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Segmentation of Liver Regions in the Abdominal CT Image by Multi-threshold and Watershed Algorithm

Pil Un Kim[†], Yun-jung Lee[††], Gyu-dong Kim[†††], Youngjin Jung[††††], Jin Ho Cho[†††††], Yongmin Chang[††††††], Myoung Nam Kim[†††††††]

ABSTRACT

In this paper, we proposed a liver extracting procedure for computer aided liver diagnosis system. Extraction of liver region in an abdominal CT image is difficult due to interferences of other organs. For this reason, liver region is extracted in a region of interest (ROI). ROI is selected by the window which can measure the distribution of Hounsfield Unit (HU) value of liver region in an abdominal CT image. The distribution is measured by an existential probability of HU value of lever region in the window. If the probability of any window is over 50%, the center point of the window would be assigned to ROI. Actually, liver region is not clearly discerned from the adjacent organs like muscle, spleen, and pancreas in an abdominal CT image. Liver region is extracted by the watershed segmentation algorithm which is effective in this situation. Because it is very sensitive to the slight variance of contrast, it generally produces over segmentation regions. Therefore these regions are required to merge into the significant regions for optimal segmentation. Finally, a liver region can be selected and extracted by prior information based on anatomic information.

Keywords: Liver extraction, abdominal CT, watershed segmentation

1. INTRODUCTION

The recent development of computer system has innovative influence on medical diagnosis. Medical diagnosis can be more precise and accurate using the high tech medical imaging system. Computer Aided Diagnosis (CAD) technology provides the objective, quantitative, and synthetic information for direct diagnosis by analyzing and processing the medical information from images get by x-ray, CT, MRI, and ultrasound. The radiology image instrument is available to acquire the organ images so, it plays an important role in the internal medical diagnosis. CT image is a bitmap image consisted

※ Corresponding Author : Myoung Nam Kim, Address : (700-422) 101 Dongin-dong 2 Ga Jung-gu, Daegu, Korea, TEL : +82-53-420-5266, FAX : +82-53-420-5264, E-mail : kimmn@knu.ac.kr

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† Dept. of Medical & Biological Eng., Graduate School, Kyungpook National University
(E-mail : zeros97@hanmail.net)

†† Dept. of Medical & Biological Eng., Graduate School, Kyungpook National University
(E-mail : whitegleam@paran.com)

††† Dept. of Medical & Biological Eng., Graduate School, Kyungpook National University
(E-mail : boomkgd@hotmail.com)

†††† Dept. of Medical & Biological Eng., Graduate School, Kyungpook National University
(E-mail : micro@knu.ac.kr)

††††† Dept. of Biomedical Eng., School of Medicine, Kyungpook National University
(E-mail : jhcho@ee.knu.ac.kr)

†††††† Dept. of Radiology, School of Medicine, Kyungpook National University
(E-mail : ychang@knu.ac.kr)

††††††† Dept. of Biomedical Eng., School of Medicine, Kyungpook National University

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of the HU. It is a x-ray attenuation unit which characterizes the relative density of a substance. Most of the organs have substance densities in HU. In an abdominal CT image, there are many organs, i.e. river, pancreas, spleen, and kidney. Using HU, they are detected in a CT image[1][2].

In this paper, we proposed a liver extracting procedure for computer aided liver diagnosis system. Extraction of liver region in an abdominal CT image is difficult due to interferences of other organs. For this reason, liver region is extracted in a region of ROI. ROI is selected by the window which can measure the distribution of HU value of lever region in an abdominal CT image. The distribution is measured by an existential probability of HU value of lever region in the window. If the probability of any window is over 50%, the center point of the window would be assigned to ROI. Actually, liver region is not clearly discerned from the adjacent organs like muscle, spleen, and pancreas in an abdominal CT image. Liver region is extracted by the watershed segmentation algorithm which is effective in this situation. Because it is very sensitive to the slight variance of contrast, it generally produces over segmentation regions. Therefore these regions are required to merge into the significant regions for optimal segmentation. Finally, a liver region can be selected and extracted by prior information based on anatomic information.

