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Contrast Enhancement for Segmentation of Hippocampus on Brain MR Images

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ABSTRACT

An image segmentation result depends on pre-processing steps such as contrast enhancement, edge detection, and smooth filtering etc. Especially medical images are low contrast and contain some noises. Therefore, the contrast enhancement and noise removal techniques are required in the pre-processing. In this study, we present an extension by a novel histogram equalization in which both local and global contrast is enhanced using neighborhood metrics. When checking neighborhood information, filters can simultaneously improve image quality. Most important is that original image information can be used for both global brightness preserving and local contrast enhancement, and image quality improvement filtering. Our experiments confirmed that the proposed method is more effective than other similar techniques reported previously.

Key words: contrast enhancement, histogram equalization, neighborhood metrics

1. INTRODUCTION

The development of medical imaging technologies in last three decades has grown and enormously increased its importance in the diagnosis of diseases. Diagnostic imaging techniques such as ultrasound (US), computer tomography (CT), and magnetic resonance imaging (MRI) facilitate the recognition of abnormal morphologies as symptoms of underlying conditions. For instance, hippocampus morphology has an important role in the earliest stage of Alzheimer's disease. Hence, hippocampus volumetric data has been used as an important biomarker in clinical studies [1-5]. A typical 3D data set is a group of 2D slice images acquired by US, CT, and MRI. A good precision and accuracy are required to detect the hippocampus because few slices contain the hippocampus in the slices. Although there are many different segmentation approaches, their accuracies are depended on pre-processing steps. Most medical images are low contrast and contain some noises. Therefore, the contrast enhancement and noise removal techniques are required in the pre-processing.

In contrast enhancement methods, histogram equalization (HE) is the most well-known technique because of its simplicity and processing speed. HE can be categorized into two main processes: global histogram equalization (GHE) and local histogram equalization (LHE) [6]. In GHE, the histogram of the whole input image is used to compute

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a histogram transformation function. As result, the dynamic range of the image histogram is flattened and stretched, and the overall contrast is improved [7].

GHE is an attractive tool in many contrast enhancement applications. However, it changes the original image's brightness, while reducing the quality of the original image and in some cases causes a washout effect (Fig. 1). In contrast, LHE uses a sliding window method, in which local histograms are computed from the windowed neighborhood to produce a local intensities remapping for each pixel. The intensity of the pixel at the center of the neighborhood is changed according to the local intensity remapping for that pixel. LHE is capable of producing great contrast results but is sometimes thought to over-enhance images.

To overcome the washout effect, brightness-preserving extensions of GHE have been developed, such as brightness-preserving bi-histogram equalization (BBHE) [8], dualistic sub-image histogram equalization (DSIHE) [9], minimum mean brightness error bi-histogram equalization (MMBEBHE) [10] and other methods [11-17]. All of the methods mentioned above feature the same weakness: they have not considered the enhancement of noisy images and the image visualization is not enhanced on some images that have the histograms with a few large bins containing most of the information in the input image.

Eramian [18] generalized the GHE method, which allows any number of neighborhood metrics on image pixels in place of the pixel. The neighborhood metric defines a set of temporary sub-bins.

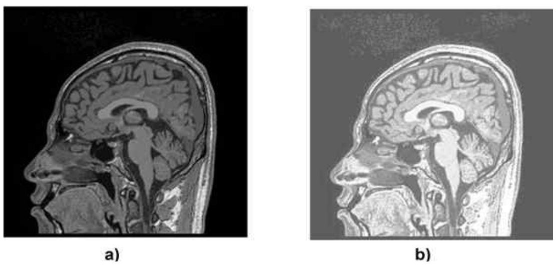

Fig. 1. a) Original b) result of GHE.

This allows one to choose neighborhood metrics that can order pixels using different criteria and to separate pixels that would be in the same bin in the original histogram into several sub-bins defined by neighborhood metric (Fig 2). However all previous works can not remove noise with contrast enhancement simultaneously.

