Bone Image Enhancement Based on Fuzzy Techniques

Cheng Dansong[1], Cheng Heng-Da[1,2], Tang Xianglong[1],Yu Zhiguo[3]

[1] Department of Computer Science, Harbin Institute of Technology
[2]Department of Computer Science, Utah State University
[3]The 5th hospital of Harbin

Abstract

An image enhancement method for edges detection in medical image, based on fuzzy logic, is proposed in this paper. S-function is used as membership function to transform spatial domain into fuzzy domain, and power-law transformation is applied to contrast manipulation in fuzzy domain. Experimental results of different images show the effectiveness of the paper.

1. Introduction

Image processing, as an important step in computer-aided diagnosis, is always the hot topic involved in image enhancement. This paper as a part of a broken-bone treatment system has several tasks, which can be stated as that of enhancing edges, filtering out impulse noise and contouring extraction. Among these entire tasks, enhancing edges is fundamental. Some techniques for this problem have been proposed in the literature [1].

Usually, gradient operator is classical method involved in image enhancement. The Prewitt, Sobel and Laplacian methods all use gradient operator to process image [1]. In Prewitt method, the tiny changes are accentuated for the first order differential. Prewitt method has good effect on many kinds of images, but it will fail if one image has some noises, because one-dimensional difference will enlarge the effects of noise. As compared to the disadvantages of Prewitt method, Sobel method stresses one important smooth feature, which is more effective. In these two methods, they applied a threshold value to notice the result, but it is determined by experience. Especially for medical images with large variation in gray levels, the threshold value is difficult to be determined. Some directed experiments demonstrated inefficiency of the above methods to process the broken-bone images. It is illustrated in the 3rd section in this paper.

Jorge A [2] presented a adaptive image enhancement algorithm aimed to smooth the radiometrically uniform areas across an image and, at the same time, sharpen the borders between them. It detected the edges or boundaries between image regions, and then enhancing the image. Didier [3] and C-S.Lee et al. [4] proposed some enhancement techniques emphasizing removal of noise. For the main purpose of this paper is to detecting and localizing the edges of broken-bone image, the existing approaches are not appropriate for this task.

The paper utilizes fuzzy set theory to develop an approach to enhance and detect the edges in the image. Firstly, The image data is smoothed by Gaussian function. Then, the smoothed image is differentiated with respect to the directions *x* and *y* to get the *original edge feature*. Thereafter, the paper adopts S-function as membership to transform the spatial domain into fuzzy domain, and the parameters of S-function is determined adaptively according to each image. Subsequently, Power-law transformation is applied in fuzzy domain to realize contrast manipulation. Defuzzification is the last step of the approach.

2. Fuzzy Logic Approach to Image Enhancement

Since edge detection is the main purpose, the paper proposed fuzzy method focusing on enhancing edges, at the meantime, noise in the images should be filtered out. As a result, the method should concurrently have the above two properties. Firstly, Gaussian filter is used in the process to smooth the image. Then, an enhancement algorithm based on fuzzy logic is adopted to sharpen edges further.

2.1. Preprocessing

Before the transformation of the image information from spatial domain into fuzzy domain, some preprocessing should be carried out. The image data is smoothed by Gaussian function of width specified by the user parameter, which is 3 in the experiments:

$$e(i,j) = G_e(g(i,j)) \qquad (1)$$

where $e(i,j)$ and $g(i,j)$ are gray levels at the coordinates (i,j) in the result image, signified as I_G, and original image respectively, while G_e is Gaussian function.

