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An Adaptive Histogram Equalization Algorithm on the Image Gray Level Mapping *

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Abstract

The conventional histogram equalization algorithm is easy causing information loss. The paper presented an adaptive histogram-based algorithm in which the information entropy remains the same. The algorithm introduces parameter β in the gray level mapping formula, and takes the information entropy as the target function to adaptively adjust the spacing of two adjacent gray levels in the new histogram. So it avoids excessive gray pixel merger and excessive bright local areas of the image. Experiments show that the improved algorithm may effectively improve visual effects under the premise of the same information entropy. It is useful in CT image processing.

*Keywords:*Histogram Equalization; Image Enhancement; Gray Level Mapping; Information Entropy

1. Introduction

The histogram equalization algorithm has been a conventional image enhancement algorithm for its simplicity and efficiency. It adjusts the gray level of an image according to the probability distribution function of the image and enlarges the dynamic range of the gray distribution to improve visual effects of the image [1]. The histogram equalization algorithm may be divided into two types: local histogram equalization and global histogram equalization. The local histogram equalization may well enhance local details of the image and it may be divided into three types: overlapping sub-block, nonoverlapping sub-block, and partially overlapping sub-block. The nonoverlapping sub-block method is very rarely used for its obvious square effects; the overlapping sub-block method is also not used in practice for its large amount of calculation and low processing speed; the partially overlapping sub-block method can speed up the calculation, but it is relatively complex [2]. Compared to the local histogram equalization algorithm, the global algorithm has certain advantages in processing speed, but has disadvantages in

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enhancing effects. To improve enhancing effects, references [2] to [9] introduce many improved algorithm.

Based on the conventional histogram equalization algorithm and the prophase study of [10] and [11], we analyze the relationship of the mapping gray level and introduce the definition of different gray level, gray threshold setting and identification methods. Then, we use the information entropy as the target function to get parameter β in the gray level mapping formula. According to the threshold, the improved algorithm may automatically identify the gray level of the image and adaptively adjust the spacing of two adjacent gray levels in the new histogram. Thus, it may effectively improve visual effects for any image under the premise of the same information entropy.

2. Analysis of the Histogram Equalization Algorithm

Based on the probability theory, the histogram equalization algorithm realizes the gray mapping of pixels in the image by using gray operations and transforms the histogram to one that is uniform, smooth, and has clear gray levels, so that the purpose of image enhancement can be achieved [1].

Suppose the gray value of the pixel in the original image is r (0≤r≤1) and its probability density is p(r), the gray value of the pixel in the enhanced image is s (0≤s≤1) and its probability density is p(s), and the mapping function is s=T(r). According to the physics meaning of the histogram, it is clear that every bar on the equalized histogram is of the same height. That is

$$p_s(s)ds = p_r(r)dr \tag{1}$$

Suppose s=T(r) is a monotonically increasing function in the interval and its inverse function r =T^{-1}(s) is a monotonic function also. According to (1), we can deduce

$$p_s(s) = [p_r(r)\frac{1}{ds/dr}]_{r=T^{-1}(s)} = p_r(r)\frac{1}{p_r(r)} = 1 \tag{2}$$

The mapping relationship of the conventional histogram equalization algorithm:

In discrete conditions, the relationship between i (the gray value of the pixel in the original image) and f_i (the gray value of the pixel in enhanced the image) is [1]

$$f_i = (m-1)T(r) = (m-1)\sum_{k=0}^{i}\frac{q_k}{Q} \tag{3}$$

where, m is the number of gray levels presented in the original image, q_k is the number of pixels in the image with k th gray level, Q is the total number of pixels in the image.

