Proceedings of the Seventh International Conference on Machine Learning and Cybernetics, Kunming, 12-15 July 2008

CONTRAST COMPENSATION FOR BACK-LIT AND FRONT-LIT COLOR FACE IMAGES VIA FUZZY LOGIC CLASSIFICATION AND IMAGE ILLUMINATION ANALYSIS

CHUN-MING TSAI[1], ZONG-MU YEH[2], YUAN-FANG WANG[3]

[1]Department of Computer Science, Taipei Municipal University of Education, Taipei 100, Taiwan, ROC
[2]Department of Mechatronic Technology, National Taiwan Normal University, Taipei 106, Taiwan, ROC
[3]Department of Computer Science, University of California, Santa Barbara, CA 93106, USA
E-MAIL: cmtsai@tmue.ed.tw, zongmu@ntnu.edu.tw, yfwang@cs.ucsb.edu

Abstract:

Conventional contrast enhancement methods have two shortcomings. First, most of them do not produce satisfactory enhancement results for face images with back-lit or front-lit. Second, most of them need transformation functions and parameters which are specified manually. Thus, this paper proposes an automatic and parameter-free contrast compensation algorithm for color face images. This method includes: *RGB* color space is transformed to *YIQ* color space. Fuzzy logic is used to classify the color images into back-lit, normal-lit, and front-lit categories. Image illumination analysis is used to analyze the image distribution. The input image is compensated by piecewise linear based compensation method. Finally, the compensation image is transformed back to *RGB* color space. This novel compensation method is automatic and parameter-free. Our experiments included back-lit and front-lit images. Experiment results show that the performance of the proposed method is better than other available methods in visual perception measurements.

Keywords:

Contrast compensation; Fuzzy logic classification; Image illumination analysis; Parameter-free; Color face images

1. Introduction

Contrast enhancement is developed to adjust the quality of an image for better human visual perception [1]. It is a very important preprocessing step for tasks in image processing, video processing, medical image processing, aerial image processing, and computer vision.

Current contrast enhancement algorithms based on spatial domain techniques can be divided into four main types: global, local, hybrid, and fuzzy methods. Global methods enhance the image from the information of an entire image. Duan and Qiu [2] divided the luminance range [0, 255] into 256 intervals using a hierarchical division procedure and used a control parameter to control the mapping. Sun et al. [3] proposed a dynamic specific histogram algorithm to do contrast enhancement for a real-time system due to its simplicity. Local methods enhanced the image for each pixel according to the information of its own and its neighbor. Chatterji and Murthy [4] proposed an adaptive contrast enhancement for color images. However, in their method, two parameters (e.g., enhancement function and region size) are needed to determine. Meylan and Süsstrunk [5] used a Retinex-based adaptive filter to enhance natural color images, and their results showed that the color image with halo area could be enhanced. However, it needed to choose the appropriate filter size to reduce halos images and to introduce global tone mapping for extremely high dynamic range images. Hybrid methods combined both global and local approaches. In these methods, an image is divided into non-overlay or overly regions and each region is conquered by global methods. Kim et al. [6] used partially overlapped sub-block HE (POSHE) technique to achieve contrast enhancement. However, the visual quality and computational speed-up is a trade-off problem. Furthermore, the sub-block divisor and the overlap step divisor are determined in advance. Recently, Menotti et al. [7] proposed a Multi-HE technique, which consists of decomposing the input image into several sub-images, and applying the classical HE process to each one. Their method can preserve more the brightness and produce more natural looking images than the other HE methods. However, their method need to set the weighting constant of the cost function in advance. Fuzzy contrast enhancement [8] is based in the concept of mapping a grayscale image onto a fuzzy plane. This method uses some form of membership function to enhance image. The membership function characterizes some property of an image (e.g. edginess). The process is known as image fuzzification. The membership values are then modified in some manner to improve the contrast. The modified

978-1-4244-2096-4/08/$25.00 ©2008 IEEE

membership values are then inversely transformed through the process of defuzzification to produce the enhanced image. Fuzzy enhancement algorithms are certainly suited to certain applications. But it needs to determine what these are in advance. Furthermore, the fuzzy enhancement methods often need adjustable parameters (the choice of membership function) which may affect the quality of the result.

