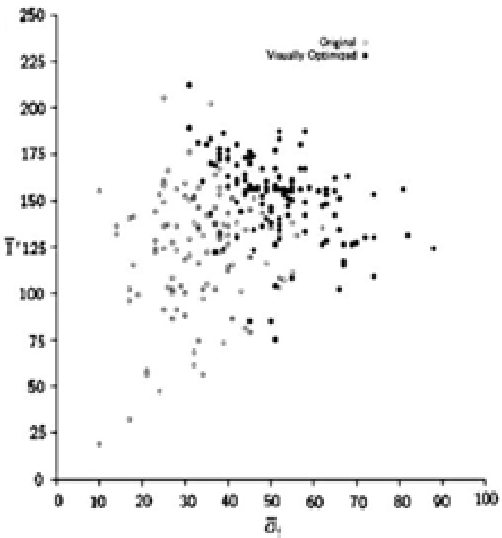



Figure 1. The ideal visual representation experiment

Figure 1 shows the actual point data group. The data provides the idea that optimal visual representation of data meets on two things. First, the average value with data that is clustered with high density and has a value of around 165, has a more optimal visual representation than data spread over a wider area. Second, the average frame of the standard deviation in the image with optimal visual representation significantly shifts to a higher value. Jobson then concluded that the ideal image has a contrast value (standard deviation) at a range of 40-80.

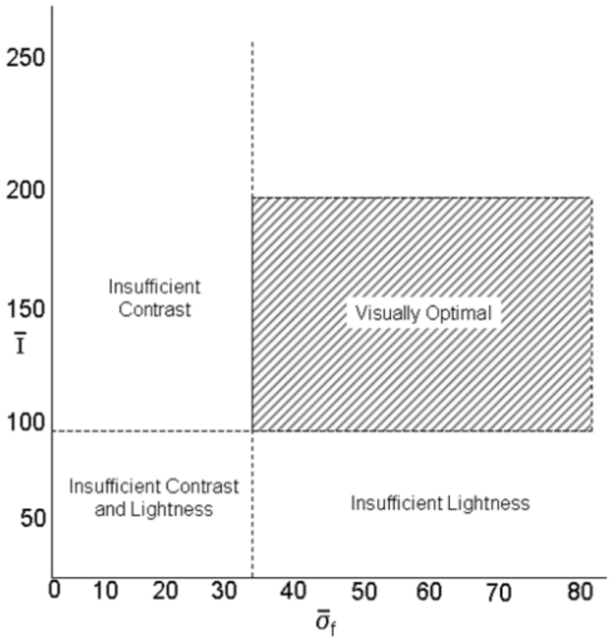



Figure 2. Image sharing based on visual representation statistics

Share images based on visual representation statistics. Based on the results of the study, Jobson divides the image into four categories, as shown in Figure 2. First, images that have deficiencies in contrast and brightness, namely images that have an average value μ below 100 (0.3921 for normalized images ) and has an average value of σ below 40 (0.1568 for normalized images). Second, images that have a deficiency in contrast, namely images that have an average value of μ of 100-200 (0.3921-0.7843 for normalized images) and an average value of σ below 40 (0.1568 for normalized images). The three images that have deficiencies in brightness, namely images that have an average value of μ below 100 (0.3921 for normalized images) and an average value of σ of 40-80 (0.1568-0.3137 for normalized images). Fourth is the ideal image (visually optimal), that is the image that has an average value μ of 100-200 (0.3921-0.7843 for normalized images) and the average value of σ is 40-80 (0.1568-0.3137 for normalized images)[9][10].

### 2.2. Increase in mean μ and σ

The method of increasing the average μ and σ image aims to strive for an increase in the average value μ and σ image so that it is included in the ideal image criteria.

