A Gray-Level Dynamic Range Modification Technique for Image Feature Extraction Using Fuzzy Membership Function

[1]Arief Bramanto Wicaksono Putra, [2]Rheo Malani, [3]Mulyanto
[1,2,3]Department of Information Technology, State Polytechnic of SAMARINDA
Email: [1]ariefbram@gmail.com, [2]anaogie@gmail.com, [3]yanto1294@gmail.com

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ABSTRACT
The features of an image must be unique so it is necessary to use certain techniques to ensure them. One of the common techniques is to modify the gray dynamic range of an image. In principle, the gray level dynamic range modification maps the gray level ranges from the input image to the new gray level range as an output image using a specific function. Fuzzy Membership Function (MF) is one kind of membership function that applies the Fuzzy Logic concept. This study uses Trapezoidal MF to map the gray dynamic range of each RGB component to produce a feature of an RGB image. The aim of this study is how to ensure the uniqueness of image features through the setting of Trapezoidal MF parameters to obtain the new dynamic range of gray levels that minimize the possibility of other features other than the selected feature. To test the performance of the proposed method, it also tries to be applied to the signature image. Mean Absolute Error (MAE) calculations between feature labels are performed to test authentication between signatures. The results obtained are for comparison of samples of signature images derived from the same source having a much smaller MAE than the comparison of samples of signature images originating from different sources.

Corresponding Author:
Arief Bramanto Wicaksono Putra
Department of Information Technology
State Polytechnic of SAMARINDA
Jl. Dr. Cipto Mangunkusumo Kampus Gunung Lipan, Samarinda 75131, East Kalimantan
Email: ariefbram@gmail.com

1. INTRODUCTION

The gray-level dynamic range modification is done for various needs. In principle, a gray level dynamic range modification is mapping the range of gray-level of the input image to the new range of gray-level as the output image [1]. The contrast-stretching technique is used to increase dynamic gray level range. Research on contrast stretching on gray levels is specifically used to maintain the intensity of the image while the contrast is enhanced, providing better consistency and display effectiveness [1]. Improvement methods are usually performed on gamma value correction with the help of artificial intelligence algorithms such as Particle Swarm Optimization (PSO) [2][3][4]. Gamma correction is a technique that maintains the average brightness of the image that produces a natural-looking image with a choice of optimal gamma values [2]. Improved contrast is achieved by maximizing the information content carried in the image via a continuous intensity transformation function [1][2]. New methods of contrast enhancement called Just Noticeable Difference (JND) are simple but efficient that can achieve increased global and local contrast levels and perceptively suppress difficulties in achieving increased contrast in complex images [5][6][7].

The feature extraction results which apply the fuzzy entropy method and the interval-valued fuzzy set of measure-based feature selection on iris objects can provide accuracy on the iris classification under study [8]. Feature extraction of these structures was made based on the radiological attenuation index denoted by the Hounsfield Units using fuzzy logic techniques, special case in neuroimaging for segmentation of brain tissues [9].

Image enhancement which refers to the image processing method to highlight certain image information and weaken or remove irrelevant information or convert the original image into a form that is more suitable for analytical processing by humans or machines with specific methods. It will require enhancement processing to adjust the dynamic range or extract a uniform color sense to meet the requirements and proposes an image enhancement method based on improved fuzzy set [10].

This study proposes a gray level dynamic range modification technique using Fuzzy Membership Function (MF) to extract Red Green Blue (RGB) image features. To test the performance of the proposed method is applied to handwritten signature authenticated with Mean Absolute Error Analysis.

2. RESEARCH METHOD

In principle this technique maps the gray level of the input image to a certain gray level expressed by Equation 1.

$$g(x,y) = f(I(x,y)) \tag{1}$$

Where $f(\ )$ is the function that maps the gray level image $I(x,y)$ to $g(x,y)$ as shown in Figure 1.

