Automatic Hepatic Tumor Segmentation Using Statistical Optimal Threshold

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Abstract. This paper proposes an automatic hepatic tumor segmentation method of a computed tomography (CT) image using statistical optimal threshold. The liver structure is first segmented using histogram transformation, multi-modal threshold, maximum a posteriori decision, and binary morphological filtering. Hepatic vessels are removed from the liver because hepatic vessels are not related to tumor segmentation. Statistical optimal threshold is calculated by a transformed mixture probability density and minimum total probability error. Then a hepatic tumor is segmented using the optimal threshold value. In order to test the proposed method, 262 slices from 10 patients were selected. Experimental results show that the proposed method is very useful for diagnosis of the normal and abnormal liver.

1 Introduction

Liver cancer, which is the fifth most common cancer, is more serious in areas of western and central Africa and eastern and southeastern Asia [1]. The average incidence of liver cancer in these areas is 20 per 100,000, and liver cancer is the third highest death cause from cancer [1]. In Korea, the incidence of liver cancer is quite high at 19% for males and 7% for females [2]. In order to improve the curability of liver cancer, early detection is critical. Liver cancer, like other cancers, manifests itself with abnormal cells, conglomerated growth, and tumor formation. If the hepatic tumor is detected early, treatment and curing of a patient may be easy, and human life can be prolonged.

Liver segmentation using CT images has been vigorously performed because CT is a very conventional and non-invasive technique. Bae et al. [3] used priori information about liver morphology and image processing techniques. Gao et al. [4] developed automatic liver segmentation using a global histogram, morphologic operations, and the parametrically deformable contour model. Park et al. [5] built a probabilistic atlas of the brain and extended abdominal segmentation including the liver, kidneys, and

spinal cord. Tsai [6] proposed an alternative segmentation method using an artificial neural network to classify each pixel into three categories. Also, Husain et al. [7] used neural networks for feature-based recognition of liver region. Pan et al. [8] presented a level set technique for the automatic liver segmentation by proposing a novel speed function. Seo et al. [9] proposed fully automatic liver segmentation based on the spine. However, most previous research has been concentrated on only liver segmentation and volume construction. In this paper, a simple automatic hepatic tumor segmentation method using statistical optimal threshold (SOT) is proposed. An automatic hepatic tumor segmentation method is presented in the following section. Experiments and analysis of results are described in the next section. Finally, the conclusion will be drawn in the last section.

2 Hepatic Tumor Segmentation

In this section, an automatic hepatic tumor segmentation method is presented. A liver structure is first segmented and then vessels in the liver are removed. Statistical optimal threshold (SOT) is found by transformed mixture probability density (MPD) and minimum total probability error (MTPE). A region of interest (ROI) of a hepatic tumor is segmented and estimated.

2.1 Liver Segmentation

The first important work to segment a hepatic tumor is to segment a liver boundary. The ROI of the liver is extracted using histogram transformation [10], multi-modal threshold [11], and maximum a posteriori decision [12]. In order to eliminate other abdominal organs such as the heart and right kidney, binary morphological (BM) filtering is performed by dilation, erosion, closing, and filling [13, 14, 15]. Fig. 1(a) shows an abnormal CT image with a tumor. Fig. 1(b) shows the ROI of the liver. Also, Fig. 1(c) shows the segmented liver image using BM filtering.

Fig. 1. Liver segmentation: (a) CT image, (b) ROI of the liver, (c) liver image segmented by BM filtering

2.2 Vessel Elimination

The liver image with a tumor obtained by BM filtering consists of the pure liver, tumor, and vessels. As vessels of the liver have no influence on tumor segmentation, vessels are eliminated from the liver. Histogram transformation for better histogram

threshold is first performed to reduce histogram noises. Then the left and right valleys, called object ranges, are calculated using a piecewise linear interpolation method [11]. The vessel range is located in the rightmost side of the histogram because pixel values are higher than other objects. Therefore, the vessel range is decided easily. Fig. 2(a) shows the liver image after vessel elimination.

