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# Contrast Enhancement through Clustered Histogram Equalization

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**Abstract:** This study proposed a contrast enhancement algorithm. Some methods enhance images depending on only the global or the local information, therefore it would cause over-enhancement usually and make the image look unnatural. The proposed method enhances image based on the global and local information. For the global part, we proposed mapping curves to find the new average, maximum and minimum intensity to try to suit the concept of Human Visual System (HVS) for obtaining the better perceptual results. For the local part, we utilized fuzzy c-means clustering algorithm to group image and we can obtain the information of intensity distribution and pixel number from each group. Then we calculate weights according to the information and enhance images by Histogram Equalization (HE) depending on the weights. The experiment results show that our method can enhance the contrast of image steadily and it causes over-enhancement with lower probability than other methods. The whole image not only looks natural but also shows detail texture more clearly after applying our method.

**Keywords:** Contrast enhancement, fuzzy c-means clustering algorithm, histogram equalization

## INTRODUCTION

There are various kinds of linear and nonlinear gray level transformation functions for contrast enhancement. One of the most popular techniques is Histogram Equalization (HE) which has been regarded as the ancestor of many contrast enhancement algorithms (Gonzalez and Woods, 1992; Jain, 1989; Kim, 1997; Kim *et al*., 1998; Zimmerman *et al*., 1988). However there are several drawbacks of this simple method. It takes only global information into account and does not contain any parameter to control the strength of enhancement; therefore this may result in over-enhancement or detail loss in some parts of the processing image and thus makes the processed image unnatural.

In order to eliminate some drawbacks of HE, There are several algorithms had proposed for improving the drawbacks of HE, such as Kim (1997), Torre *et al*. (2005) Whittle (1986), Wongsritong *et al*. (1998) and Wang and Ward (2007).

In this study, we propose an automatic contrast enhancement algorithm, combining with local and global approach. The proposed WBCHE adjusts the average intensity to the proper position, so it causes over-enhancement with lower probability than other methods. It utilizes FCM to cluster the image into four groups, so that we can obtain local information and determine the range allocated to each group. Therefore it can show the detailed texture more clearly than other one by using only global information. In addition to above mentions, there are some characteristics of whole algorithm. It would keep the character of the image and nearly no artifacts would be produced.

## LITRATURE REVIEW

In image processing, histogram refers to the intensity distribution of an image. Low Dynamic Range (LDR) sources has intensity levels between [0, L-1] where L = 256. Histogram of an image may be presented as a discrete function $h(r_k) = n_k$, where $\eta_k$ is the intensity value and $n_k$ is the number of pixels with intensity $\eta_k$ . One usually normalize $h(\eta_k)$ by the total pixel number MN (where M is the image width and N is the image height) to obtain a normalized histogram $P(\eta_k) = h(\eta_k)/MN$. Roughly speaking, $P(\eta_k)$ is the Probability Density Function (PDF) of occurrence of intensity level $\eta_k$, with at most L "bins". Therefore, Histogram operation, or intensity transformation, is a manipulation that rearranges these bins to adjust image.

One of the most important basic histogram operations is Histogram Equalization (HE). The objective of HE is to transform $P(\eta_k)$ into a uniform function in the range [0, 1], thus maximize the "entropy" of $P(\eta_k)$. However, since the objective can be fulfilled only when $P(\eta_k)$ is a continuous function, the result of HE would decline from ideal as the uniformity of $P(\eta_k)$ decreases.

To equalize the histogram, first the Cumulative Distribution Function (CDF) $C(\eta_k)$ of $P(\eta_k)$ is obtained by:

$$C(\eta_k) = \sum_{m=0}^{r_k} P(m) \tag{1}$$

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Then histogram equalization uniforms intensity levels $\eta_k$ into $s_k$ , which is given by:

$$s_k = (L-1)\times C(\eta_k) \tag{2}$$

In ideal case, when $C(\eta_k)$ is a continuous function, $P(s_k)$ becomes unique between [0,1]. A discrete histogram would cause "gaps", or several zero bins between larger $P(s_k)$ after histogram equalization, obtaining suboptimal result. HE increases contrast of sources significantly, its concept are widely adopted as basis of contrast enhancement methods. There are several modified versions of HE proposed for different uses.

