Journal of Science and Technology 54 (3A) (2016) 98-105

LIVER INTENSITY DETERMINATION IN THE 3D ABDOMINAL MR IMAGE USING NEURAL NETWORK

Le Trong Ngoc[1, 2], Kieu Duc Huynh[1], Pham The Bao[2], Huynh Trung Hieu[1, *]

[1]*Industrial University of Ho Chi Minh City, 12 Nguyen Van Bao, Go Vap, Ho Chi Minh city, Vietnam*

[2]*University of Science, Vietnam National University Ho Chi Minh City, 227 Nguyen Van Cu, Ho Chi Minh city, Vietnam*

Email: *hthieu@ieee.org*

Received: 15 June 2016; Accepted for publication: 27 July 2016

ABSTRACT

This study presents an approach to automatically identify the liver range intensity in the 3D abdominal MR images using neural network. The proposed scheme consists of three main stages. First, the T1-weighted MR images of the liver in the portal-venous phase are reduced noise by applying the anisotropic diffusion algorithm. The histogram of the 3D reduced image is determined. The function approximation is applied to the computed histogram by using the neural network. The peaks are computed and the peak corresponding to the liver region is determined. This peak plays an important role for a fully automatic liver segmentation. The another salient point of this proposed approach is that the neural network is trained by an effective algorithm called extreme learning machine, this algorithm can offer a good performance with high learning speed in many applications.

Keywords: liver segmentation, MR image, neural network, regression problem.

1. INTRODUCTION

Liver segmentation from Computerized Tomography (CT) or Magnetic Resonance Imaging (MRI) is very important to accurately evaluate patient-specific liver anatomy for hepatic disease diagnosis, function assessment and treatment decision-making. The manual liver segmentation task is not only time consuming and tedious due to the high number of slices, but also depends on skill and experience. Several approaches have been proposed for liver segmentation on CT images including image-processing techniques [1 - 3], graph-cut [4], level-set segmentation [5, 6], and machine learning techniques.

In comparison with the CT images, the number of approaches for MR images is still limited. This may be believed that the MR liver segmentation is more difficult and have more variations than CT liver segmentation. The researches have been investigated in this field include those of Karlo, et al. [7], their work compared to the CT- and MRI-based liver segmentation of resected liver specimens. A semi-automated dual-space clustering segmentation method was proposed by Farraher, et al. [8]. Their method required manually drawing a small region-of-interest (ROI) on the liver; then, it iteratively evaluated temporal liver segmentations with the repeated adjustment of parameters to obtain the final liver segmentation result. This method was evaluated on eighteen normal and nine abnormal cases. An approach based on the partitioned probabilistic model was proposed by Ruskó, et al. [9]. In this approach, the liver was partitioned into multiple regions, and different intensity statistical models were applied to these regions. Gloger, et al. [10] developed a three-step segmentation method based on a region-growing approach, probability maps, and linear discriminant analysis. Their method was evaluated with twenty normal cases and ten fatty cases. In our previous study, we proposed an approach using the fast marching algorithm, and a geodesic active contour model. The performance of this approach was evaluated on twenty-three cases [11].

As above approaches showed promising results, however, they are semi-automatic approaches. The fully automated approaches are still challenge and attract researchers worldwide. In fully automated approaches, one of important steps is to locate automatically the liver characteristics including the location or intensity (for thresholding methods). In this study, we investigate in locating the intensity of liver in the 3D abdominal MR images based on the histogram and neural network. The determined intensity was employed to extract the liver in the further steps. The salient point of this approach is that the network is trained by an effective training algorithm which can offer good performance with high learning speed.

2. MATERIALS AND METHODS

The proposed scheme for liver segmentation which covers locating the liver region is depicted in Fig. 1.

