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Investigating Metastasis Based on CT-Scan Tumor Edge Detection

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Abstract

The liver is necessary for survival and is also prone to many diseases. The CT examinations can be used to plan and properly administer radiation treatments for tumors and to guide biopsies and other minimally invasive procedure. Manual segmentation and classification of CT image is a tedious task and time consuming process which is impractical for large amount of data. Fully automatic and unsupervised methods eliminate the need for manual interaction. In this paper, we propose a histogram based method to detect metastasis liver abnormality in CT images automatically. This proposed method is composed of three steps. In the first step, all kind of noises are removed such as speckles using image filtering. The overlap between different peaks is an strong evidence of noisy image. In the second step, metastasis tumor candidates are detected using histogram based analysis and K-mean based analysis. Applying histogram based analysis algorithm leads to remove the overlap between liver and the tumor. Suspected area was recognized successfully as the outcome of histogram based analysis. Tumor Pattern shows gradual change from dark to light. The darker tune means worst damage as well as older than the lighter tune. The dark tune indicates severity and old. The light tune indicates new development of the tumor. Quantitative evaluation was done using ANOVA single factor test analysis to test whether there is any significant relation between the classes. Since $P < 0.05$, there is insignificant relation between all the classes and we reject the null hypothesis. Further, validation between manual and automated segmentation was made and found that the error between manual segmentation and automated segmentation is smaller than 1% which shows an evidence of success. In the final step, the performance capability of K-means versus HBAA was made. The error percentage in (HBAA) is (3.9 %), while in (K-mean classifier) the 35.6 %. The estimated area by (K-mean classifier) was exaggerated more than one third. The estimated area by (HBAA) was 96 % of the calculated area by the radiologist. The result is a proof of the superiority of (HBAA) over (K-mean classifier).

Keywords: Computed Technology, Liver Tumor, K-Means, HBAA

INTRODUCTION

Liver cancer is one of the most common cancers worldwide and is a type of cancer which is one the rise. It is rated as the fifth most common cancer disease endangering human life among men and ninth among women. More than 80% of these cases are affected by Hepato Cellular Carcinoma (HCC) that originates from Hepatocytes which are the predominant cells in the liver. Incidence and mortality rates are more than twice in men as compared to women. Early diagnosis of liver tumours can promote early treatment. In recent years, as medical imaging technology has developed profoundly and rapidly, digital imaging, especially Computed Tomography (CT) has been widely applied in the liver tumour diagnosis. However, diagnosis is a laborious and repetitive task, which requires the interpretation of a large volume of abdominal CT images. Consequently, such a procedure is very expensive and error prone as it requires several hours of a specialist's time. Furthermore, even a highly trained specialist could miss some important clues. In order to introduce a quantitative and objective analysis, it is possible to develop a computer-aided diagnostic tool, which automatically analyses liver tumours.

The primary site of the cancer impacts the appearance of the liver metastases. The appearance patterns indeed vary functions of the histological type of the lesion. The liver metastases keep several features from the primary cancer, which induce various appearance patterns. However, these appearance patterns are not sufficient to define the histological type of one metastasis.

DATA PRODUCTS AND INSTRUMENTS

A. Data Products

Table I. Characteristics of the CT-scan Image Data of Liver Tumor (Metastasis)

CT Image	In015: Patient-4
Date of Acquisition	14/11/2015
Resolution (in mm)	W=1.2: L =1.675
Resolution (in Pixels)	1008x832
DFOV with STND/ SS50	33.5 cm
Type of Disease	Metastasis

The Table 1 provides the specification of CT-scan image data being utilized in this study. These medical data were procured from

B. Instruments

B.1 Features of Computing Machine

- Processor: Intel ®, Core (TM) i3, CPU 550 @3.2 GHz, RAM: 2 GB
- Operating System (32-bit): Microsoft Windows 7, NVIDIA GeForce 8400 GS

B.2 CT-Scan Features

- Autonomous accuracy to 10 m (<33 ft)
- 3-5 m (from 10 to 16 ft) accuracy subsequently differential correction
- Velocity of 0.1m (0.328ft) per second and update rate of 1 per second, continuous

METHODOLOGY

A. Filtering

Figure 1 shows the raw CT scan image of a patient-2 in Metastasis. The length of the image is 1008 columns and the width is 832 rows. It was taken in 14th Nov 2015