Histogram Equalization (HE) and its variations are one of the most commonly used algorithms to perform contrast enhancement due to its simplicity and effectiveness [1], [3], [7], [9], [10], [11]. Histogram equalization can be extended to process color images [11], [12]. However, it has many shortcomings: (1) it cannot preserve the brightness illumination. (2) The result of histogram equalization produced annoying side effects, such as overhead brightness enhancement, white noise, and some unnatural results [3]. (3) It changed the hue. (4) HE and its variation methods produce unnatural looking images [7]. However, if images with back-lit or front-lit, the above described methods cannot both produce satisfactory enhancement results. Herein, we will propose a contrast compensation method to enhance the images with back-lit and reduce the images with front-lit. The back-lit images are defined as the images with bright background and dark foreground. In particular, the foreground is located at dark illumination. The front-lit images are defined as the images with dark background and bright foreground. In particular, the foreground is located at bright illumination. The conventional enhancement methods determine the enhancement transformation function and parameters by human beings in advance. Furthermore, these methods only enhance the image with back-lit and can not reduce the image with front-lit. Therefore, in this paper a contrast compensation method via fuzzy logic classification to classify the image and image illumination analysis is proposed to determine the transformation function automatically. In particular, the parameters of the transformation function are chosen automatically, too. In other words, it does not require the intervention by a human operator. Moreover, the proposal method can enhance the images with back-lit and reduce the images with front-lit.

2. Fuzzy logic classification

When taking a picture, the photographic object is placed at the center of image [13]. Thus, the spatial characteristics of an image are used to determine the input image is back-lit or front-lit. The image can be segmented into two areas: boundary background area and center foreground area by spatial position segmentation method

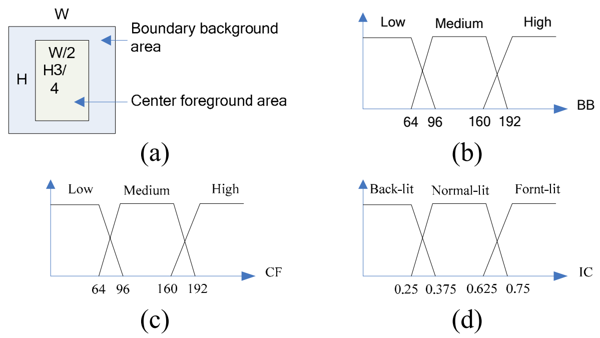


Figure 1. Fuzzy logic classification: (a) the division of an input image and (b), (c), and (d) are membership functions of the fuzzy sets of BB, CF, and IC, respectively.

(Fig. 1(a)). The luminance range of the boundary background area (*BB*) and the center foreground area (*CF*) are used to determine the input image is back-lit or front-lit. If the luminance range of the boundary background area is larger than the center foreground area, the input image is back-lit image. Otherwise, the input image is front-lit image. Due to the various illumination property and content of images, these two variables (*BB* and *CF*) have different degrees of reliability. Thus, the fuzzy inference method is used for these two variables to determine the input image is which class (*IC*, back-lit or front-lit). The luminance range of boundary background area (*BB*) and center foreground area (*CF*) are defined as follows:

if (ut_f < 128)

$$BB = F_b(ut_b + k*std_b);\ CF = F_f(ut_f - k*std_f)$$

else

$$BB=F_b(ut_b - k*std_b);\ CF = F_f(ut_f + k*std_f) \quad (1)$$

where ut_f, std_f, ut_b, and std_b is the average luminance of the center foreground area, the standard deviation luminance of the center foreground area, the average luminance of the boundary background area, and the standard deviation luminance of the boundary background area, respectively. F_b and F_f are membership function which converts *BB* and *CF* into a fuzzy degree, respectively. The constant k is used to consider the variance of the boundary background area and the center foreground area. Here, k is set as 0.5. The middle luminance value in gray level is 128. Thus, this value is used to determine the center foreground area is prone to dark or bright gray level.

