

Using Statistical Parametric Contour and Threshold Segmentation Technology Applied in X-ray Bone Images

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Abstract— *The medical image segmentation technology is quite a challenging and complicated research. Generally, an X-ray image is often giving significant information of hard tissue pathology within most assessments. Compared with medical images of Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), the advantages of X-ray imaging are inexpensive, and it is widely attempted in most of the medical examinations. The X-ray imaging has been intensively applied on clinical bone diagnostics nowadays. However, the X-ray imaging still has several drawbacks on clarifying its images when radiation intensities exposed unevenly on the examined subject. For example, on a hand X-ray image, if the image has received unequal X-ray strengths, the final image would be inexplicable to separate soft tissues. In this work, we use the technique of a statistical parametric contour with threshold X-ray image segmentation technology to overcome those drawbacks of the X-ray images. By using this approach, we can successfully separate bone from muscle tissues of hand.*

Keywords— Image processing; Image segmentation; Medical image analysis

1. INTRODUCTION

The medical image segmentation technology has many important applications in most medical service areas. It includes a lot of techniques, such as image and signal processing, statistics and basic medical science, and anatomy. Recently, most of the well-known medical images are X-ray imaging, CT, and MRI, but the X-ray image has been the most common method in providing significant data of emergency and critical care medical diagnosis. Compared with CT and MRI imaging technology, the X-ray image has its own advantage, for example the low cost and ease to achieve the images. Therefore, the X-ray imaging has been intensively applied on clinical diagnostics for years.

The assessments provided by Stolojescu *et al.* [1] and Jacob *et al.* [2] evaluated many bone image segmentation

researches, and they mentioned that there are pros and cons on every single case. The key issues for searching the most critical information, successfully processing, and segmenting the image are the goals of the research. At present the common medical image segmentation technologies includes: threshold methods, regions-based methods, edges-based methods, recognition-based methods, deformable models, wavelets-based methods, atlas-based methods, radiation active contours, and image segmentation. According to the studies of [1-2], the threshold method is the most popular method on medical image segmentation, and the second most popular approach is the radiation active contours methods.

The locations of human bones may be varieties by ages [3-5]. However, for object segmentation in an X-ray bone image, it has to locate the object in a precise region in the X-ray image to avoid some unrelated information affecting the result of segmentation. The assessments presented by Ikhsan *et al.* [6] and El Soufi [7] describe the X-ray image during pre-processing, where the premade image enhancement work can improve the segmentation performance and robustness of the subsequent image processing. When enhancing the local or global image, the CLAHE method [6-7] can enhance the image contrast of X-ray images. For the X-ray image segmentation, the most challenging problem is due to the X-ray uneven exposure strength [4,8]. Therefore, before the image segmenting, it should look for the brightness and traits of the image strength, according to the different environment, to adjust the characteristic of the images. This procedure will be helpful even when the uneven and complicated X-ray exposures on the image. In this work, we propose a high efficiency X-ray image segmenting technology, and it can enhance the clearance of X-ray image on segmenting the bone from background image. Moreover, it also can increase the level of X-ray image capturing effect.

2. BASIC TECHNIQUES OF OBJECT SEGMENTATION IN AN IMAGE

Considering global image segmentation, people usually employ the gray or color values of image pixels for image processing, and this kind of image segmentation method can be classified as the image gray level segmentation techniques. The techniques of image segmentation of gray value distribution segmentation method and histogram threshold segmentation method are belonged to the category of global image segmentation.