Figure 1. Raw image In015: Equilibrium Phase

Table II. Raw CT-Scan Image Information of Patient-4 in Metastasis

	No. of Columns	No. of Rows	Width	Length
In Pixels	1008	832		
In mm			123	76

DFOV = 33.5 cm, STND / SS50

Resolution of the image:

W = 1.2 mm L = 1.675

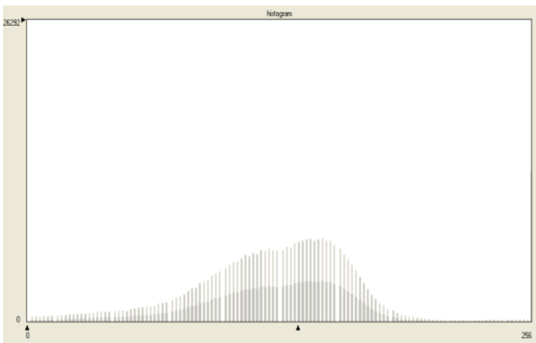

Figure 2. Histogram of the Raw In015

Figure 2 indicates different objects of the abdomen including liver. Each peak represent different object in patient abdomen. It is clear that all peaks are overlapping, makes it difficult for analysis before separate between each other.

Image filtering is an essential process to remove all kind of noise suck as speckles. The overlap between different peaks is an strong evidence of noisy image.

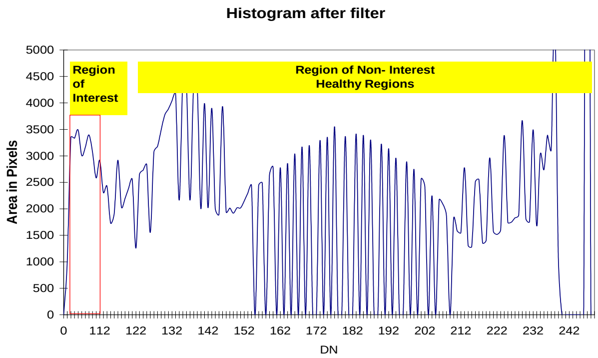

Figure 3. Histogram of the Filtered Image In015

Figure 3 indicates 3 regions. The liver in the middle and the extreme right is the blood vessels and the extreme left is liver tumor. Based on histogram analysis extracting the tumor is possible.

B. Automatic Detection of Tumor Candidates

B.1 Histogram Based Analysis

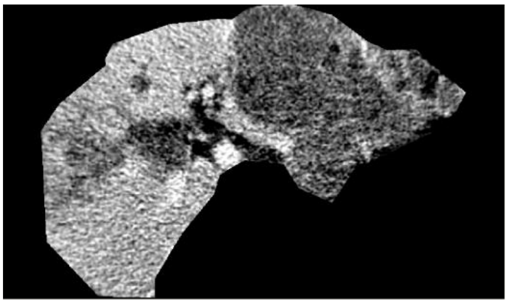

Figure 4. Liver

Liver was extracted and the rest of the abdomen was masked as shown in Figure 4.

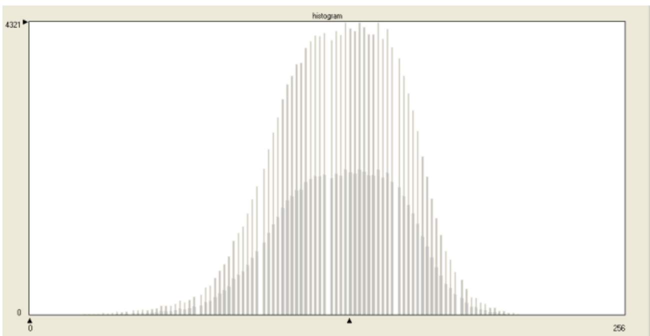

Figure 5. Histogram of Extracted Liver

Histogram of extracted liver in Figure 5 is with overlap between the liver peak and the tumor peak.