Fuzzy inference systems [14] have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The fuzzy inference rules are characterized by a collection of fuzzy membership functions, logical operations, and IF-THEN rules. The antecedents and consequents involve linguistic variables. In the proposed fuzzy inference scheme for image classification, there are two input variables, BB and CF, and one output variable IC. The two input variables have three fuzzy sets, L (low illumination), M (medium illumination), and H (high illumination). The output variable has three fuzzy sets, BL (back-lit), FL (front-lit), and NL (normal-lit). The membership functions are used for the fuzzy sets of BB, CF, and IC are shown in Figs. 1(b)-(d). Therefore, nine fuzzy interference rules are used here. Two representative rules are enumerated as follows:

1. If BB is L and CF is H then IC is FL.
2. If BB is H and CF is L then IC is BL.

Based on the center of area (COA) defuzzification method [15], the value of the *IC* corresponding to two given *BB* and *CF* values are obtained from the fuzzy inference. The inferred *IC* value represents the final estimated classification degree of the input image. That is, to determine whether the input image is back-lit image or front-lit image.

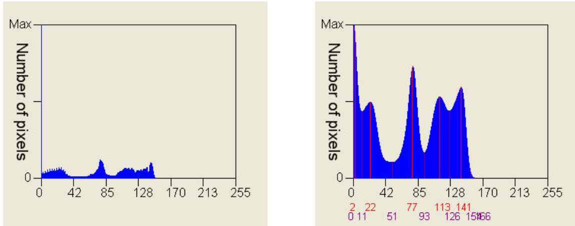
3. Image illumination analysis

Each color image can be represented by Gaussian mixtures – a more capable model to describe image illumination distributions. To reduce the computation time, the image illumination distribution at luminance domain is analyzed. Herein, each single Gaussian distribution is expressed as one peak and two valleys at luminance component. The luminance of a color image is computed first. Then, the luminance histogram $H_Y(x_k)$ is computed. The histogram of an image with brightness levels in the range [0, 255] is a discrete function $H_Y(x_k) = n_k$, where x_k is the kth brightness level and n_k is the number of pixels in the image having brightness level x_k. Finally, Gaussian smoothing filter is applied to smooth the original histogram to obtain the reliable peaks and valleys. Thus the unreliable peaks and valleys are removed. The method of the Gaussian smoothing filter is described as follows.

The Gaussian convolution of a luminance histogram $H_Y(x)$ depends upon both x and σ_g, namely, the Gaussian standard deviation. The convolution function $S_{HY}(x, \sigma_g)$ is provided by Eq. (2),

$$S_{HY}(x,\sigma_g) = H_Y(x) * g(x,\sigma_g) = \int_{-\infty}^{\infty} H_Y(u) g(x-u,\sigma_g) du$$
$$= \int_{-\infty}^{\infty} H_Y(u) \frac{1}{\sqrt{2\pi}\sigma_g} e^{-\frac{(x-u)^2}{2\sigma_g^2}} du \quad (2)$$

where "*" denotes the convolution operator and $g(x\text{-}u, \sigma_g)$ is the Gaussian function. The degree of smoothing is



(a) (b)

Figure. 2. An example for image illumination analysis to extract the luminance distributions. (a) Original histogram. (b) Selection of image luminance distribution.

controlled by the standard deviation of the Gaussian function. The larger the standard deviation σ_g, the smoother the function $S_{HY}(x, \sigma_g)$ is. The standard deviation is referred to [16]. They decided the standard deviation automatically. Equation (2) is employed to convolute the histogram $H_Y(x)$ that provides smoothing histogram. The objective of choosing the standard deviation is to smooth the most frequent "ripples" of the histogram and to leave the significant modes. That is, the major peaks in the original histogram can be distinguished. The number of peaks in the smoothed histogram is considered as the number of peaks in the original histogram. The selection of image luminance distribution is described as follows.