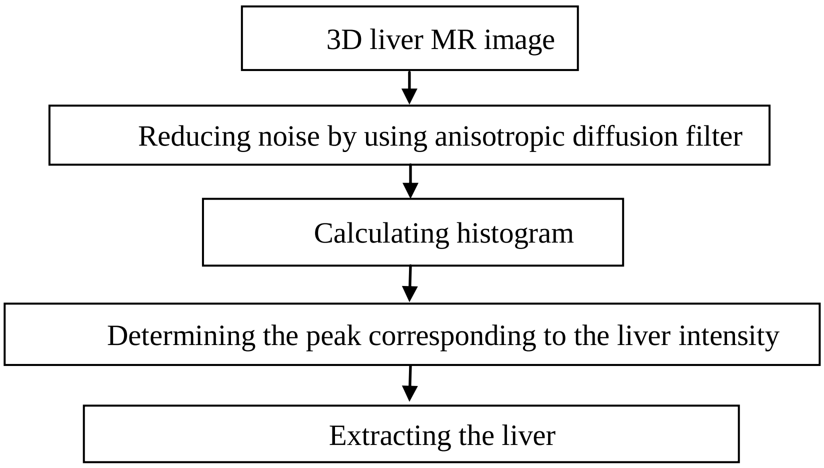

Figure 1. Overview scheme for a fully automated liver segmentation based on the intensity.

First the 3D MR abdominal image, I, is reduced noise by employing an anisotropic diffusion filter [12]. This filter follows a modified curvature diffusion equation defined by [13]:

$$\frac{\partial I}{\partial t} = |\nabla I| \nabla \cdot c(|\nabla I|) \frac{\nabla I}{|\nabla I|}, \tag{1}$$

where ▽ is the gradient operator, and c(·) is the diffusion function controlling the sensitivity of the edge contrast. The algorithm reduces the noise in the image while simultaneously preserving the major liver structures, such as major vessels and liver boundaries.

The histogram of the smoothed image is determined. The histogram of a typical image is shown in Fig. 2. From the statistics, the intensity corresponding to the liver region is around one which is the second-to-last peak of the histogram. However, the histogram is not smooth. Hence, in order to find the peaks the approximation function of histogram must be performed.

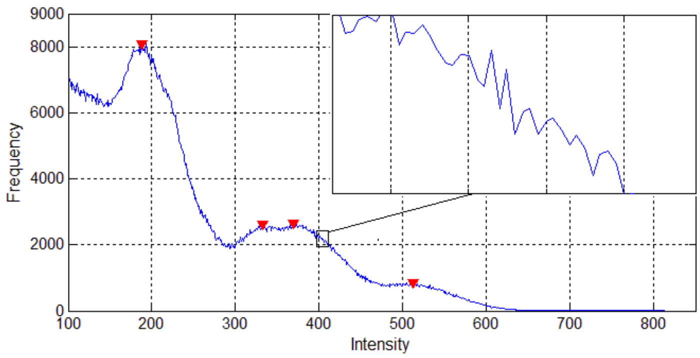

Figure 2. The histogram of a 3D abdominal MR image. The intensity corresponding to the liver is around one which corresponds to the second-to-last peak.

Let X = {$x_1, x_2,\ldots, x_n$}be the discrete intensity values from the 3D abdominal MR image and T = {$t_1, t_2,\ldots, t_n$}be its corresponding frequency values. We have to determine a smooth function $f(x)$ that can approximate the histogram of the 3D abdominal MR image. One of the popular approaches to solve this problem is to use the neural network. There are several network architectures developed by researchers. However, it has shown that the single hidden layer feedforward neural network (SLFN) can approximate any function if the activation function is chosen properly. Hence, in this research we focus on using the SLFN to approximate the function of histogram, it can be modeled by:

$$f(x) = \sum_{k=1}^{N} a_k \varphi(w_k x + b_k), \tag{2}$$

where N is the number of hidden nodes, $\varphi(\cdot)$ is the activation function, w*'s* and b*'s* are the input weights and hidden node biases, respectively, and a's are the output weights. From Eq. 2, we can see that the network weights including the biases must be determined by using the training algorithm. The main goal of training process is to determine the network weights those minimize the error function defined by:

$$E = \sum_{i=1}^{n} \| f(x_i) - t_i \|^2, \tag{3}$$

Traditionally, the network weights are determined based on the gradient descent method. One of the popular training algorithms based on the gradient descent is the back-propagation one, in which the weights are updated by:

$$W^{(i)} = W^{(i-1)} - \lambda \frac{\partial E}{\partial W}, \tag{4}$$

where W is the network weights (a's, w's or b's) and λ is a learning rate. There have been several improvements proposed for the back-propagation algorithm. Up to now, most training algorithms based on the gradient descent still suffer from the problems such as (1) local minima, (2) epochs, (3) learning rates, etc.