B.2 K-Mean Based Analysis

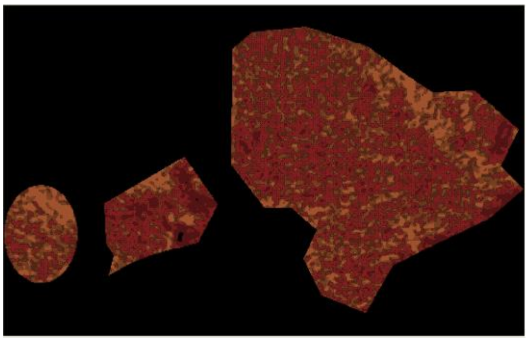

Figure 6. K-Mean Unsupervised Classification

K-Mean unsupervised classification is used to classify liver into two classes (Liver "Red color" and "hepato-cellular-carcinoma" in Yellow color. K-Mean unsupervised classification failed to discriminate between liver and tumor in the overlapped areas. The area of the tumor is larger than the real area because of the overlap. There is need for advanced technique to remove the overlap.

Applying histogram based analysis algorithm leads to remove the overlap between liver and the tumor.

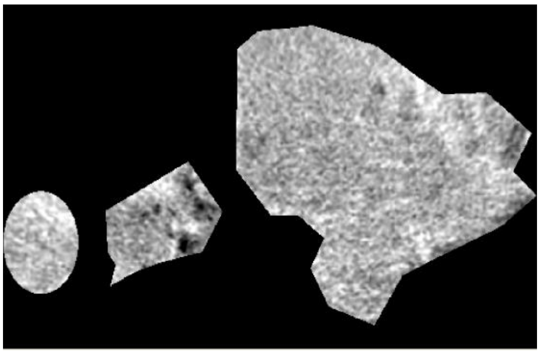

Figure 7. Metastasis

Tumor is automatically extracted using Equation 1. It is characterized by different tones from black to white, indicating different intensities.

$$\begin{cases} \dfrac{(x_i - T_{min})}{(T_{max} - T_{min})}(255-1)+1 & if\,(T_{min} \le x_i \le T_{max}) \\ 0 & if\,(x_i < T_{min} \cup x_i > T_{max}) \end{cases}$$

$$T_{min} : \mu_{tumor} - 3\sigma, T_{max} : \mu_{normal} + 3\sigma \qquad \dots \quad (1)$$

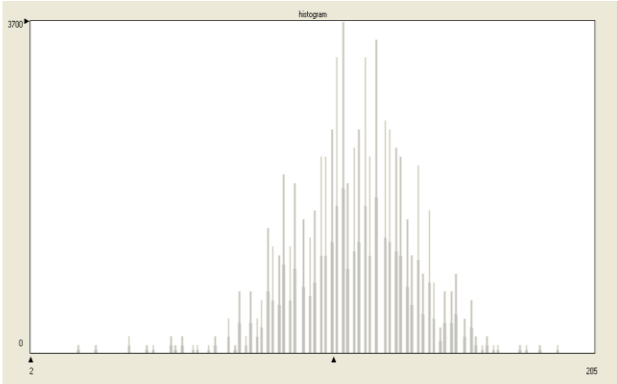

Figure 8. Histogram of the Suspected Tumor

Suspected area was recognized successfully as the outcome of histogram based analysis algorithm. It shows different tumor objects with different intensities based on the history of the objects.

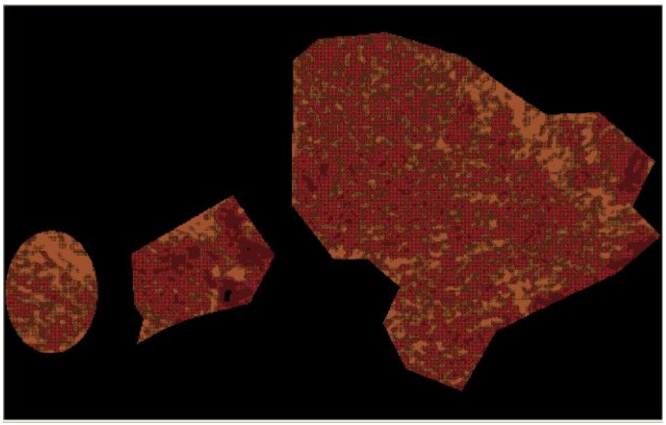

Figure 9. Classification Extracted Tumor Based on Histogram Analysis

Figure 9 indicates Tumor Pattern shows gradual change from dark to light. The darker tone means worst damage as well as older than the lighter tone. The dark tune indicates severity and early developed tumor. The light tone indicates new development of the tumor.