Here one condition is assumed that luminance distributions in images are multi-Gaussian. After the small peaks and valleys have been removed, the average differences are employed as the first derivation with which to determine the major peaks and valleys. The average difference in point x is defined by

$$S'_{HY}(x) = \frac{1}{\sigma_g - 1} \sum_{i=1}^{\sigma_g - 1} \frac{S_{HY}(x+i) - S_{HY}(x-i)}{2 \times i} \quad (3)$$

A peak is defined as a positive to negative crossover in the first derivation of the smoothed histogram. Furthermore, a valley is defined as a negative to positive crossover. All peaks and valleys from the first derivation of the smoothed histogram are discovered. In cases where the peaks and valleys are too close, they will be removed if the distance between a valley and a peak is less than the standard deviation σ_g. The remaining peaks are the candidates of the luminance distribution in the image.

Figure 2 shows an example for image illumination analysis. The input image is processed by transforming *RGB* into *YIQ*, getting the luminance histogram, smoothing the histogram, and selecting the color distributions. Each color distribution is selected by one peak and two valleys in luminance domain. The original histogram is shown in Fig. 2(a). The smoothed histogram and the selection of the luminance distribution are depicted at Fig. 2(b). There are

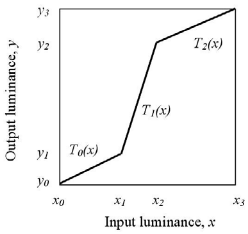


Figure 3. Piecewise linear transformation function ($k = 3$, k is the number of the input parameters).

five luminance distributions. The range of each luminance distribution is represented by one peak and its two valleys.

4. Automatic and parameter-free compensation

The proposed compensation algorithm is based on piecewise linear transformation [1]. The axiom of piece-wise linear transformation and how to build transformation function and parameters automatically are described as follows.

The piecewise linear transformation (PLT) is characterized by $2k$ parameters for k-1 line segments. When the parameters are given, the transformation line segments will be determined. That is, if given the starting position of input luminance $\{x_k, k = 0, 1... k\}$ and the starting position of output luminance $\{y_k, k=0, 1... k\}$, the k-1 transform functions $T_{k-1}(x)$ will be:

$$T_{k-1}(x) = \frac{(y_k - y_{k-1})}{(x_k - x_{k-1})} \cdot (x - x_{k-1}) + y_{k-1} \tag{4}$$

For example, if $k = 3$, form the $T_0(x)$, $T_1(x)$, and $T_2(x)$ transformation functions are shown in Fig. 3. Four input parameters and four output parameters will be specified first manually. To determine these parameters and line segments are critical for the satisfactory result of the contrast compensation. In conventional applications, parameters and line segments are manually chosen case by case. To solve this problem, an automatic and parameter-free contrast compensation algorithm is proposed in the following.

The conventional PLT-based image enhancement needs to set the number of the line segment and the values of the input and the output parameters in advance. How to decide the number of line segments automatically? Here, the number of the image luminance distribution is used to represent the number of the line segments. If the number of the image luminance distribution is k, then the number of the line segment is $k+1$. How to decide the input luminance parameter automatically? Here, the location of the valley is used to represent the input luminance parameter. The different image may have different distribution of valleys. For example, there are six line segments in the Fig. 3(b). The input luminance parameters are 0, 11, 51, 93, 126, 154, and 166. The location of these valleys and the parameters depend on which image is employed. How to determine the output luminance parameters automatically? The output parameters depend on which image is used. The determining method of input and output parameters are described in the following.

After the luminance distributions have been analyzed, many peaks are produced. If the color image has k luminance distributions $\{p_1, p_2...p_k\}$ (peak is represented by p,) then the number of the line segment is $k+1$. Each distribution is bounded by two valleys indicated as v. That is, the k luminance distributions have $\{v_0, v_1...v_k\}$ valleys. These valleys are used to be the input parameters $\{x_0, x_1...x_k\}$ of the piecewise linear transformation function. The output parameters $\{y_0, y_1...y_k\}$ are defined as follows:

$$y_k = \sum_{x=s}^{v_k} \Pr(x) \cdot 255 \tag{5}$$

where $Pr(x) = n_x/n$ is the probability of the xth luminance (gray level), n is the total number of pixels in the image and n_x is the number of times this x level appears in the image. The parameter s is the start luminance of the input image.