For this reason, we proposed a new extension of GHE which uses distinction neighborhood metric [19] for improving contrast and rearranges histogram for removing noise in this work.

This paper is organized as follows. Related works are discussed in section IIand proposed method is presented in section. Section IV contains some results and comparison between our method and other methods. Section V is our conclusions and further works.

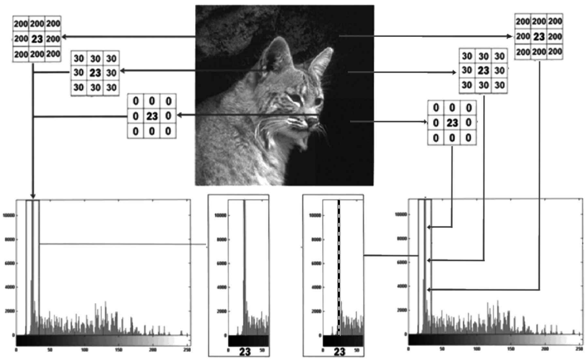

Fig. 2. Demonstration of the neighborhood metric.

2. RELATED WORKS

2.1 Global histogram equalization

Let $h(i)$ be the i-th bin of intensity level of original image f, and then $p(i)$ is the probability that the gray level of any given pixel is $i(0 \le i \le L-1)$:

$$h(i) = n_i, \text{ for } i = 0, 1, \ldots, L-1. \quad (1)$$

$$p(i) = \frac{n_i}{\sum_{i=0}^{L-1} n_i} = \frac{n_i}{N} \text{ and } \sum_{i=0}^{L-1} p(i) = 1. \quad (2)$$

where n_i is the number of pixels of i-th intensity level in image f, N is the total number of pixels of image f, and L is discrete intensity level. The cumulative distribution function (CDF) P_i is defined by (3):

$$P_i = \sum_{j=0}^{i} p_{j,} \;\; P_{L-1} = \sum_{j=0}^{L-1} p_j = 1. \tag{3}$$

GHE maps the original image into the resultant image using the intensity transformation function:

$$g(x,y) = T(f(x,y)), \tag{4}$$

where f and g are the original and resultant images, (x,y) are the 2D coordinates of the images, and T is the intensity transformation function, which maps the original image into the entire dynamic range $[I_{0,} I_{L-1}]$ and $i \in [0, L-1]$, using CDF:

$$T(I_i) = I_0 + (I_{L-1} - I_0) \cdot P_{i.} \tag{5}$$

2.2 Bi-histogram equalization (BBHE)

Let I_m be the mean of the image f and assume that $I_m \in [0, L-1]$. Based on I_m, the image is separated into two sub-images f_{m_1} and f_{m_2} as

$$f = f_{m_1} \cup f_{m_2}, \tag{6}$$

where

$$f_{m_1} = f(x,y) | f(x,y) \le I_m, \; \forall f(x,y) \in f \tag{7}$$

and

$$f_{m_2} = f(x,y) | f(x,y) > I_m, \; \forall f(x,y) \in f \tag{8}$$

Note that sub-image f_{m_1} is composed of $\{I_0, I_1, \cdots, I_m\}$ and the sub-image f_{m_2} is composed of $\{I_{m+1}, I_{m+2}, \cdots, I_{L-1}\}$.

Next, define the respective probability distribution functions of sub-images f_{m_1} and f_{m_2} as

$$p_{m_1}(I_k) = \frac{n_{m_1}^{k}}{n_{m_1}} \tag{9}$$

and

$$p_{m_2}(I_k) = \frac{n_{m_2}^{k}}{n_{m_2}} \tag{10}$$

in which $n_{m_1}^{k}$ and $n_{m_2}^{k}$ (where k=0,1,..., I_m and k= $I_{m+1}, I_{m+2}, ..., I_{L-1}$ correspondingly) represent the respective values of I_k in the two sub-images f_{m_1} and f_{m_2}, and n_{m_1} and n_{m_2} are the total values of f_{m_1} and f_{m_2} respectively. Here, $n_{m_1} = \sum_{k=I_0}^{I_m} n_{m_1}^{k}$, $n_{m_2} = \sum_{k=I_{m+1}}^{I_{L-1}} n_{m_2}^{k}$, and $N = n_{m_1} + n_{m_2}$. The respective CDFs are then defined as