A. Global Thresholding Method

The global thresholding method is only applied to the whole image for gray scale pixels. It sets a threshold value which lies in the range of 0 to 255. After the threshold classification the whole gray scale image will become a binary image. The classification can be calculated as the following equation,

$$g(x,y) = \begin{cases} 1, & \text{if } f(x,y) > T \\ 0, & \text{if } f(x,y) \leq T \end{cases} \quad (1)$$

where T denotes the threshold value, g denotes the value after binarization, and f denotes the original gray scale value.

$$\text{maximize } f = \omega_1 \omega_2 (\mu_1 - \mu_2)^2 \quad (2)$$

B. Watershed Algorithm

The watershed algorithm [9] is an image segmentation method based on Topological theory. It treats each pixel value in an image as an elevation or a contour map, and it treats each local minimum in the neighborhood as a catchment basin. If we pour water into the two catchment basins with same contour map in lower latitudes, after pouring enough water the water level will rise and finally it will form a new larger basin. By setting a watershed at a merging point of the two merged catchment basins, we can decide the contour local minimum of the new formed catchment basin from the original two smaller basins. The watershed schematic diagram is shown in Fig. 1.

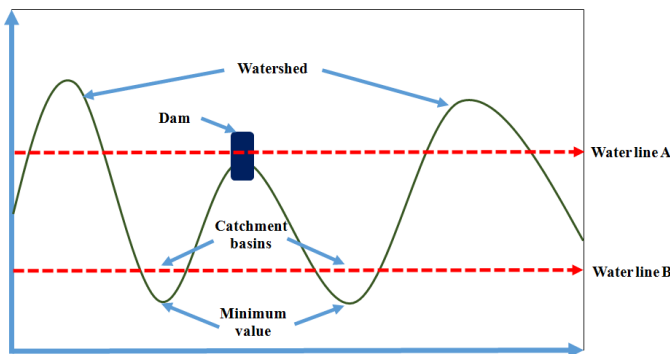


Fig. 1. Watershed schematic diagram.

C. Otsu's Method

Otsu method was proposed by Otsu [10]. It employs the gray distribution image histogram to divide the image into several clustering regions and calculates the probability gray averages and variance in each region, as described in equation (2). The greatest calculated value, *maximize f*, denotes the threshold value.

3. METHODOLOGY

A. System Flowchart

The processing flow for a bone image segmented from an X-ray image with the contour map technique is shown in Fig. 2. Firstly, it inputs an X-ray image and then selects the region of interest (ROI) for processing. Thereafter it analyzes the gray level histogram of the ROI, and then uses the contour map method to divide the image into 8 slices. The contour map approach will be described latter in this section. Finally, based on the contour map it can find the proper threshold values for bone segmentation.

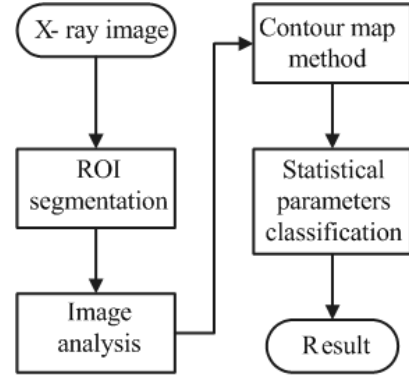


Fig. 2. Systemic flowchart.

B. Preprocessing

The original X-ray image size is 1753×1753, as shown in Fig. 3. Without loss of generality, at first we select the hand-bone images with better posture in a flat position. However, the X-ray image is in a global range, and according to the general clinical function it only needs to select the region of interest (ROI). In this research we would like to focus on discovering the complex areas of the wrist part of the hand bone. We indicate the Capitate bone as the central point of our research interests, and then extend this point outward to extract a 512×512-pixel region as shown in Fig. 4. After finishing the ROI segmentation, it converts the colorful image to the gray scale image to finish the first step of the pre-processing for bone image segmentation.

