10th Symposium on Neural Network Applications in Electrical Engineering, NEUREL-2010
Faculty of Electrical Engineering, University of Belgrade, Serbia, September 23-25, 2010

Automatic Spleen Segmentation in MRI Images using a Combined Neural Network and Recursive Watershed Transform

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***Abstract*—Accurate spleen segmentation in abdominal MRI images is one of the most important steps for computer aided spleen pathology diagnosis. The first and essential step for the diagnosis is the automatic spleen segmentation that is still an open problem. In this paper, we have proposed a new automatic algorithm for spleen area extraction in abdominal MRI images. The algorithm is fully automatic and contains several stages. The preprocessing stage is applied for required image enhancement. Then the abdominal MRI images are partitioned to different regions using combined recursive watershed transform and neural network. The feed forward neural network is trained and used for spleen features extraction. The features extracted using neural networks are used to monitor the quality of the output of watershed transform and adjusting required parameter automatically. The process of adjusting parameters is performed sequentially in several iterations. Experimental results showed the promise of the proposed algorithm.**

***Index Terms*—Spleen segmentation, morphological watershed transform, neural network**

I. Introduction

MRI is a very useful tool in modern medical diagnosis. The development and improvement in MRI imaging techniques give rise to faster, more competent and more accurate diagnostics capabilities for many diseases. Therefore, designing and developing a computer-aided diagnosis (CAD) tools for spleen MRI is necessary to increase the productivity of radiologists who interpret and diagnose hundreds of MRI images every day. The first step of a CAD system is to accurately segment spleen region in MRI images [1]. Image segmentation algorithm partitions an image into different regions depending on certain properties. It is used as a key technique for object extraction. The elementary picture elements in the segmented image are no longer the individual pixels, but instead are connected sets of pixels all belonging to the same region. Once the image has been segmented, measurements can be performed on each region and neighboring relationships between adjacent regions can be investigated. Although there are growing interests in the fields of medical image segmentation, conventional schemes don't work well with medical images because of the anatomic complexity, abnormity of tissue structures and diversity of individual organs. Accurate spleen segmentation in abdominal MRI images is a challenging issue since the grey level distribution of surrounding organs is not highly distinguishable [2]. Different algorithms are used for the segmentation of objects in abdominal MRI images which have their own advantages and disadvantages. Thresholding algorithms are one of mostly used algorithms for image segmentation; however the intensity values for spleen, liver, kidney and muscles areas are very close, so it is difficult to apply a pure threshold based techniques for abdominal MRI segmentation [3]. The K-means and fuzzy c-means methods are also not directly adapted to noisy abdominal images [2]. Snakes or active contours are extensively used in medical image segmentation [4],[5]. Active contours are useful, but they are not automatic and sensitive to the initial contours. Besides, they need properly designed internal and external energy to control the boundary evolutions. Other strategy is marker-controlled segmentation [6]. This approach is based on the idea that machine vision systems often roughly know the location of the objects to be segmented from other source. The marker methods are simple, but they don't have enough ability for automatic segmentation of objects. The watershed segmentation technique has been widely used in medical image segmentation [7], [8]. It has interesting properties that make it useful for many different image segmentation applications. Watershed transform is simple and intuitive, can be parallelized, and always produces a complete division of the image. However, it is sensitive noise and gives rise to over segmentation if directly applied to image.

In this paper, we have proposed a new method for automatic spleen segmentation in abdominal MRI images. The algorithm is fully automatic and contains several stages including preprocessing, segmentation and feature extraction using recursive watershed transform and feature extraction using neural network. The preprocessing stage is applied for required image enhancement. We then used morphological watershed transform for image segmentation due to its efficient segmentation properties. However, when pure watershed transform is applied to MRI images directly, it results in over-segmentation. To overcome the problem of over-segmentation, we used a combined neural network and watershed algorithm for image segmentation. We trained and

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978-1-4244-8819-3/10/$26.00 ©2010 IEEE

used feed forward neural networks to extract some features from MRI image. The features are also extracted from segmented image using watershed transform. The output of watershed transform is compared to neural network output and the difference is used to adjust the required parameters of the algorithm sequentially. To obtain optimum parameters for the proposed algorithm we change the parameters gradually in several iterations. We compared the results proposed algorithms with those of another method and the results showed the efficiency of proposed algorithm from the point of view of calculation complexity, segmentation quality and its convergence rate.