2.3 Statistical Optimal Threshold

After eliminating vessels, the histogram has only two peaks, and the liver image consists of the pure liver and tumor region. Therefore, the gray-level value thresholding two regions is easily calculated by using multi-modal threshold method. However, we do not know this threshold value is optimal. In order to find the SOT value, $T_{optimal}$, the histogram of the liver is transformed. The histogram with two peaks as the mixture probability density (MPD) is expressed as

$$p(x) = \frac{P_{PL}}{\sqrt{2\pi}\sigma_{PL}} \exp\left(-\frac{(x - \mu_{PL})^2}{2\sigma_{PL}^2}\right) + \frac{P_T}{\sqrt{2\pi}\sigma_T} \exp\left(-\frac{(x - \mu_T)^2}{2\sigma_T^2}\right) \quad (1)$$

where P_{PL} , μ_{PL} , and σ_{PL} are pixel occurrence, mean, variance of the pure liver and P_T , μ_T , and σ_T are pixel occurrence, mean, and variance of the tumor. Using four parameters such as μ_{PL} , σ_{PL} , μ_T , and σ_T , the transformed MPD [16] is created

- Generate numbers, $\Phi(z_{PL})$ and $\Phi(z_T)$, from a uniform distribution, $U \sim [0, 1]$.
- Find the inverse, z_{PL} and z_T , from the standard normal distribution function defined as

$$\Phi(z_{PL}) = \int_{-\infty}^{z_{PL}} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt \quad (2)$$

$$\Phi(z_T) = \int_{-\infty}^{z_T} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt. \quad (3)$$

- Converse the standard normal data to the Gaussian observations defined as

$$\hat{x}_{PL} = \mu_{PL} + z_{PL} \sigma_{PL} \quad (4)$$

$$\hat{x}_T = \mu_T + z_T \sigma_T. \quad (5)$$

- The transformed MPD is created defined as

$$p(\hat{x}) = \frac{P_{PL}}{\sqrt{2\pi}\sigma_{PL}} \exp\left(-\frac{(\hat{x} - \mu_{PL})^2}{2\sigma_{PL}^2}\right) + \frac{P_T}{\sqrt{2\pi}\sigma_T} \exp\left(-\frac{(\hat{x} - \mu_T)^2}{2\sigma_T^2}\right) \quad (6)$$

The $T_{optimal}$ is found by calculating the minimum total probability error. The total probability error (TPE) $E(T)$ from $p(\hat{x})$ is calculated as [12]

$$E(T) = P_{PL} \int_{-\infty}^T p(\hat{x}_{PL}) d\hat{x} + P_T \int_T^{\infty} p(\hat{x}_T) d\hat{x} \quad (7)$$

where T is the threshold value. Then the $T_{optimal}$ is selected by the threshold value calculating the minimum TPE. Fig. 2(b) shows the segmented tumor using the $T_{optimal}$.

Fig. 2. Tumor segmentation: (a) liver image after hepatic vessel elimination, (b) segmented tumor using the optimal threshold value

3 Experiments and Analysis

CT images to be used in this research were provided by Chonnam National University Hospital in Kwangju, Korea. The CT scans were obtained by using a LightSpeed Qx/i, which was produced by GE Medical Systems. Scanning was performed with intravenous contrast enhancement. Also, the scanning parameters used a tube current of 230 mAs and 120 kVp, a 30 cm field of view, 5 mm collimation and a table speed of 15 mm/sec (pitch factor, 1:3).

Ten patients were selected for testing the new proposed method to segregate a hepatic tumor. Five people had normal livers and the other five people had abnormal livers. 262 total slices from ten patients were used. One radiologist took part in this research in order to evaluate liver status. Fig. 3 shows examples of segmented tumors. Table 1 shows the data of evaluated slices followed by slice numbers, true negative (TN), false positive (FP), false negative (FN), and true positive (TP) [17].

Fig. 3. Examples of tumor segmentation

Table 1. Data of evaluated slices

PATIENTS	SLICES TAKEN	FREQUENCY OF TN	FREQUENCY OF FP	FREQUENCY OF FN	FREQUENCY OF TP
PAT. 01	23	21	2	0	0
PAT. 02	31	30	1	0	0
PAT. 03	24	21	3	0	0
PAT. 04	26	25	1	0	0
PAT. 05	28	28	0	0	0
PAT. 06	34	30	2	1	1
PAT. 07	23	21	1	0	1
PAT. 08	23	19	3	0	1
PAT. 09	26	16	0	3	7
PAT. 10	24	17	4	2	1
TOTAL NUM.	262	228	17	6	11