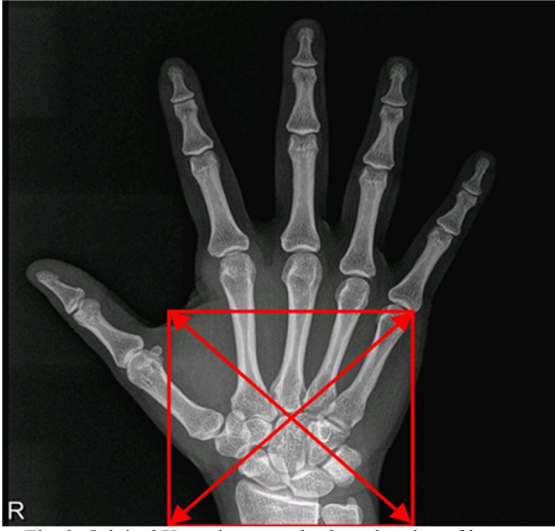


Fig. 3. Original X-ray image and selected region of interest.



Fig. 4. Original X-ray image and selected region of interest.

C. X-ray Image Analysis with Statistical Parameters

To segment an object from the image, we have to exclude the noise and segment the right object from the image. In the background subtraction approach for object segmentation, the threshold value of the object image is one of the most important issues. In order to segment a more accurate bone image from the X-ray image, we propose a new method, contour map method, to decide the threshold value of the bone image.

In an X-ray image, the brightness of the image indicates the distribution of X-ray radiation energy which the tissues and bones absorb. Therefore a proper threshold of the pixel gray scaled value in the X-ray image can assist to form a mask for bone image segmentation from the X-ray image. According to the gray scaled values of an X-ray image, the X-ray image can form a contour map as depicted in Fig. 5. Since the gray scaled value is an 8-bit number, the X-ray image is divided into 256 layers to form a contour map. The bottom layer of the contour map is called layer 0, and the layer above and

beside layer 0 is layer 1. In this manner we number the sequence of the 256 layers, and the top layer is called layer 255. For an $X \times Y$ -pixel X-ray image, if the gray scaled value of pixel (i, j) , $0 \leq i \leq X-1$ and $0 \leq j \leq Y-1$, is equal to g_{ij} , $0 \leq g_{ij} \leq 255$, then the corresponding contour map has a value in location (i, j) of layer number g_{ij} to be g_{ij} and all other layers of location (i, j) to be 0. Since the information in a layer is very restricted, it is not sufficient to identify the bone in a layer of the contour. In order to collect enough information, we have to accumulate several layers of the contour map. After testing many times, we found that 32-layer accumulating can both provide enough information for bone identification and save computation time. By this approach, the contour map can be divided into $256/32 = 8$ slices, and the schematic diagram is shown in Fig. 6. We can evaluate these 8 slices statistically to find which slices can well represent the bone image; the accumulated images of the 8 slices of a test bone image are shown in Fig. 7. Observing the 8 slices, we found the accumulation of slice 5 to slice 8 can well represent the contour of the hand bone. In this situation, the threshold value for bone image segmentation lies in between slice 4 and slice 5. In order to find the optimal threshold value, we use an X-ray histogram, whose vertical axis is the pixel numbers and the horizontal axis is the gray scaled value, for statistical evaluation. A sample wrist bone histogram is shown in Fig. 8. Under the statistical analysis, in this sample case, gray scale (layer) 128 is optimal and therefore the threshold is set to be 128. In a similar manner, the optimal threshold value can be decided for other X-ray image.

Once the threshold value is decided, we can accumulate all the layers which are greater than or equal to the threshold value to form the mask. The bone image segmentation can thus be accomplished by using background subtraction method.