Table III. Correlation between Tumor Classes

	B1	***B2***	***B3***	***B4***	***B5***	***B6***
B1	1					
B2	-0.02809	1				
B3	-0.03702	-0.08537	1			
B4	-0.03472	-0.08007	-0.10555	1		
B5	-0.03303	-0.07617	-0.10041	-0.09417	1	
B6	-0.02016	-0.04648	-0.06127	-0.05746	-0.055	1

Tumor was classified into six classes where they are not correlated, this is indicating different intensities.

Table IV. Varianace between Groups

Groups	*Count*	*Sum*	*Average*	*Variance*
B1	65534	60628	0.925138	70.27261
B2	65534	389833	5.948561	546.3866
B3	65534	738742	11.27265	1129.179
B4	65534	719308	10.97610	1217.053
B5	65534	727300	11.09806	1374.898
B6	65534	328154	5.007385	751.7031

The Variance between six classes is very large indicating no possibility of merging.

EXPERIMENTAL RESULTS

A. Performance Capability of K-Mean v/s HBAA

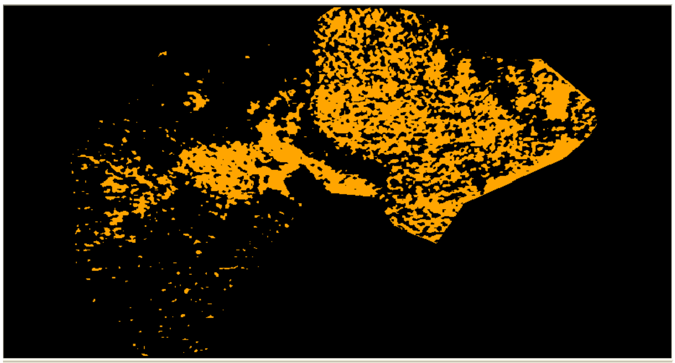

Figure 10. Exaggerated Area of Tumor by K-Mean Classifier

After extraction of liver, image was classified using k-mean classifier. The result shows exaggeration of the area of suspected tumor (yellow colour) as shown in Figure 10.

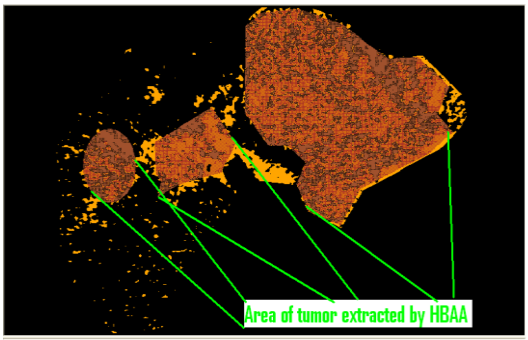

Figure 11. Area of the Tumor Extracted by HBAA

The extracted suspected tumor was extracted by Histogram Based Analysis Algorithm (HBAA) as shown in previous figure (small area in brown color). Area in yellow color is mis-classification done by K-mean classifier. The area of suspected Tumor in Pixels was calculated and compared as shown in Table 5.

Table V Area of Suspected Tumor in Pixels

Segmentation	**Manual**	**K-Mean**	**HBAA**
Image	**Area in Pixel**	**Area in Pixel**	**Area in Pixel**
In015	73,154	47,129	70,329

The comparison between (K-mean classifier) and (HBAA) shown in next table. The error percentage in (HBAA) is (3.9 %), while in (K-mean classifier) the 35.6 %. The estimated area by (K-mean classifier) was exaggerated more than one third. The estimated area by (HBAA) was 96 % of the calculated area by the radiologist. The result is a proof of the superiority of (HBAA) over (K-mean classifier).

Table VI. Validation for the Area of Suspected Tumor

	HBAA	**K-Mean**
Image	**% Error**	**% Error**
In015	**3.9%**	**35.6%**

B. ANOVA Test

Table VII. Anova single factor test

Source of Variation	**Between Groups**	**Within Groups**	**Total**
SS	5970308	3.34E+08	3.39E+08
df	5	393198	393203
MS	1194062	848.2486	
F	1407.679		
P-value	0		
F crit	2.214122		

ANOVA Single Factor Test is used to test whether there is any significant relation between those six classes. Since $P < 0.05$, there is insignificant relation between all the classes and we reject the null hypothesis.