Suppose an image has n different gray levels, and the occurrence probability of i th gray level is p_i, so the entropy of the gray level may be defined as

$$e(i) = -p_i \log p_i \tag{4}$$

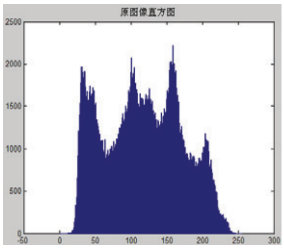
The entropy of the whole image is

$$E = \sum_{i=0}^{n-1} e(i) = -\sum_{i=0}^{n-1} p_i \log p_i \tag{5}$$

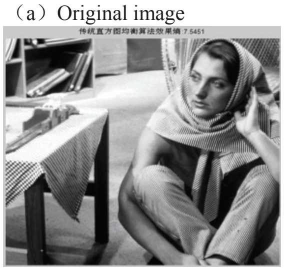
It can be proved that E will achieve its maximum if and only if $p_0 = p_{12} = \cdots = p_{n-1} = \frac{1}{n}$. That is to say the entropy of the whole image achieves its maximum when the histogram of the image has uniform distribution.

From (3), it is clear that the dynamic range has been enlarged after equalization. The essence of the equalization is to expand the quantization interval. The experimental results based on (3) are shown in fig. 1.

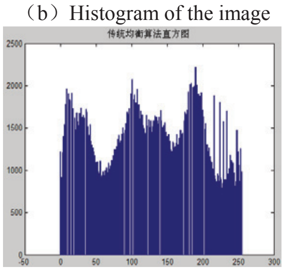
（a）Original image



（b）Histogram of the image



（c）Enhanced image



（d）Equalized histogram

Fig.1 Results of the conventional histogram equalization

From fig.1 (a) and (b), it is clear that visual effects of the original image are relatively dark and the distribution range of the histogram of the image is relatively small. From fig.1 (c), it is clear that the brightness of the enhanced image has increased and visual effects have been improved, but some local areas are too bright and some details of the image are lost. From fig. 1 (d), it is clear that the distribution range is enlarged, but excessive mergers of gray levels make some white stripes appear in the equalized histogram. According to the entropy theory, the bigger the entropy of an image is, the richer the information and details of the image are. From (5), the entropy of the original image is 7.6321 and the entropy of the enhanced image is 7.5451. So the information of the image is lost in the process of histogram equalization.

The conventional histogram equalization algorithm has three flaws:

(1) Gray levels of the enhanced image are decreased, and some details disappear;

(2) Some local areas will be too bright in certain enhanced images;

(3) Excessive mergers of gray levels make false contours appear in the image.

The paper presented an adaptive histogram-based algorithm which may effectively improve visual effects under the premise of the same information entropy.

3. Adaptive Gray Level Mapping Algorithm

Ideas: f_i is the gray value of i th gray level in the original image. Position j of mapped gray level g_j is decided by the ratio of $\sum_{k=0}^{i-1} p_k$ and $\sum_{k=i+1}^{m-1} p_k$. To achieve the uniform distribution or local uniform distribution, the algorithm compares i with j : if $j < i$, then map forward; if $j > i$, then map backward.

$$j = (m-1)\frac{\sum_{k=0}^{i-1} p_k}{\sum_{k=0}^{i-1} p_k + \sum_{k=i+1}^{m-1} p_k} \tag{6}$$

where, $\sum_{k=0}^{m-1} p_k = 1$, $p_k = \dfrac{q_k}{Q}$.

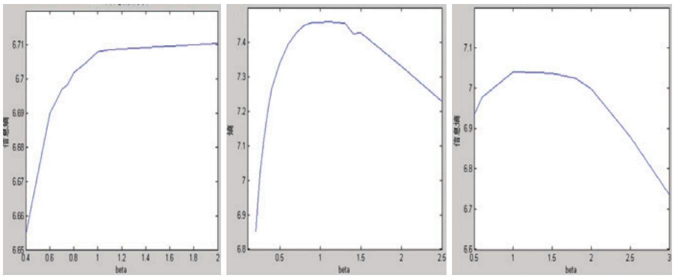
In the mapping process, the gray level with small number of pixels may be phagocytosis by the gray level with large number of neighbourhood pixels. To avoid the information loss phenomena, we introduce adaptive parameter β in gray mapping. To get better visual effects, we take the information entropy as the objective function to adaptively select β based on the gray distribution of the input image. The mapping relationship is

$$q_k = \log(q_k + 1) \tag{7}$$

$$j = (m-1)\frac{\sum_{k=0}^{i-1} p_k}{\sum_{k=0}^{i-1} p_k + \beta \sum_{k=i+1}^{m-1} p_k}, \quad \beta \in (0, +\infty) \tag{8}$$