$$P_{m_1}(I_k) = \sum_{j=0}^{k} p_{m_1}(I_j) \tag{11}$$

and

$$P_{m_2}(I_k) = \sum_{j=I_{m+1}}^{k} p_{m_2}(I_j) \tag{12}$$

Note that $P_{m_1}(I_m) = 1$ and $P_{m_2}(I_{L-1}) = 1$ by definition.

Let us similarly define the following transformation functions exploiting the CDFs

$$T_{m_1}(I_k) = I_0 + (I_m - I_0) \cdot P_{m_1}(I_k) \tag{13}$$

and

$$T_{m_2}(I_k) = I_{m+1} + (I_{L-1} - I_{m+1}) \cdot P_{m_2}(I_k) \tag{14}$$

Then the resultant image of the histogram can be expressed as

$$g(x,y) = T(f(x,y)), \tag{15}$$

in which

$$T(I_k) = \begin{cases} I_0 + (I_m - I_0) \cdot P_{m_1}(I_k) & \text{if } I_k \le I_m \\ I_{m+1} + (I_{L-1} - I_{m+1}) \cdot P_{m_2}(I_k), & otherwise \end{cases} \tag{16}$$

2.3 Histogram equalization with neighbor hood metric (HENM)

Let r be sub-bins of the i-th bin, h(i), of intensity level of image f and r is produced by a neighborhood metric. The number of total sub-bins is R which equals r $\cdot$ L and the range of r depends on the chosen neighborhood metrics.

$$h(r) = n_r, \; \text{for } r = 0, 1, ..., R-1. \tag{17}$$

$$p_r = \frac{n_r}{\sum_{r=0}^{R-1} n_r} = \frac{n_r}{N} \text{ and } \sum_{r=0}^{R-1} p_r = 1. \tag{18}$$

where n_r is the number of occurrences of the r-th sub-bin in i-th intensity of image f and N is the total number of pixels in image f. Then the CDF, P_r, is defined by (19):

$$P_r = \sum_{r=0}^{R-1} p_r \tag{19}$$

GHE maps the original image into the resultant image using the intensity transformation function:

$$g(x,y) = T_1(f(x,y)), \tag{20}$$

where f and g are the original and resultant images, (x, y) are the 2D coordinates of the images, and T_1 is the intensity transformation function, which maps the original image into the entire sub-bin's range, $[S_0, S_{R-1}]$ and $r \in [0, L-1]$ using CDF:

$$T_1(S_r) = T_2(S_r) \cdot (L/R) \tag{21}$$

here

$$T_2(S_r) = S_0 + (S_{R-1} - S_0) \cdot P_r \tag{22}$$

3. PROPOSED METHOD

In the proposed method, the image histogram is divided into two sub-histograms to preserve the image brightness and each histogram bin of each sub-histogram is divided by a distinction metric into sub-bins [19]. Filtering of any drawbacks during the enhancement of image contrast requires rearrangement of the histogram when checkingthe neighborhood metric (Fig. 3). This rearrangement is described below, and all filter types are possible. To check all image pixels that have been neighbors, it is necessary to extend the input image.