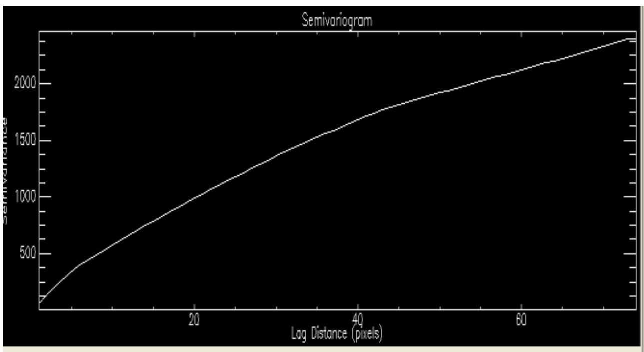

Figure 12. Horizontal Semivariogram

The horizontal exponential growth of the tumor is up to five pixels and the horizontal linear growth of the tumor is up to seventy four pixels.

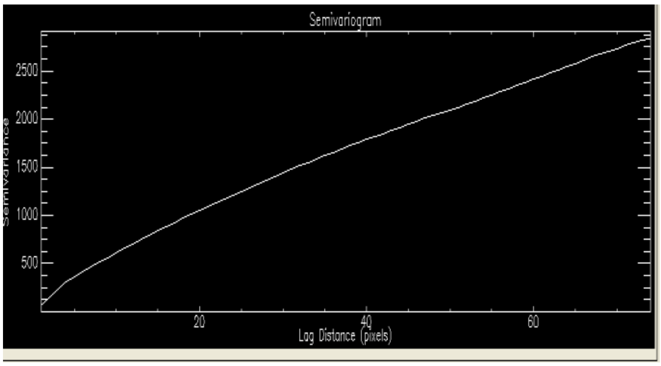

Figure 13. Vertical Semivariogram

The vertical exponential growth of the tumor is up to five pixels and the vertical linear growth of the tumor is up to seventy four pixels.

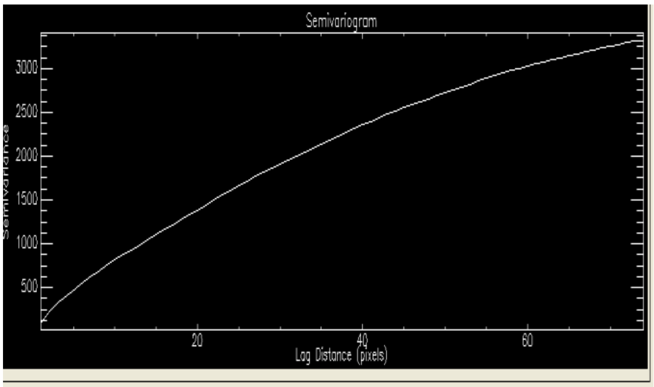

Figure 14. Positive Slope Semivariogram

The positive slope exponential growth of the tumor is up to five pixels and the positive slope linear growth of the tumor is up to seventy four pixels.

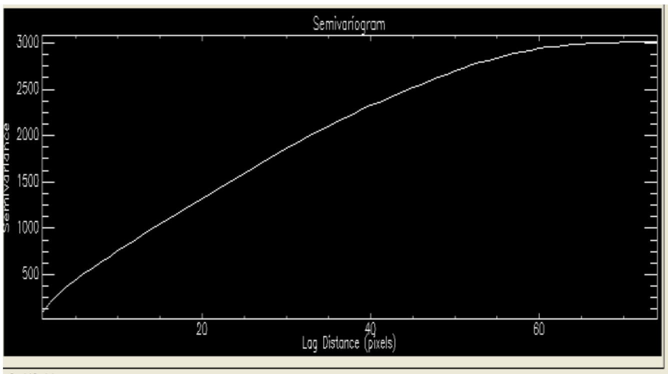

Figure 15. Negetive Slope Semivariogram

The negative slope exponential growth of the tumor is up to five pixels and the negative slope linear growth of the tumor is up to seventy four pixels.

C. Validation

Table VIII. Validation between Manual and Automated Segmentation

Segmentation	**Manual**	**Automatic**	**Standard Error**
Image	**Area in Pixel**	**Area in Pixel**	
In015	73,154	70,329	3.9%

As shown in Table VIII, the error between manual segmentation and automated segmentation is smaller than 1%. This is an evidence of success.