The equation (5) is used to enhance the image with normal-lit. In order to enhance back-lit or front-lit images, Eq. (5) must be adjusted. For the back-lit image, the foreground is located at dark illumination. The illumination value of black is smaller than 60. This set value 60 is according to the property of human vision perception stating that the brightness under 60 gray-level will be regarded as darkness [16]. Thus, Eq. (5) is adopted to shift the darkest illumination to bright illumination. That is, the dark illumination can see more clearly. Herein, we introduce a *BlackShift* parameter to resolve this problem. The *BlackShift* parameter sets as *BlackShift = 60 - MaxDarkPeak*. The *MaxDarkPeak* is the max peak which locates at the dark illumination. Thus, the output parameters $\{y_0, y_1...y_k\}$ of the back-lit images are defined as follows:

$$y_k = BlackShift + \sum_{x=s}^{v_k} \Pr(x) \cdot 255 \tag{6}$$

For the front-lit image, the foreground is located at bright illumination. The background is located at dark illumination. In particular, the foreground is lighted by the sunlight. That is, the foreground is too bright to see. The bright luminance distributions need to be transformed from bright illumination spread to dark illumination. Thus, we introduce a *WhiteShift* parameter to resolve this problem. The *WhiteShift* parameter sets as *WhiteShift = MaxBrightPeak - 223*. This set value 223 is according to the property of human vision perception stating that the brightness above 223 gray-level will be regarded as brightness. In particular, the skin of the face is influenced by the illumination. If the illumination is brighter, the color of the skin will be near to bright. Thus, the *WhiteShift* parameter is used to compress the brightness. The transformation function is designed as similar to Eq. (6). Thus, the output parameters $\{y_0, y_1 \ldots y_k\}$ of the front-lit images are defined as follows:

$$y_k = \sum_{x=s}^{v_k} \Pr(x) \cdot 255 - WhiteShift \tag{7}$$

5. Experimental results and discussion

The proposed contrast compensation algorithm for color face images was implemented as a Windows-based application on a Pentium (R) D 3.00GHZ and 504MB PC. The experiments use various color face images. Most of the images are obtained from "Oulu Face Video Database [17]," internet, and capture by ourselves. Some examples are presented as follows.

The compensation results for back-lit image are shown in Fig. 4. A back-lit image is shown in Fig. 4(a) and its histogram is shown in Fig. 4(b). The result by our method is shown in Fig. 4(c). Figure 4(d) is the histogram of Fig. 4(c). The result by histogram equalization is shown in Fig. 4(e). Figure 4(f) is the histogram of Fig. 4(e). The result by contrast stretching is shown in Fig. 4(g). Figure 4(h) is the histogram of Fig. 4(g). From Fig. 4, the result by contrast stretching is similar to original image. Thus, the contrast stretching cannot enhance the back-lit image. The result by histogram equalization is too bright. From visual perception, the result of the proposal method is better than the result of the histogram equalization.

The compensation results for front-lit image are shown in Fig. 5. A back-lit image is shown in Fig. 5(a) and its histogram is shown in Fig. 5(b). The result by our method is shown in Fig. 5(c). Figure 5(d) is the histogram of Fig. 5(c). This histogram is compared with the original histogram. The proposal method reduces the bright illumination. The result by histogram equalization is shown in Fig. 5(e). Figure 5(f) is the histogram of Fig. 5(e). The result by contrast stretching is shown in Fig. 5(g). Figure 5(h) is the histogram of Fig. 5(g). From Fig. 5, the result by contrast stretching is similar to original image. Thus, the contrast stretching cannot enhance the front-lit image. The skin enhancement result by histogram equalization is still too bright. The color of the polo shirt by our method is superior to histogram equalization does. From visual perception, the foreground result of the proposal method is better than histogram equalization does.