Increasing the average value μ is done by adding pixel values with absolute values of the average pixel difference with neighboring pixels, using the following equation :

$$g(x,y) = \frac{1}{9}\sum_{i=x-1}^{x+1}\sum_{j=y-1}^{y+1}(|f(x,y) + f(i,j)|)$$

where *g(x,y)* is the result pixel value, *f(x,y)* is the original pixel value, and *f(i,j)* is the pixel difference value with neighboring pixels.

Calculation of pixel difference values is done by using a 3x3 filter. This is based on the assumption that the larger the filter is used, the greater the blur process will occur, which will cause the lower SNR (Signal to Noise Ratio) value.

Increasing the average value of σ is done by using unsharp masking. The unsharp masking process is generally divided into three steps. First, make the image blurry from the original image. Second, to reduce the original image with blurry images. The results of this reduction are then used as a mask. Third, combine the mask with the original image. The result of the process is an image that looks sharper than the original image.

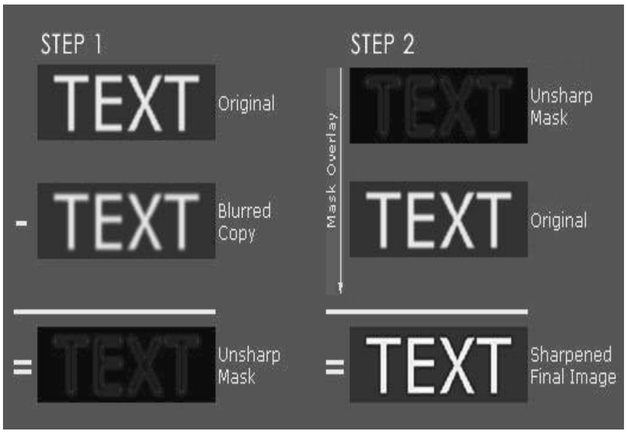



Figure 3. Unsharp masking process

### 2.3. Local Contrast, Weight and Image Merger

Local contrast is one method of measuring image quality based on differences in intensity in small areas. This method works in the Ii image, where i = 1, 2 which is two normalized grayscale images. For each point (x, y) on Ii, local contrast is defined as the following equation :

$$Ci(x,y) = max(Ni(x,y)) - min(Ni(x,y)$$

where *Ni(x,y)* is a representation of a local image with a size of 3x3 which is centered on the point *(x,y).* While max (.) And min (.) Are the maximum and minimum values of local images. Thus local image contrast is formed from the difference in intensity in each local image with a size of 3x3.

After knowing the local contrast, the next step is to determine the local contrast differences from C1 and C2 by using the following equation:

$$D(x,y) = C2(x,y) – C1(x,y)$$

Image merging weight is determined by the following equation :

$$W = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{e}^{-\boldsymbol{a}\,(\widehat{\boldsymbol{D}} - \boldsymbol{b})}}$$

where *a = 5, b = - (min(D) / (max(D) – min(D)),* and $\widehat{D} = D - min\ (D)/(max(D) - min(D))$

For the merged image, it is determined by the following equation:

$$R = \widehat{W}.I_2 + (1 - \widehat{W})I_1$$

where $\widehat{W} = (W - \min\ (W)/(\max(W) - \min(W)$ is the normalized weight.

### 2.4. Fidelity Criteria

A process carried out in an image can result in loss of information on the image of results. Therefore a criterion is needed to measure the correctness of the results of the process. These measurement criteria are called Fidelity Criteria.

There are two types of criteria that can be used to measure the truth of the results of a process in an image, namely subjective truth criteria and objective fidelity criteria.

Subjective truth criteria are done by asking people directly about the quality of the image. Assessment can be done by comparing the result image with the original image, then a rating scale is created where each scale is related to quality. For example, the rating scale is (5, 4, 3, 2, 1) which represent quality (very good, good, same, bad, very bad). Assessment is carried out by using a certain sample size, then the results of the assessment of each sample are taken the average value[11].

Objective truth criteria are carried out by measuring the difference in distortion between the original image and the result image, so that this objective approach is often called Difference Distortion Measure.

Here are some methods that can be used to measure the truth of the results of a process in an image.