CONCLUSION

The proposed algorithm is capable of Detecting Liver, Detecting Tumor, Detecting tumor development, Classifying the tumor into different classes according to the intensity of growing cells, Locating the most affected portion for each segment (Dark Tumor Region), Locating the new affected portion for each segment (Light Tumor Region).

K-Mean unsupervised classification is used to classify liver in two classes (Liver and Tumor). In all the analyzed images, K-Mean unsupervised classification failed to discriminate between liver and tumor in the overlapped areas. The area of the tumor is larger than the real area because of the overlap. There was need for advanced technique to remove the overlap.

Applying histogram based analysis algorithm leads to remove the overlap between liver and the tumor. Tumor was classified into six classes where they are not correlated, this is indicating different intensities. The Variance between six classes is very large indicating no possibility of merging. ANOVE Single Factor Test is used to test whether there is any significant relation between those six classes. Since $P < 0.05$, there is insignificant relation between all the classes and we reject the null hypothesis.

The impacts of applying the proposed algorithm in treatment plan are:

- Reducing the required dose whether it is chemotherapy or Radio-therapy
- The location of the most damaged part is clear and easily to be operated.
- The new growing cells can easily be located and surrounded for suppressing the diffusion / spread.

The validation of the algorithm indicates very small error between manual segmentation and automated segmentation. The comparison between (K-mean classifier) and (HBAA) shown in Table VI. The error percentage in (HBAA) is very small compared to the calculated area by the radiologist while the estimated area of the suspected tumor done by (K-mean classifier) was usually exaggerated compared to the calculated area by the radiologist. The result is a proof of the superiority of (HBAA) over (K-mean classifier).

REFERENCES

[1] Junsung Choi, *Imaging of Hepatic Metastases*, Cancer Control, 2006, Vol. 13, No. 1, pp. 6-12.

[2] Ahmedin Jemal, Freddie Bray, Melissa M. Center, Jacques Ferlay, Elizabeth Ward and David Forman, *Global Cancer Statistics,* CA: A Cancer Journal for Clinicians, 2011, Vol. 61, No. 2, pp. 69-90, doi:10.3322/caac.20107.

[3] James C. Gee, Martin Reivich, Ruzena Bajcsy, *Elastically Deforming a Three-Dimensional Atlas to Match Anatomical Brain Images*, Journal of Computer Assisted Tomography, 1993, Vol. 17, No. 1, pp. 225-236, doi:10.1097/00004728-199303000-00011.

[4] T. F. Cootes, C. J. Taylor, D. H. Cooper and J.Graham, *Active Shape Models-Their Training and Application*, Computer Vision and Image Understanding, Vol. 61, No. 1, pp. 38-59, doi:10.1006/cviu.1995.1004.

[5] Zhao-You Tang, *Hepatocellular Carcinoma-Cause, Treatment and Metastasis*, World Journal of Gastroenterology, 2001, Vol. 7, No. 4, pp. 445-454.

[6] Xiang 2008 Deng Xiang and Du Guangwei. 3D Liver Tumor Segmentation Chal-lenge 2008. MICCAI Workshop, 2008. http://lts08.bigr.nl/. xiv, 40,43

[7] Li 2006 Y. Li, S. Hara and K. Shimura. A Machine Learning Approach for Locating Boundaries of Liver Tumors in CT Images. Pattern Recognition, 2006. ICPR 2006. 18th International Conference on, pages 400–403, 2006. 41, 43

[8] Luc Soler, Herve Delingette, Gregoire Malandain, Johan Montagnat, Nicholas Ayache, Christophe Koehl, Olivier Dourthe, Benoit Malassagne, Michelle Smith, Didier Mutter and Jacques Marescaux, *Fully automatic anatomical, pathological, and functional seg-mentation from CT scans for hepatic surgery*, Computer Aided Surgery, Vol. 6(3), 2001, pp. 131–142, DOI: 10.3109/10929080109145999.

[9] Damon Wong, Jiang Liu, Yin Fengshou, Qi Tian, Wei Xiong, Jiayin Zhou, Yingyi Qi, Thazin Han, Sudhakar K Venkatesh and Shih-chang Wang, *A Semi-Automated Method for Liver Tumor Segmentation based on 2D Region Growing with Knowledge-Based Constraints*, Published in MICCAI Workshop, 2008.