Hard k-means clustering, is also known as c-means clustering. The k-means algorithm partitions a collection of N vector into c groups (clusters $c_i$, $i$ = 1, …, c). The aim of that algorithm is finding cluster centers (centroids) for each group. The algorithm minimizes a dissimilarity (or distance) function which is given in Eq. (3):

$$J = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{k, x_k \in G_i} d(x_k - c_i) \tag{3}$$

$c_i$ is the centroid of cluster $i$;

$d(x_k-c_i)$ is the distance between $i_{th}$ centroid ($c_i$) and $k_{th}$ data point;

For simplicity, the Euclidian distance is used as dissimilarity measure and overall dissimilarity function is expressed as in Eq. (4):

$$J = \sum_{i=1}^{c} Ji = \sum_{i=1}^{c} \left( \sum_{k, x_k \in G_i} \left\| x_k - c_i \right\|^2 \right) \tag{4}$$

Partitioned groups can be defined by a c×n binary membership matrix (U), where the element $u_{ij}$ is 1 if the $j_{th}$ data point $x_j$ belongs to group $i$ and 0 otherwise. This explanation is formulated in Eq. (5):

$$u_{ij} = \begin{cases} 1 & if \left\| x_j \le c_i \right\|^2 \le \left\| x_j \le c_k \right\|^2, \, for\, each\, k \ne i \\ 0 & otherwise \end{cases} \tag{5}$$

Since a data point can only be in a group, the membership matrix (U) has two properties which are given Eq. (6) and (7):

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1, \ldots, m \tag{6}$$

$$\sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij} = n \tag{7}$$

Centroids are computed as the mean of all vectors in group $i$:

$$c_i = \frac{1}{|G_i|} \sum_{k, x_k \in G_i} x_k \tag{8}$$

$|G_i|$ is the size of $G_i$.

The performance of the algorithm depends on the initial positions of centroids. So the algorithm gives no guarantee for an optimum solution.

Fuzzy C-Means clustering (FCM), also known as Fuzzy ISODATA, is a clustering technique which is separated from hard k-means that employs hard partitioning. The FCM employs fuzzy partitioning such that a data point can belong to all groups with different membership grades between 0 and 1.

FCM is an iterative algorithm. The aim of FCM is to find cluster centers (centroids) that minimize a dissimilarity function.

To accommodate the introduction of fuzzy partitioning, the membership matrix (U) is randomly initialized according to Eq. (9):

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1, \ldots, n \tag{9}$$

The dissimilarity function which is used in FCM is given by Eq. (10):

$$J(U, c_1, c_2, \ldots, c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2 \tag{10}$$

$u_{ij}$ = Between 0 and 1;$c_i$ is the centroid of cluster i
$d_{ij}$ = The Euclidian distance between $i_{th}$ centroid ($c_i$) and $j_{th}$ data point, $||x_j-c_i||$
$m$E [1,∞] = A weighting exponent

To reach a minimum of dissimilarity function there are two conditions. These are given in Eq. (11) and (12):

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \tag{11}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \frac{d_{ij}}{d_{kj}} \right)^{\frac{2}{m-1}}} \tag{12}$$

Detailed algorithm of fuzzy c-means is proposed by Bezdek *et al*. (1984).

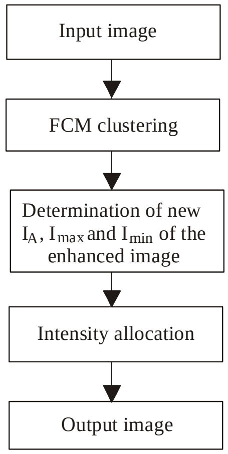


Fig. 1: Flowchart of WBCHE

By iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers to the "right" location within a data set.