Then, the histogram of the smoothed image is built as followed:

$$h_e(l_e) = \sum_{l=l_e} \delta(l) \quad (2)$$

$$\delta(l_e) = \begin{cases} 1 & e(i,j) = l_e \\ 0 & e(i,j) \neq l_e \end{cases} \quad (3)$$

where $l \in [e_{\min}, e_{\max}]$ represents the gray level of I_G. For each image shows lower contrast after smoothed by Gaussian function, histogram equalization is following to increase the contrast of the image. Based on histogram of its adjusted intensities, a serial of important feature, *key trough*, is to be determined. A *key trough* is defined as following:

- It is the lowest point in the histogram across a certain range, 5% of the entire intensity range in the experiments;
- The amount of elements between adjacent *key troughs* is more than 25% of the total elements of the image or the range between adjacent *key troughs* is more than 25% of the entire intensity range of the adjusted intensities. "Bullet" style, bullet style, bullet style

The hunt for *key troughs* begins at the maximum gray level of the equalized histogram, until all of them are found.

And then, the smoothed image is differentiated with respect to the directions *x* and *y*. From the computed gradient values *x* and *y*, the magnitude of the gradient, delivered as *original edge feature*, can be calculated using the hypotenuse function.

2.2. Fuzzification

After having built *original edge feature* histogram, the paper transforms both original image and the result image of pretreatment into fuzzy domain. The S-function and π-function are most commonly used as membership function. In this paper, the S-function is chosen as the membership function. It is defined as Eq. (4) and its figure is shown in fig.1.

$$\mu_w(l_e, x, y, z) = \begin{cases} 0, & \text{if} \quad l_e \leq x \\ \dfrac{(l_e - x)^2}{(y-x)(z-x)}, & \text{if} \quad x \leq l_e \leq y, \\ 1 - \dfrac{(l_e - x)^2}{(z-x)(z-y)}, & \text{if} \quad y \leq l_e \leq z \\ 1, & \text{if} \quad l_e \geq z \end{cases} \quad (4)$$

where l_e is the variable in the intensity domain, *x*, *y* and *z* are the parameters determining the shapes of S-function.

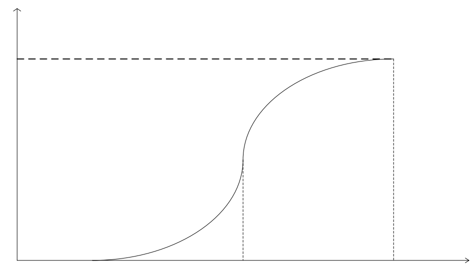


Fig.1: S-function

The result image of the pretreatment as well as the original image can be divided into four segments by the application of S-function. An appropriate choice of two thresholds *x* and *z* where *x* corresponds to black values and *z* to white values is made for each segment such that $0 < x < y < z < 255$ where *y* is a turning threshold beyond which the elements are sharpened while below are darkened. In this paper, *x* and *z* are minimum and maximum gray level of the image respectively. *y* is determined by the *key troughs* found in the preprocessing. In the broken-bone image, there are usually three dominant regions corresponding to bone, muscle and background, with bone region is the brightest. Its expression in histogram is several chief segments divided by the *key troughs*. *y* is set as the nearest *key trough* to the maximum gray level to enlarge contrast between bone and muscle.

2.3. Enhancement

Enhancement is realized referring to the mean membership value within a specific window of image fuzzy data. At first, defining a *w*×*w* filter window. The experiments choose a 3×3 window. *Mean membership value* $\overline{\mu}_w$ is calculated as followed:

$$\overline{\mu}_w(g_{ij}) = \frac{1}{w \times w} \sum_{m=i-(w-1)/2}^{i+(w-1)/2} \sum_{n=j-(w-1)/2}^{j+(w-1)/2} \mu(g_{mn}) \quad (5)$$

After $\overline{\mu}_w$ of all pixels in the image are calculated, a matrix *K*, representing the contrast ratio between membership value and mean membership value for all pixels in the image, is also constructed. $K_{\mu(g_{ij})}$, the element of *K* for the pixel at location (*i*, *j*), is defined as:

$$K_{\mu(g_{ij})} = \left|\mu(g_{ij}) - \overline{\mu}_w(g_{ij})\right| \Big/ \left|\mu(g_{ij}) + \overline{\mu}_w(g_{ij})\right| \quad (6)$$