Selection of adaptive parameter β:

From (8), it is clear that j is a monotonically decreasing function of β. If an image is relatively dark, the gray levels are excessively clustered at the low end of the histogram. To get better visual effects, j must be increased and β must be less than 1. From fig. 2(a), β is appropriately equal to 0.8. Similarly, if the brightness of an image is moderate, the gray levels are clustered in the middle of the histogram. From fig. 2(b), β is appropriately equal to 1.1. If an image is relatively bright, the gray levels are excessively clustered at the high end of the histogram, j must be decreased and β must be greater than 1. From fig. 2(c), β is appropriately equal to 1.5. Thus, the value of β is relevant with gray levels of the input image. Relationship between the entropy and β is shown in figure 2 and detailed analysis can be found in [11].



（a）Low gray levels (b) Middle gray levels (c) High gray levels

Fig. 2 Relationship between the entropy and β

Gray level definition:

Suppose a gray image has 256 gray levels. It can be divided into three types: low gray levels, middle gray levels and high gray levels. Set threshold TL=85, TH=170. If the gray value is less than 85, it may be classified as low gray levels; if the gray value is larger than 85 and less than 170, it may be classified as middle gray levels; if the gray value is larger than 170, it may be classified as high gray levels. At the same time, the pixel numbers of low, middle and high gray levels are respectively counted and recorded as *num_low*, *num_mid*, and *num_high*. The maximum of the three is found to decide the image type. If *num_low* is the largest one, it is clear that low gray level pixels are dominant in the image; the image is a very dark image. This kind image is called low gray level image, otherwise called middle gray level image or high gray level image.

For example: a 512×512 image, where *num_low*=5632, *num_mid*=21760, and *num_high*=38144, the maximum is *num_high*. So 38144 pixels cluster at the high end of the gray level and the image belongs to high gray level image.

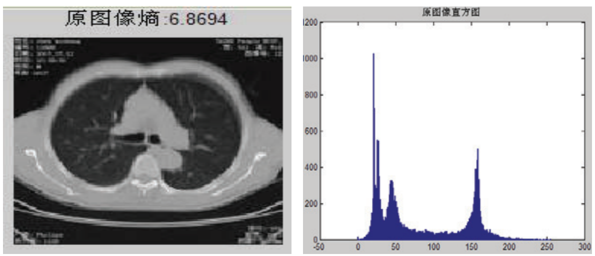
Steps of the improved algorithm:
(1) Initialization parameters and variables, read the original image.
(2) Statistics of original image gray levels, record as f_i, where $i = 0,1,\cdots n-1$.
(3) Statistics of the pixel number of certain gray level record as q_i, and calculate the entropy of the original image according to (5).
(4) Identification the gray level of pixels and recording: if $f_i < TL$, then mun_low+1; if $f_i > TH$, then mun_high+1; otherwise mun_mid+1.
(5) Comparison and adaptively adjusting β: if the maximum is mun_low, then $\beta = 0.8$; if the maximum is mun_high, then $\beta = 1.5$; otherwise $\beta = 1.1$.
(6) Histogram modification according to (7) and (8).
(7) Calculation the entropy of the modified image according to (5).
(8) Output the modified image.

The key to the above steps are step (4), (5) and (6). Step (4) and (5) will automatically identify the image gray type and automatically select parameter β. Step (6) uses the logarithmic mapping relationship to enlarge the spacing of two adjacent gray levels, and makes the distribution of the modified image well spread out over the gray level range.

