Computer-aided Detection and Diagnosis on Hepatic MR and CT Images

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ABSTRACT: ***This paper summarizes some computer-aided detection/diagnosis (CAD) schemes on hepatic MR and CT Images developed by our group, including the segmentation of the liver and tumor region; differentiation of focal liver diseases and cirrhosis. The results demonstrate that the CT scans provide good performance at shape extraction while MR images give high quality of texture classification.***

KEYWORDS: ***computer-aided detection/diagnosis (CAD), hepatic MR and CT images, image processing and analysis.***

I. INTRODUCTION

Malignant liver tumor causes 1.25 million deaths per year worldwide and MR/CT are currently the effective diagnostic modalities for the detection, characterization of liver tumors and abnormalities. However, interpretation of large volume of CT/MR images in a short time is a pressure to radiologists. In the last decade, different types of computer-aided detection/ diagnosis (CAD) systems have been developing to release radiologists from tough works, which are significant in both radiological and surgical studies because it plays an important role in reducing the mortality caused by liver cancer. Lesion detection algorithm will help the radiologists to find out the cancer in its early stage; accurate liver and tumors localization is very crucial to radiotherapy; and surgical simulation reduces the risk of living donor liver transplantation and oncological resections. Furthermore, these studies are easily to be adapted into a commercial CAD product that should have a huge potential market, especially in Asian countries.

By now the CAD products for liver are still very handful. We developed a CAD system for qualitative and quantitative diagnosis/detection of liver disease, as well as the visual surgical simulation. The sensitivity and usefulness of this system is clinically tested in different hospitals. This paper will give a brief introduction on the topic of the Segmentation of the liver region and tumor tissues on CT scans and Classification of the cirrhotic liver and differentiation of focal liver diseases in MR imaging

II. MATERIALS

Datasets were examined with different multi-detector row CT scanners that included unenhanced and three contrast enhanced phase images. Each patient received the contrast/bolus agent via a power injector at a rate of 3 ml/s, and the final average volume of contrast material was 100 ml, with slice interval, 0.625–1.25 mm; bits stored, 16 bits; pixel-spacing, 0.50–0.625 mm; spatial resolution, 512 × 512. These cases were categorized by experienced radiologists with normal and liver tumor cases confirmed.

Using a 1.5-T and a 3-T superconducting magnet (GE Medical Systems and Philips Medical Systems, respectively), MR images of 180 patients with focal liver lesions or cirrhosis were acquired. These cases were diagnosed by 2 experienced radiologists, and a majority of these cases were pathologically confirmed by biopsy or surgery. T1-weighted images, T2-weighted images at the precontrast, gadolinium-enhanced hepatic arterial, portal venous and equilibrium phase images were obtained by using a phased-array body multicoil.

III. METHODS

A. Segmentation of the liver region and tumor tissues on CT scans

Segmentation of abdominal organs: We have been developing a fully automatic method to segment the liver and other organs on multi-phase CT images, regardless of the presence of cirrhosis or tumors within the liver [1]. Our method is based on the edge detection or combined with a subtraction processing algorithm that is independent of the intensity or noise of the CT images.

Registration of liver: In order to subtract two different phase image accurately, the image registration algorithm based on phase-only correlation (POC) is applied to the two liver edge maps to detect translational shift. The phase information in the Fast Fourier transform of an image is emphasized and the correlation of a reference image and a test image is carried out with the magnitude of the complex spectra in one of the images entirely suppressed. The distribution from the POC shows a sharp peak such that a more accurate maximal correlation can be achieved in determining the translational shift. In our experiment, the power spectra of two map images are firstly calculated from FFT and then transformed into polarized coordinate as

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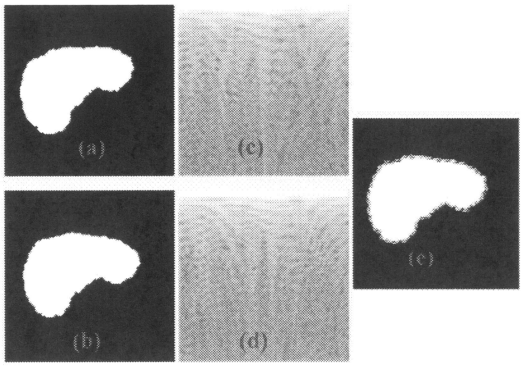