Recently, an effective training algorithm for SLFN called extreme learning machine (ELM) has been developed by Huang et al. [14]. In ELM, the minimization of error function can be equivalent to the solution of a linear system given by:

$$\begin{pmatrix} \varphi(w_1x_1+b_1) & \varphi(w_2x_1+b_2) & \cdots & \varphi(w_Nx_1+b_N) \\ \varphi(w_1x_2+b_1) & \varphi(w_2x_2+b_2) & \cdots & \varphi(w_Nx_2+b_N) \\ \vdots & \vdots & \ddots & \vdots \\ \varphi(w_1x_n+b_1) & \varphi(w_2x_n+b_2) & \cdots & \varphi(w_Nx_n+b_N) \end{pmatrix} \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_N \end{pmatrix} = \begin{pmatrix} t_1 \\ t_2 \\ \vdots \\ t_n \end{pmatrix} \tag{5}$$

This can be rewritten as:

$$\mathbf{HA} = \mathbf{T}, \tag{6}$$

where $\mathbf{A} = [a_1, a_2, \ldots, a_N]^T$, $\mathbf{T} = [t_1, t_2, \ldots, t_n]^T$, and $\mathbf{H}$ is the hidden layer output matrix defined by

$$\mathbf{H} = \begin{pmatrix} \varphi(w_1x_1+b_1) & \varphi(w_2x_1+b_2) & \cdots & \varphi(w_Nx_1+b_N) \\ \varphi(w_1x_2+b_1) & \varphi(w_2x_2+b_2) & \cdots & \varphi(w_Nx_2+b_N) \\ \vdots & \vdots & \ddots & \vdots \\ \varphi(w_1x_n+b_1) & \varphi(w_2x_n+b_2) & \cdots & \varphi(w_Nx_n+b_N) \end{pmatrix} \tag{7}$$

In ELM, the input weights and biases are chosen randomly and the output weights are determined by:

$$\hat{\mathbf{A}} = \mathbf{H}^{\dagger}\mathbf{T}, \tag{8}$$

where $\mathbf{H}^{\dagger}$ is pseudo-inverse of $\mathbf{H}$. The ELM training algorithm can be summarized as follows:

- ***The ELM training algorithm***:

  Input:

  - A training set S={(x_j, t_j) | j=1, 2,…,n}
  - Active function $\varphi(\cdot)$
  - The number of hidden nodes: N

  Output: network weights a's, w's, and b's

  Algorithm:

  - Randomly assign input weights w's and hidden layer biases b's.
  - Calculate the hidden layer output matrix $\mathbf{H}$ by Equation (7).
  - Calculate the output weight a's by Equation (8).

This is non-iterative algorithm; it can overcome problems of the back-propagation algorithm and obtain a good performance with high learning speed in many different applications. However, the number of hidden nodes is usually large which may affect the processing time for the testing stage. This issue has been addressed by improvements from researchers [14 - 17].

After determining the approximation function, the peaks can be computed easily. In this study, they are found with the quadratic interpolation. The intensity, x_l, corresponding to the last-to-second peak is determined, and the intensities corresponding to the liver region are around x_l. The liver region can be segmented based on the determined intensity.

3. RESULTS AND DISCUSSION

3.1. Data set

The database of this study consists of 10 cases of 3D MRI scans in the supine position with 1.5TMRI scanners (Avanto, Siemens) at the Medic Medical Center, which is one of the largest diagnostic imaging centers in Viet Nam. Post-contrast MR images were obtained by using the T1-weightvolumetric interpolated breath-hold examination (VIBE) sequence. A flip angle of 10 degrees was used with TR = 4.74 and TE = 2.38. The scanning parameters included collimation and reconstruction intervals ranging from 3.5 to 4 mm. Each MRI slice had a matrix size of 230×320 pixels with an inplane pixel size ranging from 1.18 to 1.4 mm. On each MRI slice that contained the liver, a board-certified abdominal radiologist carefully manually traced the liver contours. The number of slices in each case ranged from 44 to 56.

3.2. Results

Firstly, we evaluate the performance of the proposed method for identifying the liver intensity. The function approximation results corresponding to an example case are shown in Fig. 3. The 3D abdominal MR image in Fig.3a was reduced noise and the histogram was computed. A smoothed function was approximated as shown in Fig. 3b. A small part of the approximated fucntion was shown in Fig. 3c.