## THE PROPOSED ALGORITHM

We proposed an image enhancement framework named Weight Based Clustered Histogram Equalization (WBCHE). The entire block diagram is shown in Fig. 1. It consists three main parts:

- Fuzzy C-Means clustering (FCM)
- Determination of new average, maximum and minimum intensity
- Intensity allocation

The proposed method clusters the image at first and takes the information of each group to apply intensity allocation. The mechanism is to adaptively enhance the image by its own characteristic. The advantage of it is that the detailed texture can be displayed more clearly than other methods. In addition, the proposed method causes over-enhancement with lower probability than other methods, so the enhanced images are more natural than the results of other methods.

In the following sections, the blocks will be elaborated in details.

**Fuzzy c-means clustering:** FCM is the first stage in the proposed method. At first we convert the color space of the original image from RGB to HSI. The method clusters the I component image into four groups by using FCM. So we can split image histogram into four sub-histograms after applying the FCM to the input image.

We tried several numbers of clusters, such as three, four, six and eight. We found that the detailed texture would not be displayed clearly after enhancement when grouping into three clusters. For six or eight clusters, the results of enhancement would be better, but the executing time would be too large instead. Therefore we choose grouping image into four clusters to get acceptable performance of enhancement and executing time.

**Determination of $I'_A$, $I'_{\max}$ and $I'_{\min}$:** Based on Human Visual System, we proposed a simple curve to determine the new average intensity, $I'_A$, of enhanced image. HVS is more sensitive when the detail distributes on the mid-tone gray level. Therefore, based on S-curve, we try to adjust the brighter and darker images to mid-tone area. The curve is formulated as below:

$$I'_A = I_A 0.5 \times (0.6 - \left(\left(1 + \left((\exp\left(-\frac{I_A - 0.5}{0.125}\right)\right)^{-1}\right)\right) \tag{13}$$

Moreover, HVS stimulation amount to different gray levels can be approximated by an S-shaped curve Shen-Chuan *et al*. (2006) like the following form:

$$S(x) = (1+e^{-x})^{-1} \tag{14}$$

According to this curve, the dark area could be darker after eyes receive the light and so as the bright area. We want to simulate it and the intensity component value is in [0,1], so we can get the corresponding function by shifting and scaling Eq. (15):

$$S(x) = \left(1 + \exp\left(-\frac{x - 0.5}{0.07}\right)\right)^{-1} \tag{15}$$

We can obtain the new maximum intensity, $I'_{\max}$ and minimum intensity, $I'_{\min}$, of the result image, respectively by this curve. Then we enhance the contrast of the image by the new maximum and minimum intensity.

**Intensity allocation:** We try to find some parameters or information to help us to apply intensity allocation. We can obtain the intensity distribution and the number of pixel of each sub-histogram after FCM. Therefore we define two weights according to the information. One, $W_1$, is the ratio of the intensity distribution of each cluster and the whole image. The other one, $W_2$, is the ratio of the pixel number of each cluster and the whole image. And the total weight, *Weight*, is composed of $W_1$ and $W_2$ and the intensity distribution owns more weight than the pixel number. So we can calculate the weights according to the followings:
For each sub-histogram$_i$:

$$W_{1,i} = \frac{I_{i,\max} - I_{i,\min}}{\sum_{i=1}^{4}\left(I_{i,\max} - I_{i,\min}\right)} \tag{16}$$

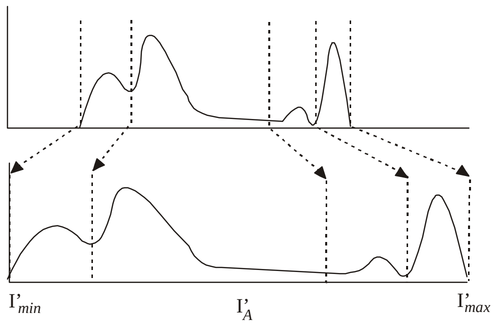


Fig. 2: An example of intensity allocation

$$W_{2,i} = \frac{PixelNumber_i}{TotalPixel} \tag{17}$$

$$Weight_i = \frac{2 \times W_{1,i} + W_{2,i}}{3} \tag{18}$$

$$\begin{cases} for\ i = 1,2: \\ range_i = \dfrac{Weight_i}{(Weight_1 + Weight_2)} \times (I'_A - I'_{\min}) \\ for\ i = 3,4: \\ range_i = \dfrac{Weight_i}{(Weight_3 + Weight_4)} \times (I'_{\max} - I'_A) \end{cases} \tag{19}$$