2. PROPOSED PROCEDURE

The proposed procedure consists of 2 strategies. Fig. 1 shows a flow chart of this procedure.

In an abdominal CT image, many organs and unnecessary regions, i.e. non body, air and patient's bed, are obstacles of the liver extraction. First, to reduce the extraction area, ROI is selected by the threshold and morphological algorithm. Next, in ROI, the liver is extracted by the watershed segmentation algorithm and region merging.

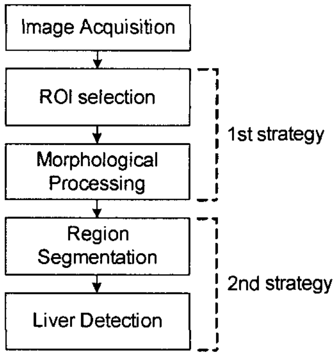


Fig. 1. A flow chart of the extraction procedure.

2.1 ROI selection by a conditional multi-threshold

Fig. 2 shows an abdominal CT image. As previously stated, it consists of many regions. These regions are classified into 3 classes as air, tissue, and bone. HU value of each class is similar. Air class has relatively low value and bone class has high value due to a substance density.

Liver belongs to the tissue class. Therefore air and bone class are unnecessary in extraction. To avoid these classes, we employed ROI based on HU. Selection of ROI consists of 2 thresholds and morphological algorithm[3].

First, tissue class is extracted by multi-threshold. In traditional threshold based on a pixel, many pixels associated in important information are lost due to noise as Salt & Paper noise. For this reason, we proposed the conditional threshold based on feature using window. Let $W(x,y)$ be a set of S×S window at center point (x,y) and $p_{W(x,y)}$ be an existent probability in $W(x, y)$. $p_{W(x,y)}$ is defined as Eq (1).

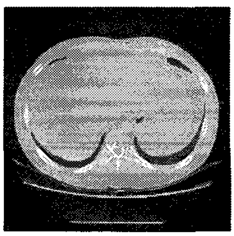


Fig. 2. An abdominal CT image.

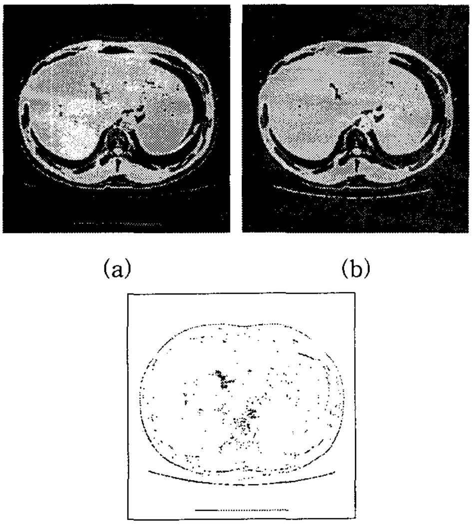
$$p_{W(x,y)} = \frac{n}{N} \quad (1)$$

where N is the number of pixels and n is the number of pixels in the range of liver HU class in a window $W(x,y)$. A thresholded image $g(x,y)$ is defined as

$$g(x,y) = \begin{cases} I(x,y) & \text{if } p_{W(x,y)} \geq C \\ 0 & \text{if } p_{W(x,y)} < C \end{cases} \quad (2)$$

where $I(x,y)$ is a original image and C is a constant. If p was not satisfied with experimental criteria C, that point would be excluded in search range. Fig. 3 shows the results of threshold and the proposed threshold.

Second, to acquire the sensitive variation image, the result image is reconstructed by HU adjustment. In other words, intensity range of the result image is expanded into all HU range. Fig. 4 shows the reconstructed image converted to gray-scale. As shown in Fig 4, liver is relatively brighter than the others. Fig. 5 shows the histogram of Fig. 4. A shape of the histogram is bimodal.


(a) (b)

(c)

Fig. 3. The result of threshold, (a) traditional threshold (b) the proposed threshold. (window size : 5x5, HU range : 1000~1200) (c) different image between (a) and (b).

Fig. 4. The reconstructed image.