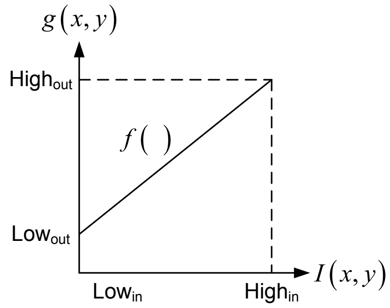


Figure 1. Representation of gray level mapping function

Figure 1 represents a linear function $f(\ )$ that maps $[Low_{in} \quad High_{in}]$ from the input image to the $[Low_{out} \quad High_{out}]$ output image. The function of the linear mapping is expressed by Equation 2.

$$\begin{aligned} Low_{in} &= \min(I(x,y)) \\ High_{in} &= \max(I(x,y)) \\ g(x,y) &= f(I(x,y)) = Low_{out} + (High_{out} - Low_{out}).\left(\frac{I(x,y) - Low_{in}}{High_{in} - Low_{in}}\right) \end{aligned} \tag{2}$$

The brightness is set by using gamma correction factor which expressed by Equation 3.

$$\begin{aligned} Low_{in} &= \min(I(x,y)) \\ High_{in} &= \max(I(x,y)) \\ g(x,y) &= f(I(x,y)) = Low_{out} + (High_{out} - Low_{out}).\left(\frac{I(x,y) - Low_{in}}{High_{in} - Low_{in}}\right)^{\gamma} \end{aligned} \tag{3}$$

The gamma correction factor is within the interval: γ = [0 ... 1]. If γ = 1 then the gray levels is mapped into a new level range linearly. If γ < 1 or γ < 1 then the gray level is mapped into a new range of levels in a non-linear fashion. This shown in Figure 2.

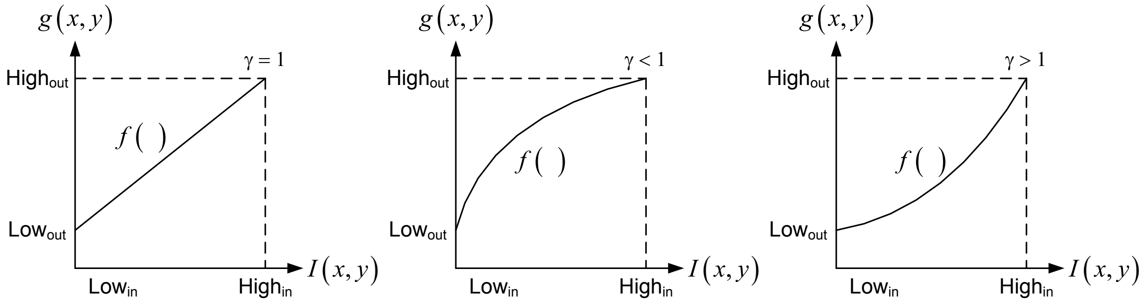


Figure 2. Representation of gray level mapping function with gamma correction factor

Sometimes the dynamic range of the processed image exceeds the capabilities of the display device so that only the brightest part is visible. To overcome this required compression of the dynamic range of the image, usually using Equation 4.

$$g\left(x,y\right)=c.\log\left(1+abs\left(I\left(x,y\right)\right)\right) \tag{4}$$

Where c is the scale constant. With c=1, function of dynamic range compression transformation is shown in Figure 3.

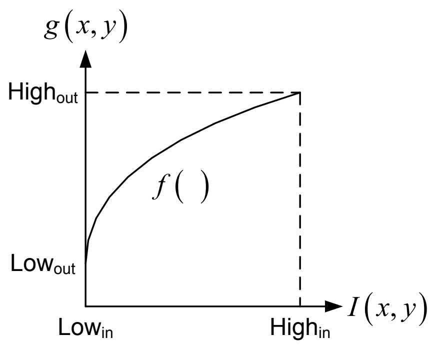


Figure 3. Representation of compression mapping function gray level (log function)

If $f(\,)$ is a Fuzzy MF it will generate an image $g(x,y)$ based on the various Fuzzy MF used. Some fuzzy MFs are shown in Figure 4.