Then, an enhancement manipulation is realized with power-law transformation of the contrast ratio matrix. The power-law transformations have the basic form:

$$s = cr^{\gamma} \quad (7)$$

where *c* and γ are positive constants. As expected, the transformations with values of γ>1 and γ<1 have exactly the opposite effects [2]. Defined an expression of Eq.(7) to get corrected contrast ratio $K'_{\mu(g_{ij})}$:

$$K'_{\mu(g_{ij})} = \left(K_{\mu(g_{ij})}\right)^{f(\mu(e_{ij}))} \tag{8}$$

$$f(\mu(e_{ij})) = (1 + \mu_0 - \mu(e_{ij}))^n \tag{9}$$

where μ_0 is the threshold of enhancement, $\mu(e_{ij}) > \mu_0$ for enhancement, and $\mu(e_{ij}) < \mu_0$ for de-enhancement. Select $\mu_0 = 0.5$ and $n = 2$ in the experiment.

Referring to the *mean membership value* $\overline{\mu}_w$ and *corrected contrast ratio* $K'_{\mu(g_{ij})}$, the modified membership value can be computed with the following equation:

$$\mu'(g_{ij}) = \begin{cases} \overline{\mu}_w(g_{ij})(1+K'_{\mu(g_{ij})}) \big/ (1-K'_{\mu(g_{ij})}) & \mu(g_{ij}) \ge \overline{\mu}_w(g_{ij}) \\ \overline{\mu}_w(g_{ij})(1-K'_{\mu(g_{ij})}) \big/ (1+K'_{\mu(g_{ij})}) & \mu(g_{ij}) < \overline{\mu}_w(g_{ij}) \end{cases} \tag{10}$$

2.4. Defuzzification

The last step of the approach is to transform the modified membership value from fuzzy domain back to spatial domain. Replace the gray level of the image at position (*i*, *j*) with g'_{ij} defined in Eq.(11).

$$g'_{ij} = \begin{cases} g_{\min} + \dfrac{g_{\max} - g_{\min}}{z-x}\sqrt{\mu'(g_{ij})(y-x)(z-x)} & 0 \le \mu'(g_{ij}) \le \dfrac{(y-x)}{(z-x)} \\ g_{\min} + \dfrac{g_{\max} - g_{\min}}{z-x}\left(z-x-\sqrt{(1-\mu'(g_{ij}))(z-y)(z-x)}\right) & \dfrac{(y-x)}{(z-x)} < \mu'(g_{ij}) \le 1 \end{cases} \tag{11}$$

where $g_{\min}$ and $g_{\max}$ are the minimum and maximum desired gray level, *x, y* and *z* are as same as that in Eq. (4).

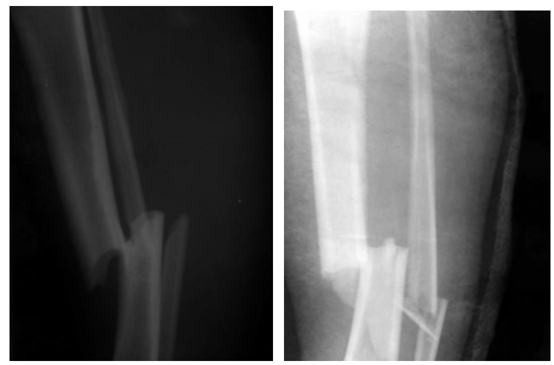
2.5. Contour Extraction

The edges of objects in images can be easily shown by the proposed method, correct contour detection is realized with an active contour method. A minimal path active contour approach using a graph search method is adopted to extract the contour in this system, which will be illustrated in another article.