3.1 Neighborhood metric

Let γ be the function that extends an image function surrounded by a "background" of zero intensity:

$$\gamma(x,y) = \begin{cases} g(x,y), & (x,y) \in [0, N-1] \times [0, M-1] \\ 0 & otherwise \end{cases} \tag{23}$$

in which an image is N pixels by M pixels in size and g(x,y) is the intensity of image pixel (x,y). The distinction metric is expressed by the following formula:

$$d_\theta(x,y) = \sum_{(x',y') \in R_\theta^{(x,y)}} t(x,y,x'y') \tag{24}$$

which requires the following distinction function:

$$t(x,y,x',y') = \begin{cases} \gamma(x,y) - \gamma(x',y'), & \gamma(x,y) > \gamma(x',y') \\ 0 & otherwise \end{cases} \tag{25}$$

in which the distinction metric, d_θ, is defined by $R_\theta^{(x,y)}$, the set of pixels forming a square in the θ by θ square neighborhood centered (x,y) on θ and is positive odd integer.

3.2 Histogram arrangement

When making histogram, we compute both distinction metric and mean value of current pixels and its neighbors. While distinction metric defines current pixels subbins location of its histogram bin, current pixels intensities are changed by their mean value of neighbors (See Fig. 3).

This rearrangement equals noise removal filter. However, it differs in that its distinction metrics are computed using the original image data. If we use the filtering process first, the distinction metrics that are computed as the changed neighbors of the filtered image and sub-bins created by the

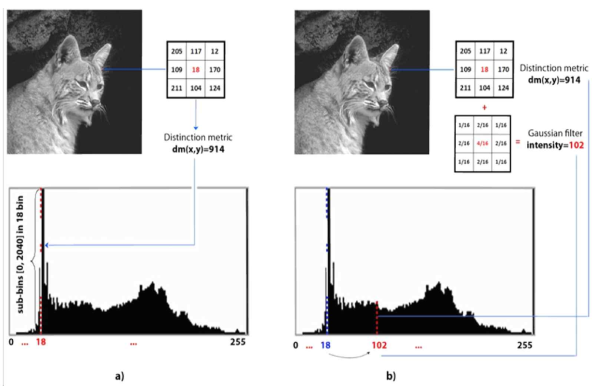

Fig. 3. Illustration of the neighborhood metric and filtering in a histogram bin. Pixels of equal intensity are arranged into a) sub-bins using neighborhood information and b) sub-bins using neighborhood information with filtering.

distinction metric do not use the original neighborhood information of the input image. Therefore, the histogram arrangement is performed with simultaneous computation of the neighborhood metric and filtering computations.

3.3 Bi-histogram equalization with neighborhood metric

The number of total sub-bins are R-1, which equals r • L. Denote the mean of the image f by m_r and $m_r \in [0, R-1]$. based on m_r, the image is separated into two sub-image f_{m_1} and f_{m_2} as

$$f = f_{m_1} \cup f_{m_2}, \tag{26}$$

where

$$f_{m_1} = f(x,y) | f(x,y) \le m_r,\ \forall f(x,y) \in f \tag{27}$$

and

$$f_{m_2} = f(x,y) | f(x,y) > m_r,\ \forall f(x,y) \in f \tag{28}$$

Next, define the respective probability density functions of sub-images f_{m_1} and f_{m_2} as

$$p_{m_1}(z_k) = \frac{n^k_{m_1}}{n_{m_1}} \tag{29}$$

and

$$p_{m_2}(z_k) = \frac{n^k_{m_2}}{n_{m_2}} \tag{30}$$

in which $n^k_{m_1}$ and $n^k_{m_2}$ (where k=0,1,...,m_r and k= $m_{r+1}, m_{r+2}, \dots, R-1$ correspondingly) represent the respective values of m_r in the two sub-images f_{m_1} and f_{m_2}, and n_{m_1} and n_{m_2} are the total values of f_{m_1} and f_{m_2} respectively. Here, $n_{m_1} = \sum_{k=0}^{m_r} n^k_{m_1}$, $n_{m_2} = \sum_{k=m_{r+1}}^{R-1} n^k_{m_2}$, and $N = n_{m_1} + n_{m_2}$, N is the total number of pixels in image f. The respective CDFs are then defined as