### 2.4.1. MSE (Mean Square Error)

Is one of the techniques used to measure the quantity of differences between estimates and the estimated truth value of the quantity, or can also be defined as sigma of the number of errors between the result image and the original image. The equation used is as follows :

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y) - I'(x,y)]^2$$

where *I(x,y)* is the pixel value in the original image, $I^1(x,y)$ is the pixel value in the result image, while M and N are the dimensions of the image.

The small MSE value on the resulting image indicates that the image is better than the result image that has a greater MSE value

### 2.4.2. PSNR (Peak Signal to Noise Ratio)

Is one technique in measuring the quality of image reconstruction without losing its original features. The equation used is as follows :

$$PSNR = 20xlog_{10}\left(\frac{b}{\sqrt{MSE}}\right)$$

where the value of b is the maximum value of the pixel image used.

A large PSNR value on the image results indicates that the image is better than the result image that has a smaller PSNR value

### 2.4.3. SNR (Signal to Noise Ratio)

Is the ratio of signal power to noise that damages the signal. The equation used is as follows :

$$SNR = 10\ log_{10}\left(\frac{\sum_{x,y} f(x,y)^2}{\sum_{x,y} f(x,y) - h(x,y))^2}\right)$$

A large SNR value on the resulting image indicates that the image is better than the result image that has a smaller SNR value.

## 2.5. Design System

The design of the algorithm used to obtain results that are in accordance with the objectives of this study is shown in the following figure 4.

The first step is to determine the input image to be tested. At this stage a selection is made whether the average value of the image and the average value of the standard deviation of the image are below the ideal image criteria as Daniel D. Jobson's findings or not (mean of µ 0.3921-0.7843 and σ 0.1568-0.3137). If the value is below the ideal image criteria, then the image will be used as an input image in the trial of this method.

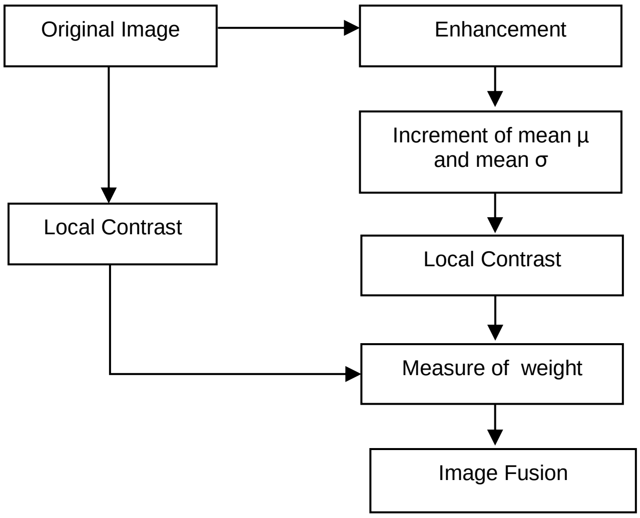



Figure 4. Block diagram

The second stage is to carry out the enhancement process in the input image using the Gamma Correction method. The basis of using this method is because Gamma Correction is proven to be able to improve image brightness, although there are still weaknesses in it, namely the loss of contrast in certain parts. Therefore this method is very appropriate if used to repair images that have less brightness values[4][5].

The third stage is to increase the average value µ and the mean value σ of the image as a result of enhancement. Increasing the average value of µ imagery is done using the method proposed in this study, namely the method of increasing the average image. While increasing the average value of σ is done by unsharp masking. The basis of using this method is because unsharp masking is proven to be able to improve image contrast[7].

The fourth stage is to look for local contrast values from the original image and images that have increased the average value µ and σ. This is done in order to be able to reduce the shortcomings of each image that will be combined especially in contrast. This local contrast value will be used as a reference to determine the weight of each image.