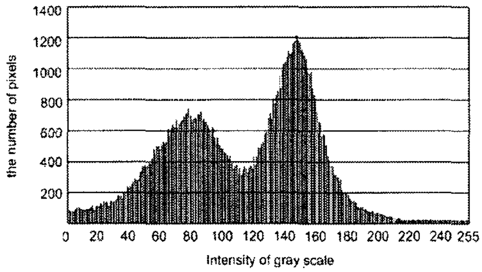


Fig. 5. The histogram of (Fig 4).

Generally, most information of liver is in the right part. So we employed the conditional threshold again. In 1st threshold, we used the public values in HU domain which are widely used. Contrary to the 1st threshold, in the 2nd threshold, the optimal values in gray scale are used. These values are measured with Otsu's method. This method is "unsupervised" in that there is no knowledge about the image before processing[4][5]. The method separates pixels into two classes C_0 and C_1 (objects and background or vice versa) by a threshold at level k. C_0 denotes pixels with levels {0, 1, 2 ,⋯, k}, and C_1 denotes pixels with levels {k+1, k+2, ⋯, T}, T being the number of gray levels. Let σ_b^2 and σ_d^2 be the between-class variance and the total variance of gray scale, respectively.

$$\sigma_b^2 = \omega_0\omega_1(\mu_1 - \mu_0)^2 \quad (3)$$

$$\sigma_d^2 = \sum_{i=0}^{T}(i-\mu_T)^2 p_i \quad (4)$$

where p_i is a probability of distribution defined as Eq (5).

$$p_i = \frac{n_i}{N} \tag{5}$$

ω_0 is probabilities of class occurrence and ω_1 probabilities of the class mean levels.

$$\omega_0 = \sum_{i=0}^{k} p_i \tag{6}$$

$$\omega_1 = 1 - \omega_0 \tag{7}$$

μ_0 is the zero-order cumulative moments of the histogram up to the kth level. μ_1 is the first-order cumulative moments of the histogram up to the kth level, μ_t is the total mean level of the original image.

$$\mu_0 = \frac{\sum_{i=0}^{k} ip_i}{\omega_0} \tag{8}$$

$$\mu_1 = \frac{\sum_{i=k+1}^{T} ip_i}{\omega_1} \tag{9}$$

$$\mu_t = \sum_{i=0}^{T} ip_i \tag{10}$$

The optimal threshold value of an image depends on the maximum value of σ_b^2. This method is based on a discriminant criterion η, which is the σ_b^2 to σ_d^2 ratio in gray level.

$$\eta = \frac{\sigma_b^2}{\sigma_d^2} \tag{11}$$

This approach is better than other popular threshold methods. In particular, it performs well in situations which have little contrast between background and object. It can separate the region even the case which a histogram is modeled by two overlapping Gaussian curves with little separation between two modes. Fig. 6 shows the result of second threshold in the reconstructed image.

As shown in Fig. 6, many regions, except liver, are included in the result image. To avoid extract those regions, we employed a morphological algorithm as opening and dilation. The process sequence consists of two openings and two dilations[3]. From the result image, ROI is decided. Fig. 7 shows a selected ROI - not latticed area.

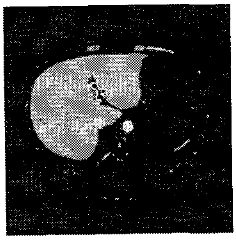


Fig. 6. The result of second threshold.

Fig. 7. A selected ROI.

2.2 Watershed Segmentation

The watershed segmentation often produces more stable segmentation results, including continuous segmentation boundaries. This approach also provides a simple framework for incorporating knowledge-based constraints in the segmentation process[3][6]. In such a topographic interpretation, three types of points are considered.

1) Points belonging to a regional minimum.

2) Points at which a drop of water, if placed at the location of any of those points, would fall with certainty to a single minimum.

3) Points at which water would be equally likely to fall to more than one such minimum.