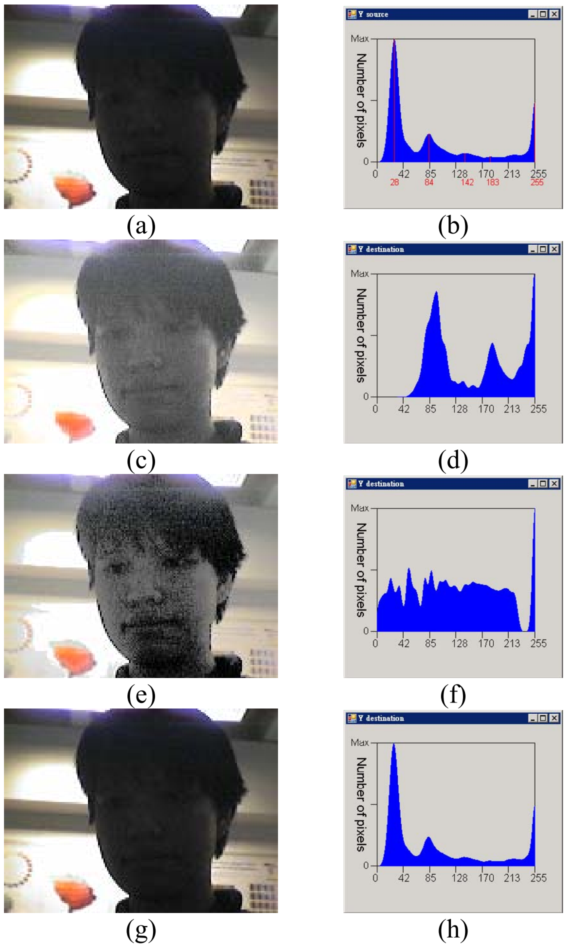
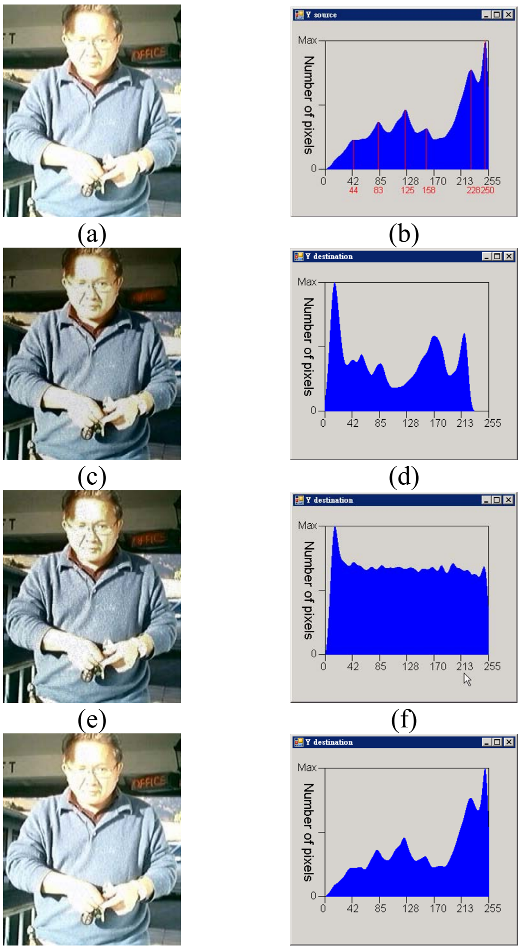


Figure. 4. Compensation results for back-lit image. (a) a back-lit image. (b) The histogram of (a). (c) Result by our method. (d) The histogram of (c). (e) Result by histogram equalization. (f) The histogram of (e). (g) Result by contrast stretching. (h) The histogram of (g).