(a) (b)

Figure 4. Fuzzy MF: (a)Triangular MF; (b).Trapezoidal MF

Triangular MF is expressed by Equation 5, whereas Trapezoidal MF is expressed by Equation 5 and 6.

$$f(x,a,b,c)=\begin{Bmatrix} 0 & x \le a \\ \frac{x-a}{b-a} & a \le x \le b \\ \frac{c-x}{c-b} & b \le x \le c \\ 0 & c \le x \end{Bmatrix} \tag{5}$$

$$f(x,a,b,c,d)=\begin{Bmatrix} 0 & x \le a \\ \frac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \frac{d-x}{d-c} & c \le x \le d \\ 0 & d \le x \end{Bmatrix} \tag{6}$$

If fuzzy MF is implemented to the image it will act as a masking that passes certain pixel intensity values to a new pixel intensity value depending on fuzzy MF selection and parameter settings used. If the image data type is double/float then the original dynamic range of gray-level is in range [0…1]. If Trapezoidal MF which used as shown in Figure 5, all the pixels intensity values that meet $I(x,y) \le 0.5$ will be mapped into $g(x,y)=1$, whereas the pixel intensity value that satisfies $I(x,y)>0.5$ will be mapped into $g(x,y)=(1-I(x,y))/0.5$.

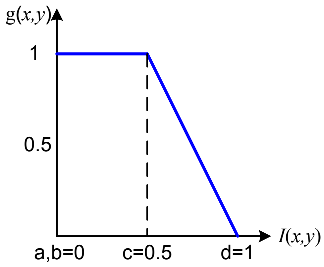


Figure 5. Example of trapezoidal MF

This concept will be applied to each component R, G and B of the RGB image. The *c* parameter of Trapezoidal MF is determined by the proportion of the number of pixel intensity values of each component against the total pixel intensity value of the image, expressed by Equation 7.

$$\begin{aligned} & sumR=\sum_{i=1}^{M}\sum_{j=1}^{N} I_R(i,j) \quad sumG=\sum_{i=1}^{M}\sum_{j=1}^{N} I_G(i,j) \quad sumB=\sum_{i=1}^{M}\sum_{j=1}^{N} I_B(i,j) \\ & r=\frac{sumR}{sumR+sumG+sumB} \\ & g=\frac{sumG}{sumR+sumG+sumB} \\ & b=\frac{sumB}{sumR+sumG+sumB} \end{aligned} \tag{7}$$

If the RGB image with size $M \times N$ denoted by $I(x,y,d)$ where d is the index of R, G and B component, it will generate 3 (three) gray images as the result of gray level mapping by using Trapezoidal MF, which expressed by Equation 8.

$$\begin{aligned} R_{fuzz}(x,y) &= f\left(I(x,y,1),0,0,r,1\right) \\ G_{fuzz}(x,y) &= f\left(I(x,y,2),0,0,g,1\right) \\ B_{fuzz}(x,y) &= f\left(I(x,y,3),0,0,b,1\right) \end{aligned} \tag{8}$$

The fuzzyfication results of the three components of the image are then combined into a fuzzyfied image by using Equation 9.

$$I_{feat}(x,y) = \min\left(I_{fuzz}(x,y,1), \min\left(I_{fuzz}(x,y,2), I_{fuzz}(x,y,3)\right)\right) \quad (9)$$

Image feature is obtained by applying fuzzy AND operator between R, G, and B components by using Equation 10.

$$I_{feat}(x,y) = \min\left(I_{fuzz}(x,y,1), \min\left(I_{fuzz}(x,y,2), I_{fuzz}(x,y,3)\right)\right) \quad (10)$$

Typically, the image features are expressed in labels. It is necessary to specify the length of the feature label. In order for the feature label is not too long, then the image feature needs to be converted into a new feature image that has length column = length of feature label. If the length feature label is L, then (Equation 11):