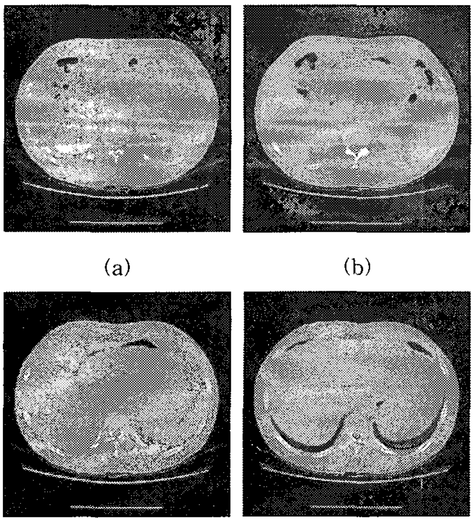
For a particular regional minimum, the set of points satisfying condition ① is called the catchment basin or watershed of that minimum. The points satisfying condition ② form crest lines on the topographic surface and are termed divide lines or watershed lines. This segmentation generally results of over-segmentation. Therefore, the over-segmentation regions need to be optimized by using correlation of every region pairs[6].

3. RESULTS

Fig. 8 shows the abdominal CT images acquired a 512×512, HU image from 16th channel multi-slice CT of GE. As shown in Fig. 8, the boundary, where liver and serratus anterior muscle adjoin, is difficult to discern with the naked eye due to the similar HU value.

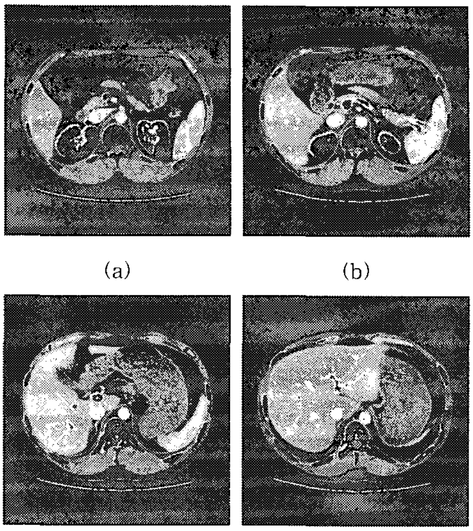
The range of the 1st threshold is between 1000 and 1200 HU. For the conditional threshold, window size set 5×5 and the existent probability set 50%. After thresholding, the result images of the 1st threshold were converted to gray scale image. Fig. 9 shows the converted images of Fig. 8.

As shown Fig. 9, liver regions can be clearly discriminated from the CT image. It is the reason that the intensity difference between liver and serratus anterior muscle was incremented approximately 10 times by converting image from HU scale (range : 0~2000) to gray scale (range : 0~255), and much adjacent organs were almost eliminated by 2 times conditional thresholding.



(a) (b) (c) (d)

Fig. 8. The abdominal CT images for processing.



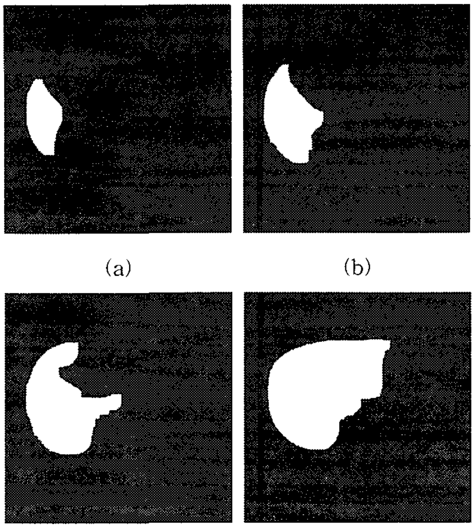
(a) (b) (c) (d)

Fig. 9. The converted CT images.

The each ranges of the 2nd threshold are (d) : 100~181, (a) : 110~200, (b) : 115~200, and (c) : 110~200 by Otsu's method. ROI is selected base on the results of the 2nd threshold after a morphological algorithm by 9×9 structuring element. Fig. 10 shows the ROI of Fig 8., respectively.