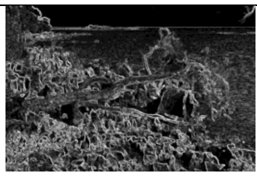
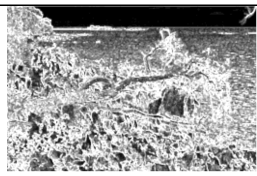
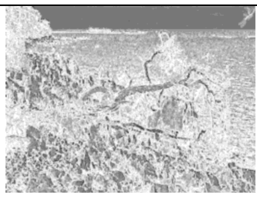
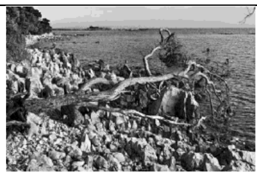
The fifth stage is to determine the weight value of the original image and the image that has increased the average value µ and σ. This weight value is used to determine how big the portion of each image is when merging. The weight value used is based on the local contrast value of each image. This is done in order to be able to reduce the shortcomings of each image that will be combined especially in contrast.

The sixth step is to combine the two images with the weights that have been obtained.

## 3. Results and Analysis

To find out how much the success of the research is carried out, it is necessary to test the proposed method.

Table 1. Trials

| Image | Information |
|---|---|
|  | Input image |
|  | Enhancement (Gamma correction) |
|  | Increment of mean μ and mean σ |
|  | Local Contrast |
|  | Local contrasts have increased mean values μ and σ |
|  | Measure of weight |
|  | Output image |

The statistical data of the visual representation of the trial are as follows :

Table 2. Visual Representation Statistical Data

| | Mean of μ | Mean of σ |
|---|---|---|
| Input image | 0.3306 | 0.1526 |
| Gamma correction | 0.5561 | 0.1253 |
| Proposed method | 0.3961 | 0.1773 |

From these data it can be seen that the results of gamma correction are only able to increase the average value of μ imagery but experience a decrease in the σ average image value.

While the results of the proposed method are able to increase the average value of µ and the average value of σ imagery, where the increase value is included in the ideal image range (mean value µ 0.3921-0.7843 and the mean value σ is 0.1568-0.3137)

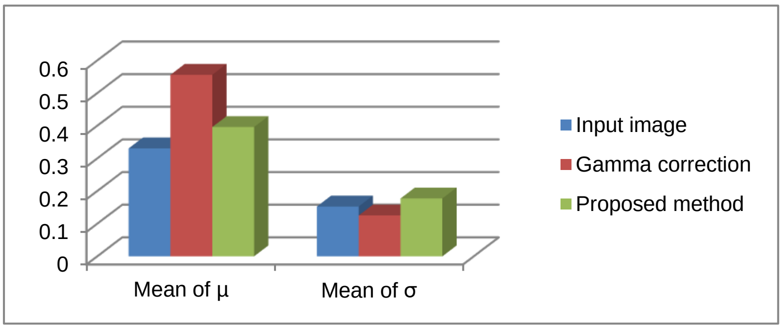
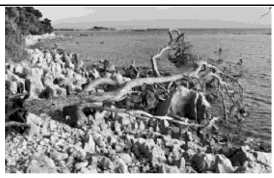



Figure 5. Statistical graph of visual representation

### 3.1. Comparison Method

Another method used as a comparison is the Qiang Chen method and the Hadiq method. The results of the comparison are shown in the following table :

Table 3. Comparison method

| Result | Method |
|---|---|
|  | Qiang Chen method |
|  | Hadiq method |
|  | Proposed method |

The fidelity criteria data from the comparison of the three methods can be seen in the following table :

Table 4. Fidelity criteria

| | Qiang Chen method | Hadiq method | Proposed method |
|---|---|---|---|
| MSE | 1659.20 | 1274.30 | 602.67 |
| PSNR | 15.93 | 17.08 | 20.33 |
| SNR | 8.92 | 10.07 | 13.32 |

From the fidelity criteria data it can be seen that the results of the proposed method have smaller MSE values and have PSNR and SNR values greater than the previous two methods.