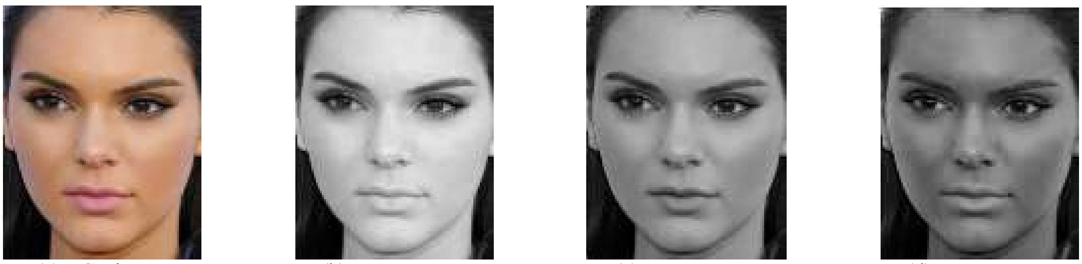
$$\begin{aligned} meanI_{feat}(j) &= \sum_{i=1}^{M} I_{feat}(i,j) \quad j = 1...N \\ I_{newfeat} &= reshape\left(meanI_{feat}, [N/L \quad L]\right) \end{aligned} \quad (11)$$

The feature label is expressed by Equation 12.

$$feature(j) = \sum_{i=1}^{N/L} I_{newfeat}(i,j) \quad j = 1...L \quad (12)$$

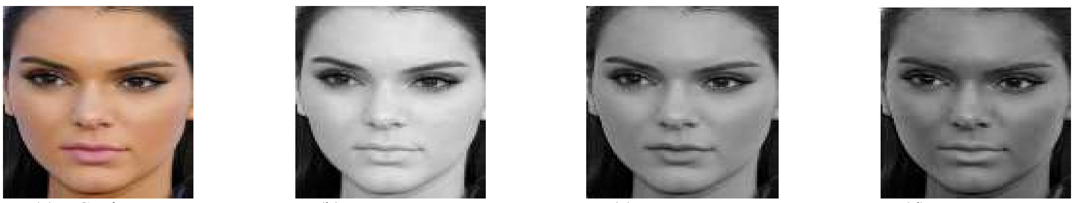
3. RESULTS AND ANALYSIS

The image used as the test of the proposed method is as shown in Figure 6. In order for the resulting feature to be compact, it needs to be converted into the same row-column size. This study used a 200x200 template for test image conversion as shown in Figure 7. By applying Equation 7 on the test image then obtained r = 0.4194, g = 0.3181, b = 0.2625. By applying Equation 8 and 9 then obtained the fuzzyfied image as shown in Figure 8. Image feature then obtained by applying Equation 10 as shown in Figure 9.



(a) RGB image (b) R component (c) B component (d) B component

Figure 6. Test image (253x199x3)



(a) RGB image (b) R component (c) B component (d) B component

Figure 7. Test image after resizing (200x200x3)

(a) fuzzyfied R component (b) fuzzyfied G component (c) fuzzyfied B component (d) fuzzyfied image

Figure 8. Fuzzyfied image

Figure 9. Image feature

If the length of the feature label is L = 20 then the feature label is obtained by using Equation 11 and 12 as shown in Figure 10.

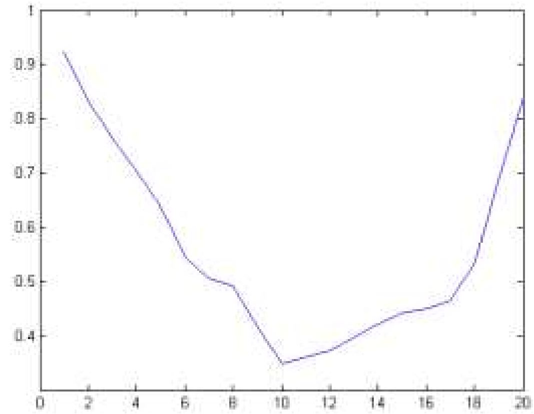
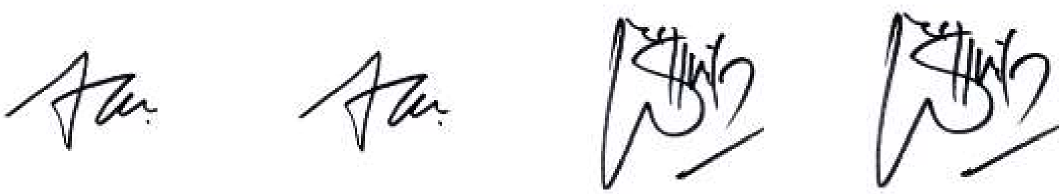


Figure 10. Feature label visualization (L = 20)

To test the performance of the proposed method, it also tries to be applied to the signature image which its samples as shown in Figure 11. Signatures 1 and 2 are from the same source, as are the signatures 3 and 4. The feature labels of the samples of signature image are shown in Table 1. Mean Absolute Error (MAE) calculations between feature labels are performed to test authentication between signatures, with results as shown in Table 2.