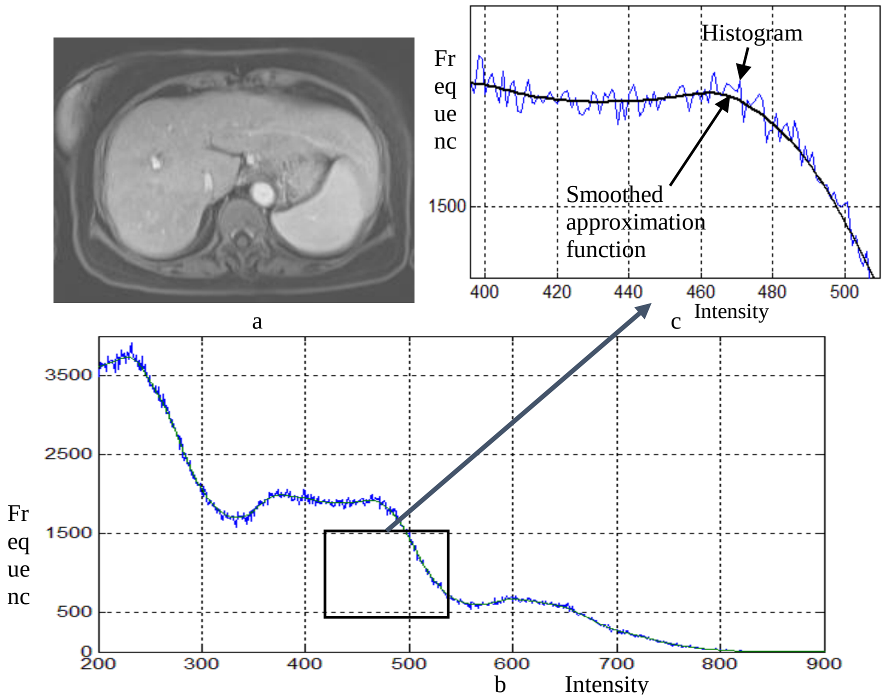

Figure 3. The results of the smoothed function approximation from histogram.

From this result we can see that the neural network trained by ELM can generate a smoothed function that can approximate the histogram. From the smoothed function the peaks can be determined and the second-to-last peak are located that can compute the intensity to identify liver region.

The intensity range of liver in the 3D MR image is identified correctly (the accuracy of 100% with 10 cases in our dataset). Let x_l be the intensity value corresponding to the second-to-last peak; the intensity distribution of the liver is around this value. Two thresholds are calculated by the following:

$$\begin{aligned} lowerThreshold &= x_l - \tau \\ upperThreshold &= x_l + \zeta \end{aligned} \tag{9}$$

where τ and ζ are user-defined parameters. We have tried on a thresholding method combining with the level set algorithm and the morphological operations for post-processing in liver segmentation. Compared to the manually tracing method, the fully automated scheme with locating the liver intensity region by the neural network can obtain a percentage volume error of 8.7 %. The accuracy of the liver segmentation was 99.0 ± 0.4 % and the overall mean of the Dice coefficients was 91.0 ± 2.8 %. The computerized liver segmentation scheme reduces the processing time significantly; from 24.3 ± 3.7 min per case for the manual method to 1.02 ± 0.8 min per case on a PC (CPU: Intel, core i7, 2.8 GHz).

4. CONCLUSIONS

Developing a fully automated scheme for liver segmentation is a challenge and has been investigated by researchers worldwide. In the intensity based methods, identifying the intensity range of liver is an important step. In this study, we investigate in identifying the intensity range of the liver in the 3D MR abdominal images by using the histogram and neural network. The neural network is used for the function approximation of the histogram. The network is trained by an effective training algorithm which can offer high learning speed with good performance. For evaluation on ten cases, the smoothed functions can approximate the histogram quite well; the intensity of the liver range is identified correctly. Combining with the post-processing steps of the liver segmentation, the proposed method significantly contributes to the fully automated scheme for liver segmentation which can offer the high accuracy with the reduced processing time.