The organization of the paper is as follows. Section 2 describes the proposed algorithm for spleen segmentation. Section 3 represents the results and finally conclusion appears in section 4.

II. AUTOMATIC SPLEEN SEGMENTATION SYSTEM

Figure 1 shows the block diagram of the proposed system. The proposed system is an intelligent system for spleen segmentation in abdominal MRI images, which consist of different stages including preprocessing, segmentation and feature extraction using recursive watershed transform and feature extraction using neural network. The preprocessing stage consists of image enhancement including noise elimination and edges distinguishing. We applied three consecutive processes on input image in preprocessing stage including morphological smoothing, Gaussian filtering and morphological gradient. We used morphological watershed transform for spleen area extraction due to its efficient segmentation properties. However, when pure watershed transform is applied to MRI images directly, it results in over-segmentation. To overcome the problem of over-segmentation, we used a combined neural network and watershed algorithm for image segmentation as it is shown in Fig. 1.

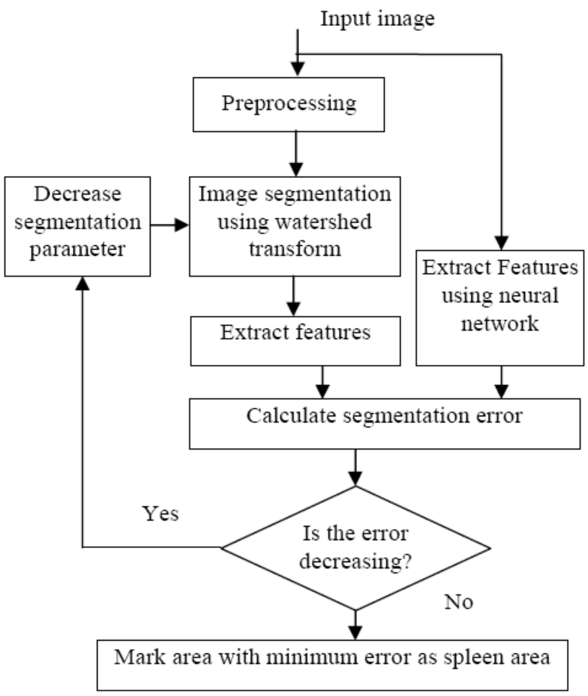

Fig. 1. Block diagram of the proposed system

We trained and used feed forward neural networks to extract some features from MRI image. The features are also extracted using segmented image using watershed transform. The features that are extracted from the output of watershed transform are compared to neural network outputs and the difference is used to adjust the required parameter of the algorithm sequentially. To obtain optimum parameter for the proposed algorithm we change the parameter gradually in several iterations. In each iteration the segmentation error is calculated which is the multiplication of squared error between the features extracted by neural network and watershed transform. In the case of decreasing error we adjust the parameters of the algorithm and repeat the segmentation algorithm again, otherwise the algorithm terminates. The spleen area is extracted using the output of watershed transform with optimum parameter value.

A. *Preprocessing*

Most of abdominal MRI images are noisy and the edges of objects are not clear enough in these images. Hence the usual segmentation algorithms, leads to not recognizing main edges as well as recognizing additional boundaries. To handle this problem, we applied preprocessing stage to the input image before applying the main segmentation stage. The proposed preprocessing algorithm is the combination of different morphological operations [9]. Three different processes are applied to prevent the generation of insignificant regions in the main segmentation stage. These processes are morphological smoothing, Gaussian filtering and morphological gradient.

Morphological smoothing is used to remove dark artifacts as well as noise. Morphological smoothing technique that is used in our system is the combination of dilation and an erosion operator which is called closing operator and it is defined as follow:

$$MSI = A \bullet B = (A \oplus B) \ominus B \tag{1}$$

where A is the original image, B is defined as structuring element with desired dimensions and MSI is the morphological smoothed image. In Eq. 1, $\ominus$ is defined as erosion operator and $\oplus$ is defined as dilation operator. The closing operator eliminates small dark noises in grayscale image.

We then apply Gaussian filter. The kernel for Gaussian filter is calculated using Eq. 2 and applied to the output of previous step i.e. MSI to produce GFI as follows.