(a) Signature 1 (b) Signature 2 (c) Signature 3 (d) Signature 4

Figure 11. Samples of signature image

Table 1. Feature label

Label	Signature 1	Signature 2	Signature 3	Signature 4
1	0.0000323	0.0000265	0.0002114	0.0103495
2	0.0000294	0.0000147	0.0003994	0.2266311
3	0.0095815	0.0130311	0.0006490	0.2646815
4	0.0259372	0.0264309	0.1968994	0.1749998
5	0.0261692	0.0265778	0.2607968	0.1135490
6	0.0260810	0.0256100	0.1520693	0.1478946
7	0.0250191	0.0252778	0.1236905	0.1452327
8	0.0587910	0.0752824	0.1497977	0.1152596
9	0.0993966	0.1183107	0.1202694	0.1086935
10	0.1535009	0.1461933	0.1011034	0.2295550

Label	Signature 1	Signature 2	Signature 3	Signature 4
11	0.1334324	0.1101133	0.2190919	0.2422755
12	0.0396653	0.0562463	0.2328689	0.2019400
13	0.0946605	0.0983494	0.1946612	0.1960608
14	0.0994250	0.1064707	0.1727980	0.1212460
15	0.1240452	0.1291140	0.1833259	0.2084323
16	0.0985604	0.0586464	0.1357806	0.0927590
17	0.0353750	0.0428881	0.0800603	0.0860503
18	0.0340059	0.0153808	0.0975008	0.1063838
19	0.0052230	0.0001529	0.1181172	0.1086246
20	0.0002676	0.0007350	0.0213199	0.0215274

Table 2. MAE calculation between feature labels

Label	S1-S2	S1-S3	S1-S4	S2-S3	S2-S4	S3-S4
1	0.0000059	0.0001791	0.0103171	0.0001850	0.0103230	0.0101380
2	0.0000147	0.0003700	0.2266017	0.0003847	0.2266164	0.2262317
3	0.0034495	0.0089325	0.2551000	0.0123821	0.2516505	0.2640325
4	0.0004937	0.1709622	0.1490626	0.1704685	0.1485690	0.0218996
5	0.0004087	0.2346276	0.0873799	0.2342189	0.0869712	0.1472477
6	0.0004710	0.1259883	0.1218136	0.1264593	0.1222846	0.0041747
7	0.0002587	0.0986714	0.1202136	0.0984127	0.1199549	0.0215422
8	0.0164914	0.0910067	0.0564687	0.0745154	0.0399773	0.0345381
9	0.0189142	0.0208728	0.0092969	0.0019587	0.0096173	0.0115759
10	0.0073076	0.0523975	0.0760540	0.0450899	0.0833616	0.1284515
11	0.0233191	0.0856595	0.1088431	0.1089786	0.1321622	0.0231836
12	0.0165809	0.1932036	0.1622747	0.1766227	0.1456938	0.0309289
13	0.0036888	0.1000007	0.1014002	0.0963119	0.0977114	0.0013996
14	0.0070458	0.0733731	0.0218210	0.0663273	0.0147753	0.0515520
15	0.0050689	0.0592808	0.0843871	0.0542119	0.0793183	0.0251064
16	0.0399140	0.0372202	0.0058014	0.0771342	0.0341126	0.0430216
17	0.0075131	0.0446852	0.0506752	0.0371722	0.0431622	0.0059900
18	0.0186251	0.0634949	0.0723779	0.0821200	0.0910031	0.0088831
19	0.0050701	0.1128942	0.1034017	0.1179643	0.1084717	0.0094926
20	0.0004674	0.0210524	0.0212599	0.0205850	0.0207925	0.0002075
MAE	**0.0087554**	**0.0797436**	**0.0922275**	**0.0800752**	**0.0933264**	**0.0534799**

From Table 2 it is found that the smallest MAE is between Signature 1 and 2, and between Signatures 3 and 4. This proves that the authentication of Signature 1 and 2 are correctly derived from the same source, as are the signature 3 and 4. The visualization of feature labels is shown in Figure 12.