3. Experiments and Results

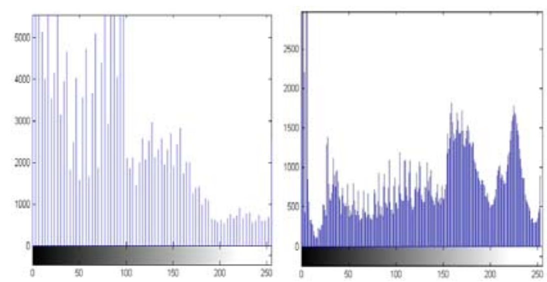
In this section, the paper shows some experimental results of the proposed approach. Two original images are shown in Fig.2 (a), and (b). The edges of the fracture part are intricate and illegible. The nearest *key troughs* to the maximum gray level of the equalized histogram, calculated automatically, are 111 and 152 respectively. Fig.3 (a) and (b) show the histogram after equalization of Fig.2 (a) and (b). Fig.4 and Fig,5 show the results of Sobel and Laplacian operators respectively. Fig.6 is the processed images of the proposed method. It is clear that the edges of the bone in Fig.4 and Fig.5 are not extracted out efficiently. Especially, the edges of the fracture part are hardly to notice Compared with Fig.4, the edges in Fig.6 (a) and (b) are more legible and integrated edges, and easy to be extracted obviously.

The broken-bone treatment system has been tested in the 5th Hospital of Harbin with about 30 cases, among which 25 cases were male while 5 were female. 95 percent cases showed high performance of the system.



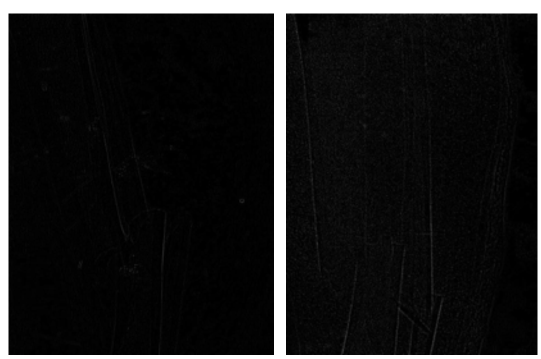
(a) (b)

Fig.2: Original images



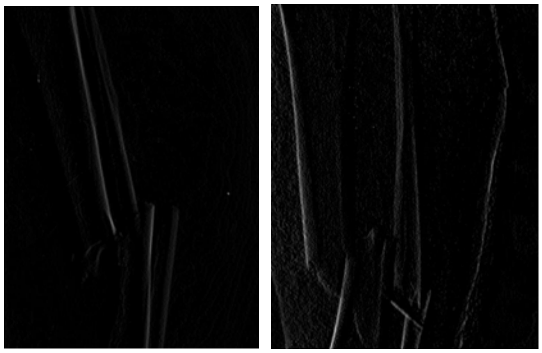
(a) (b)

Fig. 3: (a) (b) Histograms of adjusted intensities for Fig.2 (a) and (b) respectively



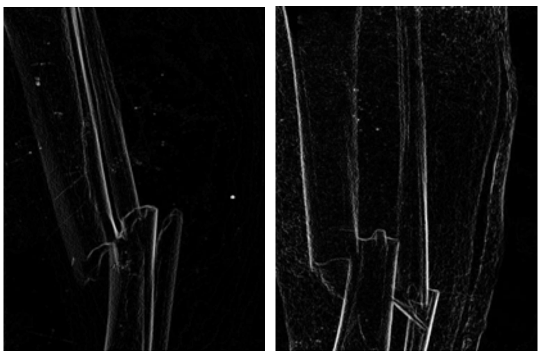
(a) (b)

Fig.4: Result images of Laplacian filter for Fig.2



(a) (b)

Fig.5: (a) and (b) are result images of Sobel



(a) (b)

Fig.6: (a) and (b) of proposed method

4. Conclusion

The paper proposed a new image enhancement method for edge detection. First, a Gaussian function is used to filter out the noises. Then the differentiated image is transformed to fuzzy domain with S-function. Power-law transformation is applied in fuzzy domain. Defuzzification is the last step of the approach. The paper has tried several methods on medical images. By the proposed method, the enhanced images have enough local enhancement for details.

Though, there are several factors influence the performance of this method, such as selection of edge-detecting operator in the pretreatment, the parameter y of S-function and the parameters of Eq.(11). In the further research will dig out the inherent law.

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