$$P_{m_1}(z_k) = \sum_{j=0}^{k} p_{m_1}(z_j) \tag{31}$$

and

$$P_{m_2}(z_k) = \sum_{j=m_{r+1}}^{k} p_{m_1}(z_j) \tag{32}$$

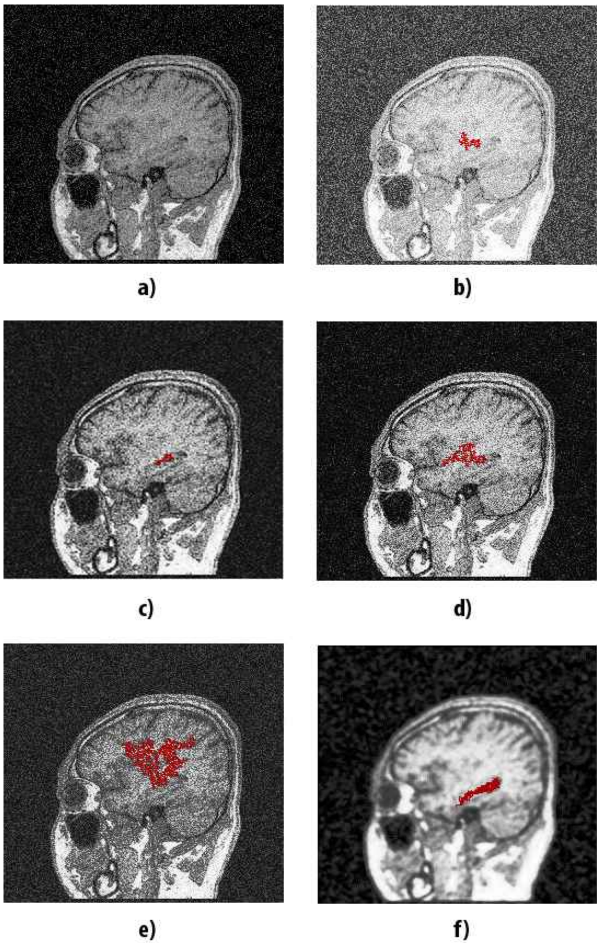

Fig. 4. a) Image with uniform noise, b-f) its segmentation results enhanced by GHE, BBHE, DSIHE, MMBEBHE, and proposed HENMN.

Note that $P_{m_1}(m_r) = 1$ and $P_{m_2}(R-1) = 1$ by definition.

Then the resultant image of the histogram can be expressed as (20)

$$g(x,y) = T_1(f(x,y)),$$

in which f and g are the original and resultant images, (x,y) are the 2D coordinates of the images, and T_1 is the intensity transformation function, which maps the original image into the entire sub-bin's range, z, using CDF:

$$T_1(z_k) = T_2(z_k) \bullet (L/R) \tag{33}$$

where

$$T_2(z_k) = \begin{cases} 0 + (m_r - 0) \bullet P_{m_1}(z_k), & \text{if } k \le m_r \\ m_{r+1} + (R - 1 - m_{r+1}) \bullet P_{m_2}(z_k). & otherwise \end{cases} \tag{34}$$

4. EXPERIMENTAL RESULTS

We tested our proposed HENMN method on MRI Brain images which are acquired by GE 3.0T MRI of Inje University Haeundae Paik Hospital, Korea. We present the results of experiments comparing the proposed method to GHE, BBHE, DSIHE, and MMBEBHE. In the experiment, we tested the proposed method on two different patient images effected by uniform and Gaussian noises comparing to GHE, BBHE DSIHE and MMBEBHE methods.

Fig. 4 shows that the brain image is effected the uniform noise and then improved by different contrast enhancement methods. Region growing method is used for the hippocampus segmentation and all results are failed except our proposed method's result. As shown Fig. 4, our proposed mehtod is more effective than other existing methods because it used two preprocessing methods simultaneously: filtering and contrast enhancement. In this experiment, we used mean filter because it is commonly used uniform noise removal applications.