Figure 2. Registration result from the liver edge maps on unenhanced (a) to the portal venous phase (b) images with a largest liver slice. The power spectra of two map images are firstly calculated from FFT and then transformed into polarized coordinate in (c) and (d), respectively. Calculating the shift between (c) and (d) by POC method, θ is calculated as the rotation angle from which a registered image (e) is derived, corresponding to image (a). Therefore, rotation is turned into shift problem.

shown in Figs. 1(c) and (d), from which the POC is applied to determine the shift of the power spectrum images, that equal to the rotation angle θ in spatial domain. Secondary the non-contrast edge map image is rotated by θ to keep the same direction with portal venous edge map image. Finally the POC method is again to apply to the two maps for finding out the shift parameters.

Extraction of hepatic tumor: To detect the metastatic liver tumor, hemangioma, cyst on CT scans, two liver edge maps on unenhanced and portal venous phase images are firstly extracted and registered using phase-only correlation method. The initial tumors are derived from the subtraction of edge and gray maps as well as the score from spherical gray-level differentiation searching filter. Finally the false-positives (FPs) are eliminated by shape and texture features [2].

Extraction of HCC: The presence of some unclear edge tumors such as hepatocellular carcinoma (HCC) is indicated by high- and low-intensity regions in arterial and equilibrium phase images, respectively. We propose an automatic method for detecting HCC based on edge detection and subtraction processing [3]. Within a liver area segmented according to our scheme, black regions were selected by subtracting the equilibrium phase images with the corresponding registered arterial phase images. From these black regions, the HCC candidates were extracted as the areas without edges by using Sobel and LoG edge detection filters. The FP candidates were eliminated by using 6 features extracted from the cancerous and the surrounding liver regions. Finally, an expansion process was applied to acquire the 3D shape of the HCC.

Surgical planning: We also constructed a probabilistic atlas generation method for liver region segmentation only using non-contrast torso CT Images [4], as well as developed an automated hepatic vessels segmentation method [5]. A 3D surgical planning simulation is built by projecting the 3D organ and vessel labels into a 2D plane so that we can view

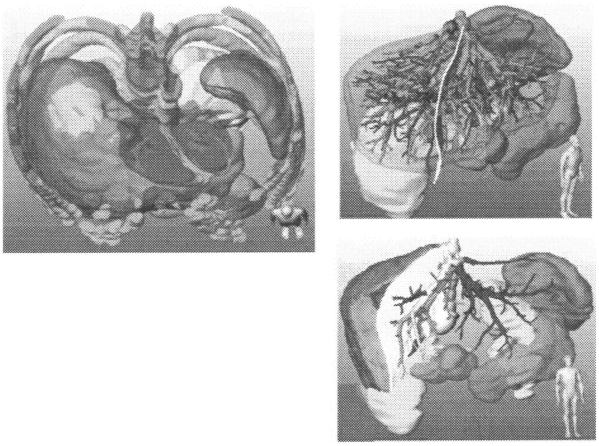

Figure 1. An interactive simulation system is developed for surgeons' preoperative surgical planning that enable to view the liver resections effects on the screen by using the visual reality technology.

the surgical effects on the screen by using the visual reality technology. Prior to surgical treatment of liver tumors, computer-aided liver surgery has proven to be a useful tool for supporting radiologists and surgeons in planning liver resections or living donor transplantation. Figure 2 shows an example of using an interactive simulation system for liver resection planning.

B. Classification of the cirrhotic liver and differentiation of focal liver diseases in MR imaging

Patients with chronic viral hepatitis are at great risk of developing complications such as hepatocellular carcinoma, cirrhosis, and resulting liver failure. Hepatocellular carcinoma is the most frequent and life-threatening complication, particularly in patients who are positive for hepatitis C virus. The degree of liver fibrosis is a critical predictive factor for the occurrence of hepatocellular carcinoma, and the cumulative incidence of hepatocellular carcinoma was significantly higher in patients with severe fibrosis (F3 and F4) than in those with no or mild fibrosis (F0 to F2). Thus, the early detection and accurate staging of hepatic fibrosis or cirrhosis has become a critical issue in radiology practice.