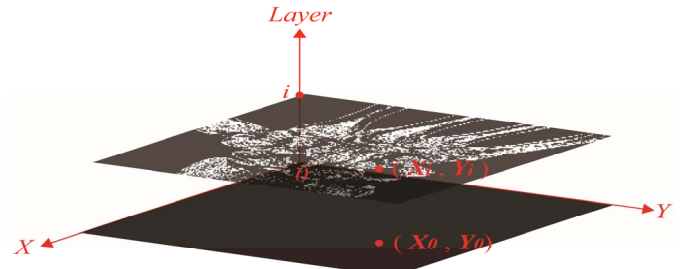


Fig. 5. Contour map

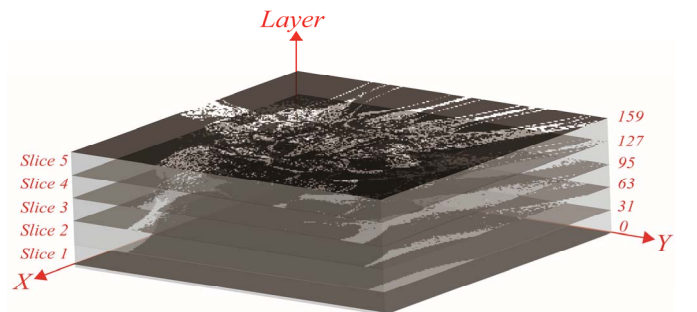


Fig. 6. Slices in the contour map.

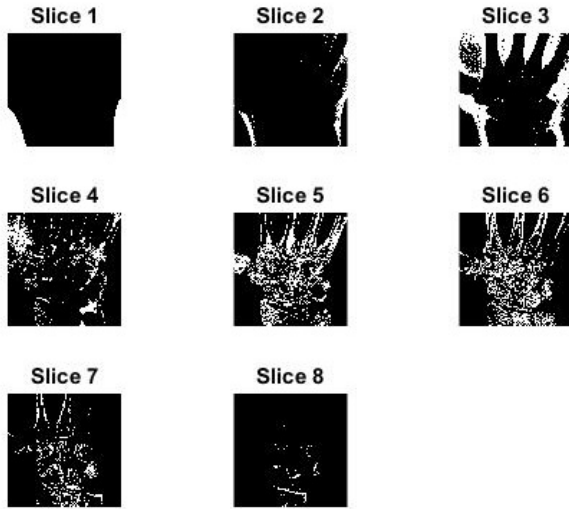


Fig. 7. The accumulated hand bone image of the 8 slices in the contour map.

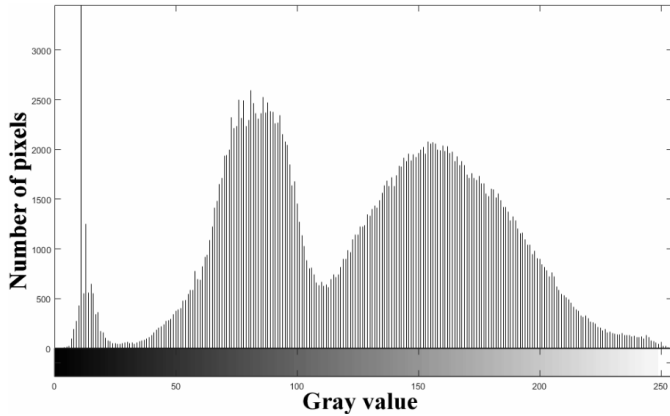


Fig. 8. Wrist bone image histogram.

4. EXPERIMENTAL RESULTS

A. Medical image sources and data set

The X-ray images of this research are provided by the department of medical imaging of Cheng Hsin General Hospital, Taiwan, with the removal of the link medical image data. All the samples are collected from 20 years old male people with their right wrist, and the resolution of the X-ray image is with 1753×1753 pixels. This research case has been approved and examined by Institutional Review Board of Cheng Hsin General Hospital (CHGH-IRB, No. (482) 104-18-2).

B. Results and comparisons

From the histogram distribution of the ROI of the original wrist image, the gray scale distribution of the bone almost concentrates in the range of 120 to 255, and therefore the threshold values can be decided. The segmentation results of the proposed method, Otsu method, and watershed method are indicated in Figs. 9, 10, and 11, respectively. From those 3

segmentation results, obviously the separation of the foreground and background of our proposed approach is much better than that of the other two approaches.



Fig. 9. X-ray image segmented result from our proposed method.