Acknowledgements. This research is funded by the Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number 102.01-2013.47. This is partially supported by Industrial University of Ho Chi Minh city under grant number IUH.KTT11/16. The authors are grateful to Phan Thanh Hai, MD, and Nguyen Thanh Dang, MD for preparing images and their clinical advice.

REFERENCES

1. Gao L., Heath D. G., Kuszyk B. S., Fishman E. K. - Automatic liver segmentation technique for three-dimensional visualization of CT data, Radiology **201** (1996) 359-364.
2. Bae K. T., Giger M. L., Chen C. T., et al. - Automatic segmentation of liver structure in CT images, Med. Phys. **20** (1993) 71-78.

3. Hermoye L., Laamari-Azjal I., Cao Z., et al. - Liver segmentation in living liver transplant donors: comparison of semiautomatic and manual methods, Radiology **234** (2005) 171-178.
4. Beichel R., Bauer C., Bornik A., et al. - Liver segmentation in CT data: A segmentation refinement approach, Proc. MICCAI Workshop 3-D Segmentat. Clinic: A Grand Challenge (2007) 235–245.
5. Kenji Suzuki, Ryan Kohlbrenner, Mark L. Epstein, et al. - Computer-aided measurement of liver volumes in CT by means of geodesic active contour segmentation coupled with level-set algorithms, Med. Phys. **37** (5) (2010) 2159-66.
6. Kenji Suzuki, Mark L. Epstein, Ryan Kohlbrenner, Shailesh Garg, Masatoshi Hori, Aytekin Oto, Richard L. Baron - Quantitative Radiology: Automated CT liver volumetry compared with interactive volumetry and manual volumetry, Medical Physics and Informatics, AJR **197** (2011) W706-712.
7. Karlo C., Reiner C. S., Stolzmann P., et al. - CT- and MRI-based volumetry of resected liver specimen: comparison to intraoperative volume and weight measurements and calculation of conversion factors, Eur. J. Radiol. 75, (2010) e107-111.
8. Farraher S. W., Jara H., Chang K. J., Hou A., Soto J. A. - Liver and Spleen Volumetry with Quantitative MR Imaging and Dual-Space Clustering Segmentation, Radiology **237** (2005) 322-328.
9. Rusko L, Bekes G. - Liver segmentation for contrast-enhanced MR images using partitioned probabilistic model, Int. J. Comput. Assist. Radiol. Surg. **6** (2011) 13-20.
10. Gloger O, Kuhn J, Stanski A, Volzke H, Puls R - A fully automatic three-step liver segmentation method on LDA-based probability maps for multiple contrast MR images, Magn. Reson. Imaging **28** (2010) 882-897.
11. Hieu Trung Huynh, Ibrahim Karademir, Aytekin Oto, Kenji Suzuki - Computerized liver volumetry on MRI by using 3D geodesic active contour segmentation. Medical physics and Informatics, AJR **202** (2014) 152-159.
12. Whitaker R. T., and Xue X. - Variable-conductance, level-set curvature for image denoising, Proc. IEEE Int. Conf. Image Processing (2001), 142-145.
13. Perona P, and Malik J. - Scale-Space and edge detection using anisotropic diffusion, IEEE Transactions on Pattern Analysis Machine Intelligence **12** (1990) 629-639.
14. Huang G.-B., Zhu Q.-Y., Siew C.-K. - Extreme learning machine: Theory and applications", Neurocomputing **70** (2006) 489-501.
15. Hieu Trung Huynh and Yonggwan Won - Extreme Learning Machine with Fuzzy Activation Function", the Int'l Joint Conference on INC, IMS and IDC, IEEE CS (2009) 303-307.
16. Hieu Trung Huynh and Yonggwan Won - Training Single Hidden Layer Feedforward Neural Networks by Singular Value Decomposition, The Int'l on Computer Sciences and Convergence Information Technology, IEEE CS (2009) 1300-1304.

17. Hieu Trung Huynh and Yonggwan Won - Small Number of Hidden Units for ELM with Two-Stage linear Model, IEICE Trans. on Information and Systems **E91-D**(4) (2008)1042-1049.
18. Hieu Trung Huynh, Jung-ja Kim and Yonggwan Won - An improvement of Extreme Learning Machine for Compact Single-Hidden Layer Feedforward neural Networks, International Journal of Neural Systems **18**(5) (2008) 433-441.