It is possible to do sequentially filtering technique then contrast enhancement method however, it has two advantages: Our experimental results confirmed that this does not increase the computational cost because the filtering process is done by our proposed arrangement of making the histogram while checking neighborhood metrics simultaneously. If the two methods, i.e., histogram equalization and filtering, are performed sequentially, the first method uses the original image data and next method uses the data altered by the first. With combined histogram equalization and filtering, the original data can be used for both method Fig. 5 illustrates that original image is effected by gaussian noise and then improved by comparing enhancement methods. Then also they are filtered by gaussian filter for all enhanced images.

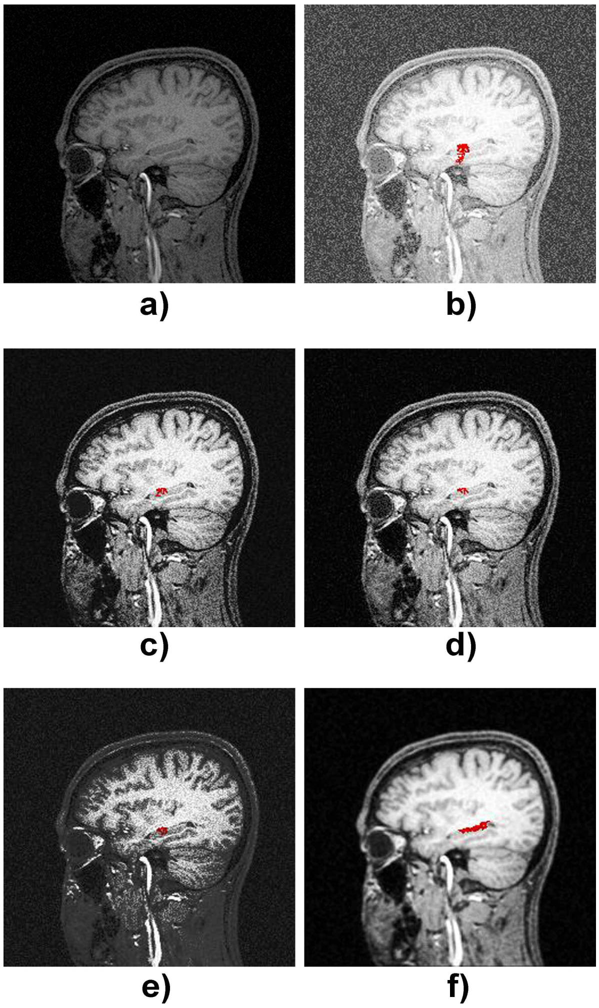

Fig. 5. a) Image with gaussian noise, b–f) its segmentation results enhanced by GHE, BBHE, DSIHE, MMBEBHE, and proposed HENMN and filtered by gaussian filter sequentially.

Table 1. Template Matching Fitting percent (%)

Methods	Image I	Image II
GHE	17	15
BBHE	38	11
DSIHE	24	9
MMBEBHE	16	10
FHENM	93	55

Table 1 shows that the fitting percent between the expert and segmentation methods. We can easily see that our proposed contrast enhancement method can remove the noise effectively and its segmentation results is more correctly than other compared methods results.

5. CONCLUSION

In this work, we proposed a new contrast enhancement method to extract morphological structure of the hippocampus which is difficult to segment due to similarity of surrounding intensities. The proposed HENMN can improve image contrast and remove noise simultaneously. Our experiment proves that HENMN was very effective pre-processing when segmenting hippocampus using region growing segmentation method. In near future we focus on improvement of segmentation accuracy by testing other segmentation method and checking filter etc, because we tested mean filter in this work.

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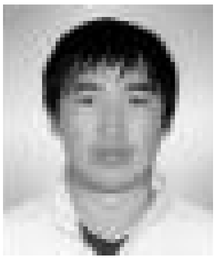

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