Fig. 10. X-ray image segmented result from Otsu method.

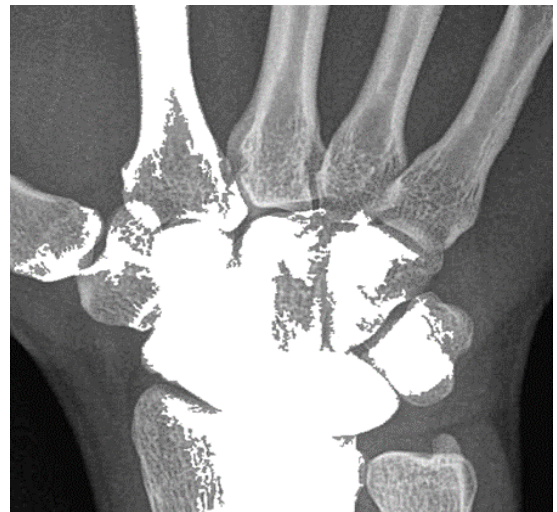


Fig. 11. X-ray image segmented result from Watershed method.

Fig. 12 shows the 3D contour map of the segmented bone image, which indicates that the bone with higher density in the X-ray image may absorb more radiation energy. Besides, we use similarity measurement for quantity evaluation. The similarity measurement can be found by the (3),

$$\|S\| = \sqrt{\sum_{i=0}^{n-1} (x_{1i} - x_{2i})^2} \quad (3)$$

where $\|S\|$ denotes the difference (similarity) between the ground truth and testing data; x_{1i} is the ground truth data, and x_{2i} is the testing data. Table 1 shows the similarities of the proposed approach, Otsu approach, and watershed approach, respectively. The smaller the similarity value, the better the performance is. From Table 1, we can find that the proposed method outperforms the other two approaches.

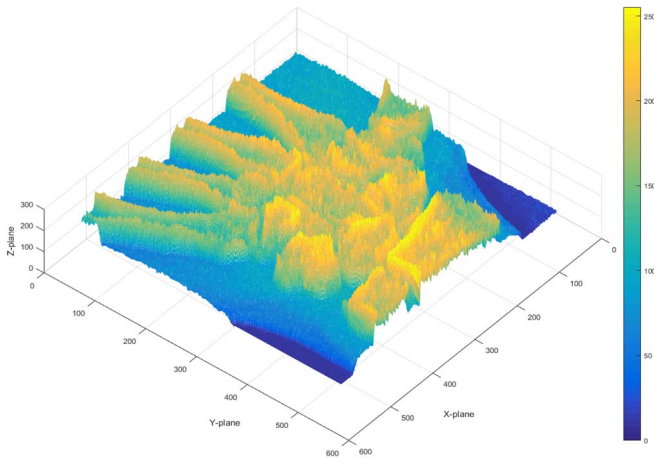


Fig. 12. Wrist bone in the contour map 3D view model.

Table 1. Similarity error comparison

Segmentation processing	Similarity (error) value
Watershed method [9]	3.6355e+04
Otsu's method [10]	1.0563e+04
This work	2.3823e+03

5. CONCLUSION

We have proposed a new medical image segmentation method for X-ray image. The proposed method employs gray scale image value contour line distribution characteristics to calculate the range of foreground images parametric of the ROI. The proposed X-ray image segmentation method outperforms other approaches. This approach can be further applied in machine learning or image identification fields to provide better image segmentation information.

ACKNOWLEDGEMENTS

This research is partially supported by Ministry of Science and Technology, Taiwan, under grant number: MOST 104-2221-E-032-043-MY2, MOST 104-2221-E-034-013-MY2, Cheng Hsin General Hospital (CHGH105-Industry-university cooperative research project-3), and National Taipei University of Nursing and Health Sciences (105D006-3). The authors would like to thank all colleagues and students who contribute to this work.

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