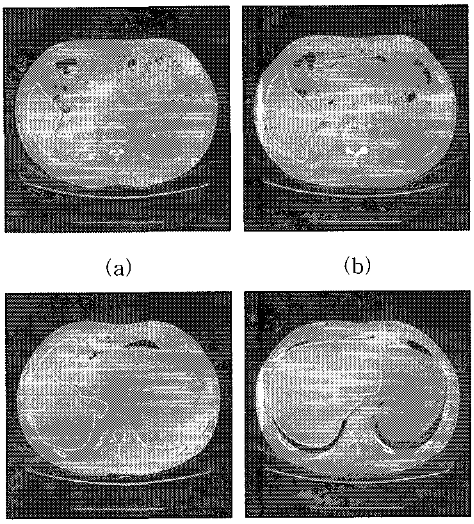
An abdominal CT image is masked with ROI. And then, the masked images were segmented by watershed algorithm. Because it is very sensitive to the slight variance of contrast, it generally produces over segmentation regions. To overcome and reduce the over-segmentation, regions were merged by image intensity. Sometimes extracted liver has a rough boundary. For smooth boundary of liver, we employed the morphological algorithm by the spherical structuring element called "rolling ball" [3]. Fig. 11 shows the final results of the liver extraction by proposed method.

The results of the liver extraction were validated by comparing with the results of manual



(a) (b) (c) (d)

Fig. 10. The result of ROI selection.



(a) (b) (c) (d)

Fig. 11. The final results of the liver extraction.

extraction. In addition, the results of active contour model which is used widely in liver segmentation, were validated. Validation methods are the size ratio of objects, the correlativity and the square root average error E_s between the reference contour and the comparison contour[7].

The correlation coefficient (ρ) is

$$\rho = \frac{1}{N}\sum_{i=0}^{N}\frac{(R(i)-\overline{R})(C(i)-\overline{C})}{\sigma_R \sigma_C} \tag{12}$$

where $R(i)$ indicates the distance between the center of gravity and the control points in the reference contour, $\overline{R}$ and σ_R indicate the average and standard deviation of $R(i)$, $C(i)$ indicates the distance between the center of gravity and the control points in the comparison contour, $\overline{C}$ and σ_C indicate the average and standard deviation of $C(i)$.

$$E_s = \sqrt{\frac{1}{N}\left\{\sum_{i=0}^{N-1}(r(i)-c(i))\right\}^2} \tag{13}$$

E_s denotes the distance error value between the control points $r(i)$ on the reference contour and the control points $c(i)$ on the comparison contour, and N represents the number of control points on the comparison contour.

Table 1 shows that the results are compared the manual segmentation with the proposed extraction method and the active contour model. Table 1 represents that the result of the proposed extraction method is almost similar to the manual result. Therefore, in extracting liver from the abdomen CT image, the proposed extraction method is objectively robust and efficient.

Table 1. The results are compared the manual segmentation with the proposed extraction method and the active contour model

	Proposed Method			Active Contour		
	C_{size}	ρ	E_{rms}	C_{size}	ρ	E_{rms}
Fig. 1	1.000	1.012	0.988	0.992	1.024	1.813
Fig. 2	1.056	1.037	1.645	1.073	1.025	2.970
Fig. 3	1.040	0.890	1.392	0.947	0.876	5.775
Fig. 4	1.010	0.960	2.215	0.930	0.922	4.596

4. CONCLUSIONS

CAD can be defined as a diagnosis that is made by a doctor who uses the output from a computerized analysis of medical images as a 'second opinion' in detecting lesions and in making diagnostic decisions[8]. For CAD of liver, we proposed the extraction procedure of the liver in an abdominal CT image. To reduce the influence of adjacent organs, ROI is employed by the conditional threshold. As shown in Fig. 7, ROI includes the liver efficiently without other regions. As shown in Fig. 11., we had the final results of the liver extraction by the proposed procedure. This procedure will be useful in CAD of liver.

5. REFERENCES

[1] C. E-Liang, C. Pau-Choo, C. Ching-Liang, T. Hong-Ming, and C. Chein-I, "An Automatic Diagnostic System for CT Liver Image Classification," *IEEE Trans. on Biomedical Engineering*, Vol. 45, Issue 6, pp. 783-794, 1998.