6. Conclusions

This study has presented a contrast compensation method by fuzzy logic classification and image illumination analysis for color face images. The input images are classified by fuzzy logic classification method into back-lit, normal-lit, and front-lit first. Then, the illumination of the input image was analyzed to obtain the image illumination distributions. Each distribution is represented by one peak and two valleys. These peaks and valleys are used to be the parameters of the piecewise linear transformation. The performance analysis indicated that our method is efficient and effective by comparing with histogram equalization and contrast stretching.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure. 5. Compensation results for front-lit image. (a) a front-lit image. (b) The histogram of (a). (c) Result by our method. (d) The histogram of (c). (e) Result by histogram equalization. (f) The histogram of (e). (g) Result by contrast stretching. (h) The histogram of (g).

Acknowledgements

This work was supported by the Ministry of Economic, R.O.C., under Grants MOEA-96-EC-17-A-02-S1-032 and National Science Council, R.O.C., under Grants NSC 96-2221-E-133-001-

References

[1] Gonzalez R. C. and Woods R. E., Digital Image Processing, 2nd Edition, Prentice Hall, 2002.

[2] Duan J. and Qiu G., "Novel histogram processing for colour image enhancement," Proc. of ICIM2004 Conf., pp. 55-58, 2004.

[3] Sun C. C., Ruan S. J., Shie M. C., and Pai T. W., "Dynamic contrast enhancement based on histogram specification," IEEE Trans. on Cons. Elec., Vol. 51, No. 4, pp. 1300-1305, 2005.

[4] Chatterji B. N. and R Murthy. N., "Adaptive contrast enhancement for color images," Proc. of ICICS1997 Conf., Vol. 3, pp. 1537-1541, 1997.

[5] Meylan L. and Süsstrunk S., "Color image enhancement using a retinex-based adaptive filter," Proc. of CGIV2004 Conf., Vol. 2, pp. 359-363, 2004.

[6] Kim J. Y., Kim L. S., and Hwang S. H., "An advanced contrast enhancement using partially over-lapped sub-block histogram equalization," IEEE Trans. on CSVT, Vol. 11, No. 4, pp. 475-484, 2001.

[7] Menotti D., Najman L., Facon J., and de A. Araujo A., "Multi-histogram equalization methods for contrast enhancement and brightness preserving," IEEE Trans. Cons. Elec., Vol. 53, No. 3, pp. 1186–1194, 2007.

[8] Cheng H. D. and Xu Huijuan, "A novel fuzzy logic approach to contrast enhancement," Pattern Recognition, Vol. 33, No. 5, pp. 809-819, 2000.

[9] Chen S. D. and Ramli A. R., "Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation," IEEE Trans. Cons. Elec., Vol. 49, No. 4, pp. 1301–1309, 2003.

[10] Chen S. D. and Ramli A. R., "Minimum mean brightness error bihistogram equalization in contrast enhancement," IEEE Trans. Cons. Elec., Vol. 49, No.4, pp. 1310–1319, 2003.

[11] Bockstein I. M., "Color equalization method and its application to color image processing," J. Opt. Soc. Am., Vol. 3, No. 5, pp. 735–737, 1986.

[12] Pichon E., Niethammer M., and Sapiro G., "Color histogram equalization through mesh deformation," Proc. of ICIP 2003 Conf., Vol. 2, pp. 117-120, 2003.

[13] Chin C. L. and Lin C. T., "Detection and compensation algorithm for backlight images with fuzzy logic and adaptive compensation curve," Inter. Journal of Pattern Recognition and Artificial Intelligence, Vo. 19, No. 8, pp. 1041-1057, 2005.

[14] Jang J.-S. R. and Sun C.-T., Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, Prentice Hall, 1997.

[15] Yeh Zong-Mu and Li Kuei-Hsiang, "A Systematic Approach for Design of Multistage Fuzzy Control Systems," International Journal of Fuzzy Sets and Systems. Vol. 143, pp. 63–85, 2004.

[16] Tsai C. M. and Lee H. J., "Binarization of color document images via luminance and saturation color features," IEEE Trans. IP, Vol. 11, No. 4, pp. 434-451, 2002.

[17] Martinkauppi B., Soriano M., Huovinen S., and Laaksonen M., "Face video database," Proc. of CGIV2002 Conf., Poitiers, pp. 380-383, April 2002.