Texture analysis of fibrosis: Liver parenchymal textures on the MR images of 52 patients who underwent partial hepatectomy were processed by the computer algorithm and reviewed by two radiologists. The texture features using the GLCM method were processed by an artificial neural network program containing a three-layer learning algorithm of the back propagation, composed of a seven-unit input layer, a six-unit hidden layer, and a one unit output layer. The radiologists assigned confidence levels for the presence of hepatic fibrosis. Degrees of hepatic fibrosis were determined semiquantitatively by a pathologist. Algorithm outputs and radiologists' interpretations were correlated with degrees of fibrosis using Spearman's rank correlation analysis, and diagnostic

performances were evaluated using receiver operating characteristic curve analysis [7].

Texture and shape analysis of cirrhosis: To improving the above classification method, we integrate two shape features calculated from a segmented liver region to the texture analysis. The degree of cirrhosis was derived by integrating the shape and texture features of the liver into a 3-layer feedforward ANN [8].

Texture analysis of cirrhosis: Besides the shape and texture features, the changes of liver volume are also an important parameter to the cirrhosis analysis. The enlargement of the left lobe of the liver and the shrinkage of the right lobe are helpful signs in MR imaging in the diagnosis of cirrhosis of the liver. To investigate whether the volume ratio of left-to-whole (LTW) is effective to differentiate a cirrhotic liver from a normal liver, we developed an automatic algorithm for segmentation and volume calculation of the liver region in MR imaging [9]. The 3D liver is divided into left and right lobes along the umbilical fissure. The volume (V) of each part is calculated slice by slice. The degree of cirrhosis is defined as the ratio of $LTW = Vleft/(Vright + Vleft)$. 22 cases including normal and cirrhotic liver on MR and CT slices are used for 3D segmentation and visualization.

Cine-tagging analysis of fibrosis: The cine-tagging MR imaging of the heart using a spatial modulation of magnetization (SPAMM) sequence is a useful tool to evaluate the kinetics of cardiac muscles. Cine-tagging MR imaging can provide supplementary information about liver motion, which enables the detection of stiffness of liver segments. Although a limitation of MR cine-tagging at 1.5 T was that the tag lines fade and the edges blur shortly due to longitudinal relaxation, the tag lines at 3 T may well last longer due to prolonged T1 relaxation times of organs. We proposed a method to evaluate liver stiffness that is corresponding to the degree of fibrosis, by means of bending energy (BE) analysis using the thin-plate spline method. We have preliminarily evaluate the feasibility and the potential usefulness of MR elastography of the liver at 3 T with cine-tagging and BE analysis for the evaluation of hepatic fibrosis [10].

Classification of focal liver lesions: The differentiation of focal liver lesions in MR imaging is primarily based on the intensity and homogeneity of lesions with different imaging sequences. We developed a CAD system named LiverANN for classifying the pathologies of focal liver lesions into five categories using the artificial neural network (ANN) technique [11]. On each MR image, a region of interest (ROI) in the focal liver lesion was delineated by a radiologist. The intensity and homogeneity within the ROI were calculated automatically, producing numerical data that were analyzed by feeding them into the LiverANN as inputs. Outputs were the following five pathologic categories of hepatic disease: hepatic cyst, hepatocellular carcinoma, dysplasia in cirrhosis, cavernous hemangioma, and metastasis, as shown in Fig. 3. 320 MR

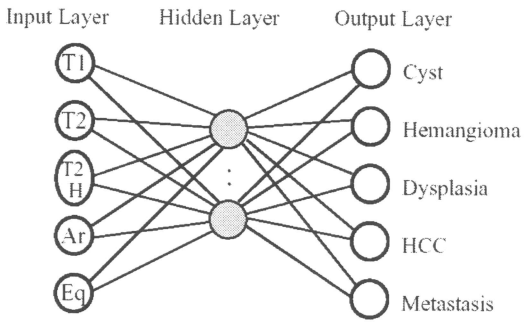

Figure 3. A multi-layer feed-forward network used in LiverANN can automatically find out the internal connections between inputs and outputs by learning from samples in which a backpropagation algorithm was employed. T2H=Homogeneity of T2-weighted imaging; Ar=arterial; Eq=equilibrium; HCC=Hepatocellular carcinoma.

images of 80 patients (four images per patient) who had focal liver lesions were obtained. These cases were diagnosed by two experienced radiologists, and the majority of them were confirmed pathologically from biopsy or surgery. A total of 50 focal liver lesions, including liver cysts, cavernous hemangiomas, dysplasias in cirrhosis, HCCs, and metastases, were used to train the ANN, whereas the remaining 30 cases, which were separated into the five categories of liver diseases (each category contained six cases), were used to test the performance of the ANN.