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp\left[\frac{\left(-x^2-y^2\right)}{2\sigma^2}\right] \tag{2}$$

$$GFI = MSI * G \tag{3}$$

where σ is the standard deviation of the Gaussian filter and * represents 2D convolution. We used morphological gradient as the last step of preprocessing stage. Morphological gradient is defined as the subtraction of an eroded version of the input image from the dilated version of it as follow:

$$MGI = (GFI \oplus B) - (GFI \ominus B) \tag{4}$$

where B is the structuring element. The morphological gradient operator results in highlighting the boundaries in input image. We applied the morphological gradient on the Gaussian Filtered Image (GFI), because it will raise the main edges and eliminate the unnecessary edges [10]. The benefit of using morphological gradient relative to other gradient operations is its less dependence to direction of edge [9].

The size, shape and direction of structuring element are important factors to have proper output. We used 3×3 square structuring element as follow:

$$B = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{5}$$

B. Image Segmentation and Feature Extraction using Recursive Watershed Transform

After applying necessary preprocessing, the algorithm for spleen area extraction is applied. We used watershed transform for spleen area extraction from abdominal MRI images. The watershed transform [11-12-13] is a popular segmentation method coming from the field of mathematical morphology.

Generally watershed transform is applied to gradient of image, however applying the watershed transform directly results in a myriad of small regions, which makes the result hardly useful. Applying preprocessing stage removes some noisy areas; however the output is not satisfactory for automatic spleen area extraction. To handle this problem we applied watershed transform to the scaled and thresholded gradient image (*STGI*), where *STGI* is defined as follow:

$$STGI = \begin{cases} SC \times MGI & MGI > \left(\min\left(MGI\right)/SC\right) \\ \min\left(MGI\right) & o.w. \end{cases} \tag{6}$$

where *SC* is a scale factor between min(*MGI*)/max(*MGI*) and 1. The watershed transform is applied to *STGI*. Changing the value of *SC*, changes the number of areas detected by watershed transforms. For the value of *SC*=1, the *MGI* is the same as *STGI* and all areas in *MGI* are detected by watershed transform. Decreasing *SC* removes small peaks in *MGI*. Therefore areas related to small peaks are removed by watershed transform. The value of

$$SC=\min(MGI)/\max(MGI) \tag{7}$$

removes all peaks in *STGI* and no area is detected by watershed transform.

The value of *SC* has a major effect on the accuracy of spleen extraction algorithm. To obtain optimum value for *SC,* we set *SC=1* initially and reduce the parameter gradually in several iterations to obtain optimum *SC* value using the following algorithm:

- Calculate *STGI* image using current *SC* value.
- Segment *STGI* image by applying watershed transform.
- Extract special features from the segmented image.
- Compare the feature extracted from watershed transform with feature extracted using neural network and calculate segmentation error.
- If the segmentation error is decreasing, reduce *SC* value and repeat the algorithm, otherwise use the output of watershed transform to extract spleen area.

We used shape based features for obtaining optimum *SC* value. The spleen, liver, kidney and muscles areas are the biggest areas in abdominal MRI image. Therefore, among the segmented regions by watershed transform, twenty biggest regions are selected. Then, four shape based features are extracted for each region which are the center of mass in *x* and *y* directions and the perimeter and area of the region. To make the features more robust against the size variation of the input image we normalize the extracted feature using the input dimension. The normalized features are given by:

$$CMx_i = \frac{\sum_{j=1}^{N_i} x_{ij}}{R \times N_i} \tag{8}$$

$$CMy_i = \frac{\sum_{j=1}^{N_i} y_{ij}}{C \times N_i} \tag{9}$$

$$A_i = \frac{N_i}{R \times C} \tag{10}$$

$$P_i = \frac{M_i}{R + C} \tag{11}$$

where CMx_i, CMy_i, A_i and P_i are normalized center of mass in *x* and *y* directions, normalized area and normalized perimeter for region *i* respectively. *R* and *C* are also the height and width of input image and M_i and N_i are the number pixels in the area and perimeter of region *i*.

When the features are extracted they are compared with the features extracted using neural network and segmentation error is calculated. To calculate he segmentation error, we first calculate the error between the features of region *i* and features of neural network as follow:

$$E_i=(CMx_i-CMx)^2(CMy_i-CMy)^2(A_i-A)^2(Pi-P)^2 \tag{12}$$

where *CMx, CMy*, *A* and *P* are features extracted by neural network and E_i is the error for region *i*. The segmentation error, *E*, is considered as the minimum of E_i as follow:

$$E = \min_{i=1}^{20}\left(E_i\right) \tag{13}$$

C. Feature Extraction using Neural Network

We used feed forward neural network to estimate the required features from the input image without segmentation. We utilized four different neural networks which are trained individually for the estimation four features discussed before.