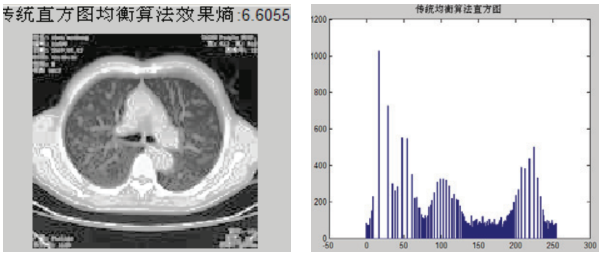
4. Simulation Experiments And Analyses

Experiment 1: Intrathoracic computed tomography (CT) image.

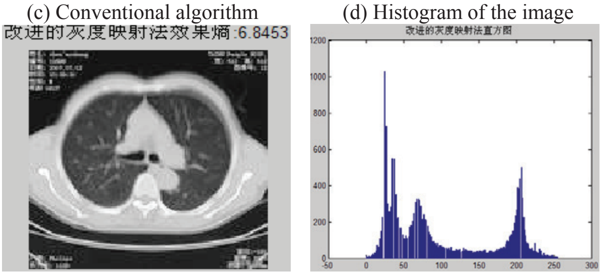
Results of the conventional algorithm and the improved algorithm are shown in fig. 3. Fig. 3 (a) shows the original image. The entropy of the original image is 6.8694. The original image appears very dark when displayed and the intervals of various intrathoracic organs and the edge in the image are not clear. Fig. 3 (c) shows the enhanced image using the conventional histogram equalization algorithm. Some local areas are too bright and some details of the image are lost in the equalized image. The entropy of the image is 6.6055. Fig. 3 (d) is the histogram of the equalized image. Fig. 3(e) shows the improved image using the improved histogram equalization algorithm proposed in this paper. The entropy of the image is 6.8453. According to the improved algorithm, statistics results are *num_low*=19040, *num_mid*=560, *num_high* ≈ 0, and β is automatically equal to0.8. Visual effects of the improved image are obviously improved and the intervals of various intrathoracic organs and the edge in the image are clear. It avoids the phenomena of too bright local areas which make some details of the image lose.



(a) Original image (b) Histogram of the image



(c) Conventional algorithm (d) Histogram of the image

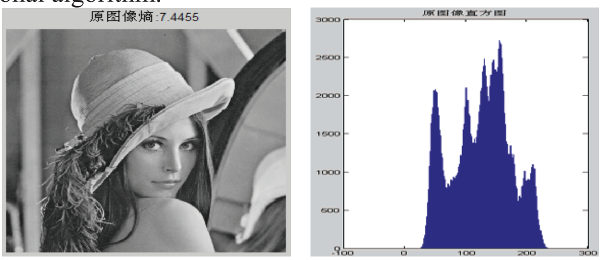


(e) Improved algorithm (f) Histogram of the image

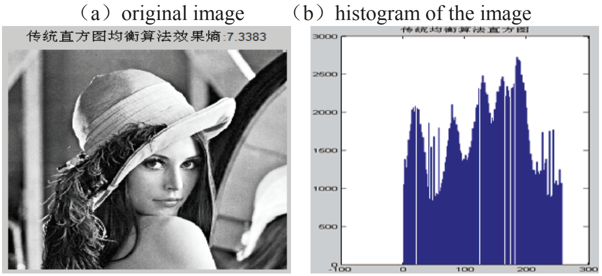
Fig.3 Comparative experiment of intrathoracic CT image

Experiment 2: Lena image

As shown in fig. 4 (c), the conventional histogram equalization algorithm makes some details of the image lose, for example: left eyelashes can not be seen clearly and facial lines appear abrupt, the whole image gives people rigid visual stimulus. According to the improved algorithm, statistics results are *num_high* =35840, *num_mid* = 151552, *num_low* = 74752, and β is automatically equal to 1.1. As shown in fig. 4 (e), the facial lines appear softness, the brim feathers are clear, full image is desirable to the person visual sense. As shown in fig. 4 (f), it is clear that the improved algorithm retains distribution characteristics of the image, the grayscale merger is also reduced, and the image quality is greatly improved than the traditional algorithm.