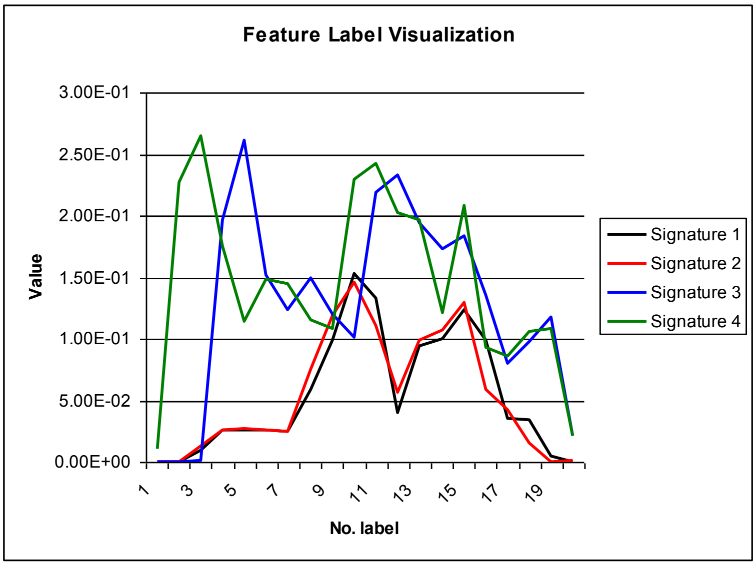


Figure 12. Feature label visualization

4. CONCLUSION

This study has applied Trapezoidal MF as a dynamic range mapping function of the gray level of an RGB image on each component. The Trapezoidal MF parameter is arranged based on the proportion of pixel intensity distribution of each component of the RGB image. The image features generated from this dynamic range modification process serve as a reference for generating feature labels. The uniqueness of the feature label is obtained through the authentication test of the signature image already done. If the comparison of two samples of the signature image produces a very small MAE value it can be said that both samples have very similar and authentic feature labels from the same source. The test results show that the comparison of the sample of signature images originating from the same source has an MAE that is much smaller than the comparison of the sample of the signature image originating from different sources. This proves the proposed method is capable of producing a unique label feature.

Future work is how to further enhance the uniqueness of the label features through modification and/or combination of methods and tested with more varied test samples.

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BIBLIOGRAPHY OF AUTHORS

Arief Bramanto Wicaksono Putra. Born in Balikpapan, January 20, 1983. Completed undergraduate (D4) majoring in Information Technology at Electronic Engineering Polytechnic Institute of Surabaya in 2006. Completed postgraduate study of Electrical Engineering Department at Brawijaya University Malang in 2014. Beginning in 2008 working as a lecturer in the Department of Information Technology, State Polytechnic of Samarinda until now
Areas of interest: Robotics & Artificial Intelligent, Computer Vision, Computer Networks

Rheo Malani. Born in Samarinda, August 23, 1978. Completed undergraduate (S1) majoring in Computer Science at STIMIK Widya Ciptha Darma of Samarinda in 2003. Completed postgraduate study of Information System Department at Diponegoro University Semarang in 2013. Beginning in 2005 working as a lecturer in the Department of Information Technology, State Polytechnic of Samarinda until now
Areas of interest: Computer Networks, Machine Learning, Secure System

Mulyanto. Born in Samarinda, February 13, 1975. Completed undergraduate (S1) majoring in Computer Science at Indonesia University of Jakarta in 1999. Completed postgraduate study of Computer Science Department at Gajah Mada University Jogjakarta in 2016. Beginning in 2008 working as a lecturer in the Department of Information Technology, State Polytechnic of Samarinda until now
Areas of interest: Computer Networks, Artificial Intelligent, Modelling & Simulation