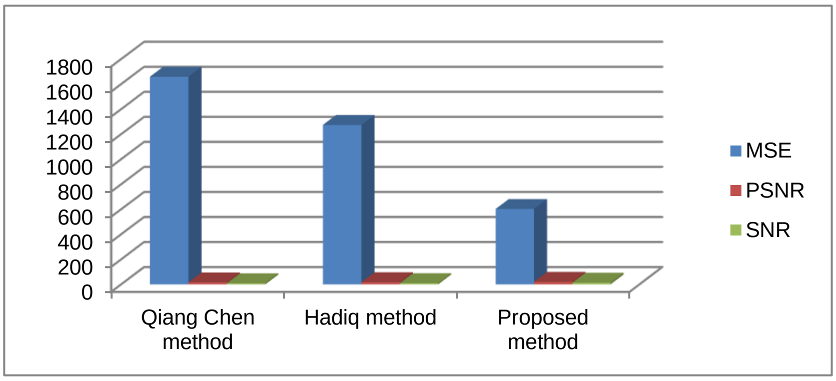



Figure 6. Statistical graph of comparison method

All stages of the trial are then used to test 500 (five hundred) images consisting of images that have deficiencies in brightness, deficiencies at the level of contrast, and images that have deficiencies in brightness and contrast. The result is 74 (seventy four) images that cannot be repaired optimally using the proposed method. As for the other 426 images, the proposed method is able to improve image deficiencies.

## 4. Conclusion

The conclusions obtained from the research conducted that the proposed method is able to make the enhancement image become an ideal image according to the statistical criteria of visual representation, which has an average of μ between 0.3921 - 0.7843 and the mean value σ between 0.1568 - 0.3137. Based on the results of the fidelity criteria of the 500 trial images conducted on the proposed method and the previous two methods, 85.2% of the results of the proposed method have better quality than the previous two methods. The proposed method can only be applied to grayscale images. For this method, it needs to be further developed so that it can be applied to color images.

## References

[1] Awcock, G.J, & Thomas, R, *Applied Image Processing*, McGraw-Hill, 2016.
[2] Daniel J. Jobson, Z. Rahman, G. A. Woodell, *The Statistic of Visual Representation*, Visual Representation Processing, Proc. SPIE 2015, XI, 1-13.
[3] D.J. Jobson, Z. Rahman, G.A. Woodell, *A multiscale Retinex for bridging the gap between color images and the human observation of scenes*, IEEE Transactions on Image Processing, 2017, 6 (7), 965–976
[4] Fisher, Perkins, Walker, Wolfart, *Hypermedia Image Processing*, Department of Artificial Intelligence University of Edinburgh – UK, 2017.
[5] G. Deng, *An entropy interpretation of the logarithmic image processing model with application to contrast enhancement*, IEEE Transactions on Image Processing, 2016, 18 (5), 1135–1140
[6] Hadiq, Agus Zainal Arifin, Isye Arieshanti, *Perbaikan Kualitas Citra Dengan Metode Fusi Berbasis Pada Statistik Representasi Visual*, National Seminar X – ITS, Surabaya, 2010.
[7] Huang Kaiqi, Wu Zhenyang, Wang Qiao, *Image enhancement based on the statistics of visual representation*, Elsevier, 2016, 23(1), 51-57.
[8] Qiang Chen, Xin Xu, Quansen Sun, Deshen Xia, *A Solution To Deficienscies of Image Enhancement*, Elsevier, 2015, 3 (2), 12-22.
[9] Rafael. C. Gonzales, Richard. E. Woods, *Digital Image Processing*, Addison-Wesley, 2015.
[10] Rafael C. Gonzalez, Richard E. Woods, Steven L. Eddins, *Digital Image Processing Using MATLAB*, Tata McGraw Hill Publication, 2015.
[11] S.E. Ghrare, M.A.M. Ali, M.Ismail, K.Jumari, *The Effect of Image Data Compression on the Clinical Information Quality of Compressed Computed Tomography Images for Teleradiology Applications*, European Journal of Scientific Research, 2018, 23(1), 6-12.