After the calculation, we allocate the histogram to $[I'_{\min}, I'_{\max}]$ depending on rang $e_i$. That is, the order of intensity allocated for the sub-histograms in output image histogram are maintained in the same order as they are in the input image, i.e., if sub-histogram$_i$ is allocated the intensity to $[i_{start}, i_{end}]$ , then $i_{start} = (i\text{-}1)_{end} = (i\text{-}1)_{end}+1\times bin$ and $i_{end} = i_{start}+rang\ e_i$ . For the first sub-histogram$_j$, $j_{start} = I'_{\min}$ . An example of such allocation is presented in Fig. 2.

As mentioned above, the advantage of applying enhancement after clustering is that the detailed texture can be displayed more clearly than other methods. Moreover, the proposed method causes over-enhancement with lower probability than other methods, so the enhanced images are more natural than the results of other methods.

## CONCLUSION

We proposed an automatic contrast enhancement algorithm, combining with local and global approach. The proposed WBCHE adjusts the average intensity to the proper position, so it causes over-enhancement with lower probability than other methods. It utilizes FCM to cluster the image into four groups, so that we can obtain local information and determine the range allocated to each group. Therefore it can show the detailed texture more clearly than other one by using only global information. In addition to above mentions, there are some characteristics of whole algorithm. It would keep the character of the image and nearly no artifacts would be produced.

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## REFERENCES

Bezdek, J.C., R. Ehrlich and W. Full, 1984. FCM: The fuzzy c-means clustering algorithm. Comput. Geosci., 10(2-3): 191-203.

Gonzalez, R.C. and R.E. Woods, 1992. Digital Image Processing. 2nd Edn., Reading, Addison-Wesley, MA.

Jain, A.K., 1989. Fundamentals of Digital Image Processing. Englewood Cliffs, Prentice-Hall, NJ.

Kim, Y.T., 1997. Contrast enhancement using brightness preserving bihistogram equalization. IEEE T. Consumer Electr., 43(1): 1-8.

Kim, Y.K., J.K. Paik and B.S. Kang, 1998. Contrast enhancement system using spatially adaptive histogram equalization with temporal filtering. IEEE T. Consumer Electr., 44(1): 82-86.

Shen-Chuan, T., C. Yi-Ying, C. Jen-Hao and C. Chao-Yu, 2006. High dynamic range compression with detail refinement in network communication. Proceeding of the IASTED International Conference WEB Technologies, Applications and Services, July 17-19, Calgary, AB, Canada, pp: 156-161.

Torre, A., A.M. Peinado, J.C. Segura, J.L. Perez-Cordoba, M.C. Benitez and A.J. Rubio, 2005. Histogram equalization of speech representation for robust speech recognition. IEEE Trans. Speech Audio Proc., 13(3): 355-366.

Wang, Q. and R. Ward, 2007. Fast image/video contrast enhancement based on weighted threshold histogram equalization. IEEE T. Consumer Electr., 53(2): 757-764.

Whittle, P., 1986. Increments and decrements: Luminance discrimination. Vis. Res., 26(10): 1677-1691.

Wongsritong, K., K. Kittayaruasiriwat, F. Cheevasuvit, K. Dejhan and A. Somboonkaev, 1998. Contrast enhancement using multi-peak histogram equalization with brightness preserving. Proceedings of IEEE Asia-Pacific Conference on Circuits and Systems, Chiangmai, Taiwan, pp: 455-458.

Zimmerman, J., S. Pizer, E. Staab, E. Perry, W. McCartney and B. Brenton, 1988. Evaluation of the effectiveness of adaptive histogram equalization for contrast enhancement. IEEE T. Med. Imag., 7(4): 304-312.