（a）original image （b）histogram of the image



（c）conventional algorithm （d）histogram of the image

(e) Improved algorithm

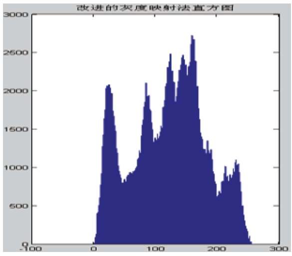

(f) histogram of the image

Fig.4 Comparative experiment of Lena image

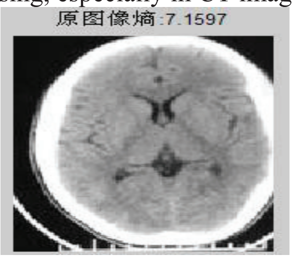
Experiment 3: Brain CT image.

Fig. 5 (a) shows the original image which has bright edges but details of intracranial structures can not be seen clearly and edge boundaries are not clear. Fig. 5 (c) shows the enhanced image using the conventional histogram equalization algorithm, details of intracranial structures can be seen clearly but the edge boundaries are relatively blurred. According to the improved algorithm, statistics results are *num_high* = 8540, *num_mid*=4620, *num_low* = 3360, and β is automatically equal to 1.5. As shown in fig. 5(e), details of the intracranial structures can be seen clearly and the edge boundaries are relatively clear.

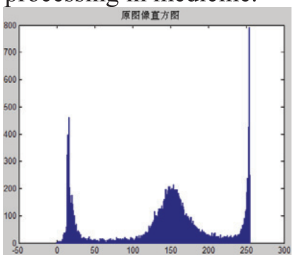
From the above analyses, it is clear that the algorithm proposed in this paper can automatically identify the image gray type, automatically select parameter β , adaptively adjust the spacing of two adjacent gray levels, and improve the image quality.

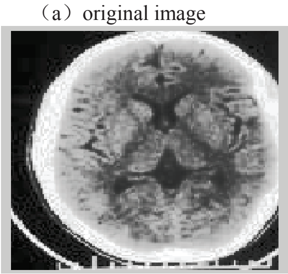
5. Conclusions

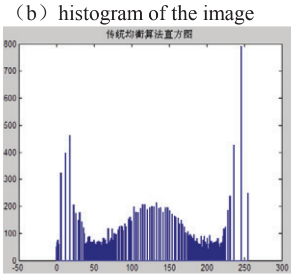
Based on the conventional histogram equalization algorithm, the paper presented an adaptive gray level mapping algorithm which takes the entropy and visual effects as the target function. The selection rule of parameter β in different conditions and the identification method of the image gray type are also presented. Experiments show that the improved algorithm may effectively improve visual effects. It retains details of the image and avoids too bright local areas and false contours. It has a good application prospect in image processing, especially in CT image processing in medicine.

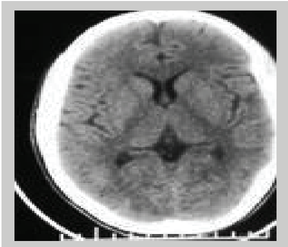


(a) original image

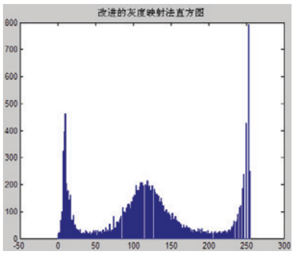

(b) histogram of the image


(c) conventional algorithm


(d) histogram of the image



(e) Improved algorithm



(f) histogram of the image

Fig. 5 Comparative experiment of brain CT image

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