IV. RESULTS

In a case of organ segmentation, the POC method is apply to the two maps for finding out the shift parameters between two phase MDCT images. Registration result is shown in Fig. 1 with the liver edge maps on unenhanced (a) to the portal venous phase (b) images with a largest liver slice. The power spectrum of two map images are firstly calculated from FFT and then transformed into polarized coordinate in (c) and (d), respectively. Calculating the shift between (c) and (d) by POC method, θ is calculated as the rotation angle from which a registered image (e) is derive, corresponding to image (a). Liver, kidneys, spleen, bones are extracted successfully by our method within 8 minutes on a PC (Intel Core2 Quad CPU 2.66 GHz with 4 GB RAM), that is a reasonable and acceptable time for clinical applications.

The detection of the metastatic liver tumor, hemangioma, and cyst on CT scans achieved the TP rate at 88% with average 2.1 FPs per case. In the experiment using CT images of 44 patients with 44 HCCs, we successfully extracted 97.7% (43/44) HCCs successfully by our proposed method, with an average number of 2.1 FPs per case.

3D visualization of the result of organs with the hepatic vessel and tumor result, a surgical planning simulation system as shown in Fig.2 is constructed to enable the surgeons to view the operate effects interactively.

By using MR elastography of the liver at 3T with cine-tagging and bending energy in 22 patients, six had a fibrosis

score of F0, one had F1, seven had F2, three had F3, and five had F4. Mean BE value with 16-mm sagittal grid was greater with fibrosis score F0 (1.54±0.63) than with ≥F1 (0.97± 0.12, P=0.013) as well as with ≤F1 (1.48±0.60) than with ≥F2 (0.96±0.36, P=0.019). The whole hepatic volume of the cirrhotic liver (931 ± 307 cm3) was slightly lower than that of the normal liver (1070 ± 412 cm3), while the volume of the left lobe in the cirrhotic liver (238 ± 53 cm3) was larger than that of the normal liver (176 ± 69 cm3). The volume ratio of LTW was relatively higher in the cirrhotic liver (25.6% ± 4.3%) than in the normal liver (16.4% ± 5.4%). The ANN-based method classified liver cirrhosis with a training accuracy of 100% on the 100 ROIs included in the training set. In the testing of the whole liver region, 82% (9/11) cirrhotic and 100% (7/7) normal cases were correctly differentiated from 18 test cases by using the shape and texture analysis as compared to 55% (6/11) cirrhotic and 100% (7/7) normal cases by using the texture analysis alone. According to the ROC analysis, the Az value (the area under the ROC curve) improved from 0.57 to 0.84 by integrating the shape features into ANN inputs.

The initial results showed that the LiverANN could classify 50 cases of the training dataset and 30 test cases into the five types of focal liver lesions; the training accuracy in the former set was 100%, whereas the testing accuracy in the latter set was optimally 93.3% (28/30). The LiverANN wrongly categorized two HCCs as metastases.

V. CONCLUSION

In this study, we summarize several Computer-aided detection/diagnosis (CAD) schemes on hepatic MR and CT images developed by our group. The segmentation of liver and its surrounding organs is undertaken on CT scans because of its high special resolution that can accurately express the shape features.

Our results imply that MR images give high quality of texture classification: ANN using shape and texture inputs, volume of liver segments, and MR elastography with BE analysis had potential in discrimination for the patients with moderate or advanced hepatic fibrosis from those with healthy liver or slight fibrosis, as well as the classification types of focal liver lesions.

We have established a CAD system for aiding decision-making with regard to the diagnosis of liver cancer or supporting radiologists and surgeons in planning of liver resections or living donor transplantation by using multiphase CT/MRI images. The results are very promoting and it is expected that employing CAD in clinical practice would reduce the mortality caused by liver cancer.

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