[2] A. Ahmadian, A. Mostafa, M.D. Abolhassani, and Y. Salimpour, "A Texture Classification Method for Diffused Liver Diseases Using Gabor Wavelets," *IEEE-EMBS 27th Annual International Conference-Engineering in Medicine and Biology Society*, pp. 1567 - 1570, 2005.

[3] R.C. Gonzalez and R.E. Woods, *Digital Image Processing*, Prentice Hall, New Jersey, 2001.

[4] N. Otsu, "A Threshold Selection Method from Grey Level Histogram," *IEEE Trans. on Syst. Man Cybernet.*, SMC-8, pp. 62-66, 1978.

[5] http://www.gisdevelopment.net/aars/acrs/1999/ps5/ps5069pf.htm

[6] K. Haris., S.N. Efstratiadis, N. Maglaveras, and A.K. Katsaggelos. "Hybrid Image Segmentation Using Watersheds and Fast Region Merging," *IEEE Trans. on Image Processing*. Vol. 7. No. 12. pp. 1684-1699, 1998.

[7] M.N. Kim, *Auto Detection of Left Ventricular Endocardial Boundary on B-mode Short Axis Echocardiography*, PhD Thesis, Kyungpook National University, Daegu, Korea, Dec. 1994.

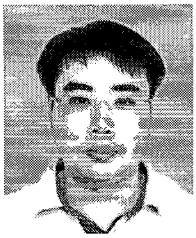
[8] http://www.wma.net/e/publications/pdf/2000/giger.pdf

Pil Un Kim

He received the B.S. degree in Computer Engineering from Kyungwoon University and the M.S. degree in Medical and Biological engineering from Kyungpook National University, Korea in 2001 and 2003, respectively. At present, he is in a Ph.D. degree course of the same university of his M.D. degree course. His research interests include the object detection and extraction in medical digital image, biomedical signal analysis using processor, and computer aided diagnosis.

Yun-jung Lee

She received the B.S. degree in Electrical engineering from Kyungpook National University and the M.S. degree in Medical and Biological engineering from Kyungpook National University, Korea in 2003 and 2005, respectively. At present, she is in a Ph.D. degree course of the same university of her M.D. degree course. Her research interests include hearing protection.



Gyu-dong Kim

He received the B.S. degree in electronics from Kyungpook National University, Korea in 2001. At present, he is in a M.S. degree course in Medical and Biological engineering of the same university of his B.S. degree course, Korea. His research interests include active noise cancellation for hearing protection.

Youngjin Jung

He received the B.S. degree in electronics from Kumoh National University, Korea in 2005. At present, he is in a M.S. degree course in Medical and Biological engineering of Kyungpook National University. His research interests include voice tactile recognizer and bio-signal processing with FPGA.

Jin Ho Cho

He received a B.S. degree in electrical engineering, in 1977, M.S. and Ph.D. in Electronics from Kyungpook National University, Daegu, Korea, in 1979 and 1988, respectively. He is currently chief professor of Medical and Biological Engineering at Kyungpook National University, a professor in the School of Electrical Engineering & Computer Science and a Director of the Advanced Research Center of Recovery of Human Sensibility. His research interests include the biomedical signal processing, sensor applications, and biomedical instrumentations.

Yongmin Chang

He received the B.S., M.S. degree in physics from Korea University in 1985, 1987 and Ph.D. in physics from University of Notre Dame in 1994. He is currently a Professor at Department of Diagnostic Radiology, Kyungpook National University, Daegu, Korea. His research interests include development of physiological imaging technology and contrast media. He has been especially active in neuro-functional imaging, molecular imaging.

Myoung Nam Kim

He received the BS, M.S. and Ph.D. degree in electronics from Kyungpook National University in 1987, 1989 and 1994 respectively. He is currently a chief professor of Department of Biomedical Engineering, School of Medicine, Kyungpook National University, Daegu, Korea. His research interests include medical image processing, biomedical signal analysis, biological modeling, and biomedical electronics. He has been especially active in medical signal analysis and quantitative analysis for medical image processing.