As the evaluation measure, sensitivity, specificity, and accuracy were calculated. As sensitivity represents the fraction of patients with disease who test positive, sensitivity is defined as

$$Sensitivity = \frac{TP}{TP + FN} . \quad (8)$$

As specificity represents the fraction of patients without disease who test negative, specificity is defined as

$$Specificity = \frac{TN}{TN + FP} . \quad (9)$$

Also, accuracy is defined as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} . \quad (10)$$

In this research, we had 0.6471 of sensitivity, 0.9306 of specificity, and 0.9122 of accuracy. These results show the proposed method is very useful for diagnosis of the normal liver. Values of FP and FN are high for tumors located in the left portal branch and tumors with a diameter less than 2 cm.

4 Conclusions

In this paper, an automatic hepatic tumor segmentation method using statistical optimal threshold was proposed. The liver structure was first segmented in order to remove other abdominal organs. Hepatic vessels were removed from the liver because

hepatic vessels were not related to tumor segmentation. Then statistical optimal threshold was calculated by a transformed mixture probability density and minimum total probability error. Finally, a hepatic tumor was segmented using the optimal threshold value. In order to evaluate the proposed method, 262 slices from 10 patients were selected. From the evaluation results, we had 0.6471 of sensitivity, 0.9306 of specificity, and 0.9122 of accuracy. These results show that the proposed method is very useful for diagnosis of normal and abnormal livers. In the future, algorithms for reducing false positives of the left portal branch will be developed.

References

1. Parkin, D. M.: Global cancer statistics in the year 2000. *Lancet Oncology*, Vol. 2. (2001) 533-54
2. Lee H.: Liver cancer. The Korean Society of Gastroenterology, Seoul Korea (2001)
3. Bae, K. T., Giger, M. L., Chen, C. T., Kahn, Jr. C. E.: Automatic segmentation of liver structure in CT images. *Med. Phys.*, Vol. 20. (1993) 71-78
4. Gao, L., Heath, D. G., Kuszyk, B. S., Fishman, E. K.: Automatic liver segmentation technique for three-dimensional visualization of CT data. *Radiology*, Vol. 201. (1996) 359-364
5. Park, H., Bland, P. H., Meyer, C. R.: Construction of an abdominal probabilistic atlas and its application in segmentation. *IEEE Trans. Med. Imag.*, Vol. 22. No. 4. (2003) 483-492
6. Tsai, D.: Automatic segmentation of liver structure in CT images using a neural network. *IEICE Trans. Fundamentals*, Vol. E77-A. No. 11. (1994) 1892-1895
7. Husain, S. A., Shigeru, E.: Use of neural networks for feature based recognition of liver region on CT images. *Neural Networks for Sig Proc.-Proceedings of the IEEE Work.*, Vol.2. (2000) 831-840
8. Pan, S., Dawant, B. M.: Automatic 3D segmentation of the liver from abdominal CT images: a level-set approach. *Proceedings of SPIE*, vol. 4322. (2001) 128-138
9. Seo, K., Ludeman, L. C., Park S., Park, J.: Efficient liver segmentation based on the spine. *LNCS*, Vol. 3261. (2004) 400-409
10. Orfanidis, S. J.: Introduction to signal processing. Prentice Hall, Upper Saddle River NJ (1996)
11. Schilling, R. J., Harris, S. L.: Applied numerical methods for engineers. Brooks/Cole Publishing Com., Pacific Grove CA (2000)
12. Ludeman, L. C.: Random processes: filtering, estimation, and detection. Wiley & Sons Inc., Hoboken NJ (2003)
13. Gonzalez, R. C., Woods, R. E.: Digital image processing. Prentice Hall, Upper Saddle River NJ (2002)
14. Shapiro, L. G., Stockman, G. C.: Computer vision. Prentice-Hall, Upper Saddle River NJ (2001)
15. Parker, J.R.: Algorithms for image processing and computer vision. Wiley Computer Publishing, New York (1997)
16. Hines, W. W., Montgomery, D. C., . Goldsman, D. M, Borror, C.M.: Probability and statistics in engineering. Wiley, Hoboken NJ (2003)
17. Rangayyan R.M.: Biomedical signal analysis. Wiley, New York NY (2002)