We utilized three layers neural networks which are trained using back propagation technique [14]. To obtain necessary inputs for the training of neural networks we first normalize the training images to the constant size of *m*×*n*. Then the average intensity values are calculated for different columns and rows of the normalized images. The result of averaging is a vector of size *m+n* for each image which is used as the input of neural networks during training and the test of neural networks. Every neural network has one output which its value during the training of neural networks is determined by manually segmenting the spleen area in the input image and calculation of the related normalized feature values.

D. Spleen Area Extraction

When the optimum value for the *SC* is obtained using the method described in section 2.2. The area with minimum error (Eq. 12), which is extracted by applying watershed transform using optimum *SC* value, is considered as spleen area.

III. Experimental Results

The proposed algorithm implemented using a Matlab program. We used 28 abdominal MRI for the test of proposed algorithm where 50% of images are selected randomly for training of the neural networks. We used four three layer neural network for the extraction of features. Neural networks have 160 neurons in the first layer, 18 neurons in the second layer, and, one neuron in the third layer. Sigmoid activation function is used in the first and second layer, and, linear function is used in the third layer. The neural networks are trained in 400000 iterations and learning rate of α=0.004. Selection of this learning rate makes the neural network training time to increase, but the obtained weights have the high reliability.

Figure 2 shows the effect of preprocessing stage on a typical abdominal MRI. We used Gaussian filter of σ=1 in our tests. Table 1 shows the effect of *SC* on the number of regions detected by watershed transform for a typical MRI image. As it is shown in this table, the number of detected regions increases by increasing SC value. Table 2 and 3 show the extracted feature for 5 test images using neural networks and recursive watershed transform with optimum *SC* value. As it is represented in table 3 the segmentation errors, *E*, are negligible.

Figure 3 demonstrates the results of segmentation using watershed transform on a typical abdominal MRI. For comparison the output of watershed transform are shown for input image, input image after applying preprocessing stage (*SC*=1) and the output of segmentation with optimum *SC* value (*SC*=0.1612). Applying the watershed transform to input image leads to over-segmentation as it is shown in Fig. 3b. In this case watershed transform segments the input image to 2163 regions. By applying preprocessing stage before the watershed transform the number of detected regions are decreased to 223 regions, however as it is depicted in Fig. 3c the spleen area are not extracted completely. By using the proposed algorithm and obtaining optimum *SC* value the spleen area is segmented completely as it is shown in Fig. 3d.

In table 4 the accuracy proposed system is compared with active contour method for 5 randomly selected MRIs. To calculate accuracy we used the following equation:

$$acc = \frac{N(A \cap B)}{N(A \cup B)} \tag{14}$$

where the *A* is the area of spleen extracted manually by an expert, *B* is the area of the spleen extracted using the algorithm, $N(A \cap B)$ is the number of pixel for the intersection of two area *A* and *B* and $N(A \cup B)$ is the number of pixel for the union of two area *A* and *B*. For the best case, when the extracted area by algorithm is the same as area extracted manually, the acc would be 1. For the active contour we used the implementation of [4] and selected the initial contour inside the spleen area. It is very important to note that the active contour method is not an automatic algorithm. However as it is shown in table 4 the accuracy of the proposed algorithm is better than active contour algorithm. The results show that although the proposed algorithm is automatic, the results of the algorithm are more satisfactory than semi-automatic approaches which require human interfere.

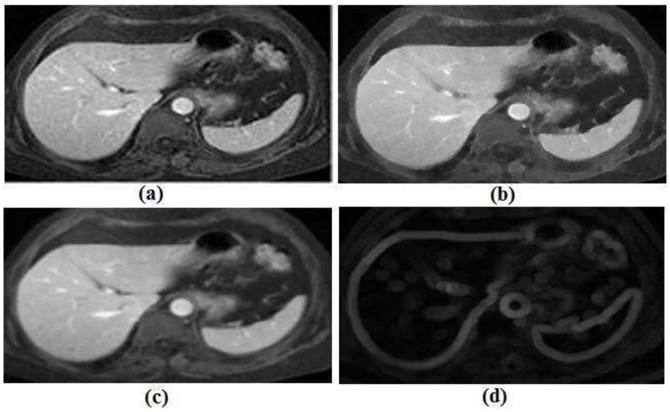

Fig. 2. The results of preprocessing stage (a) Original image (b) output of morphological smoothing (c) output of Gaussian filter (d) output of morphological gradient

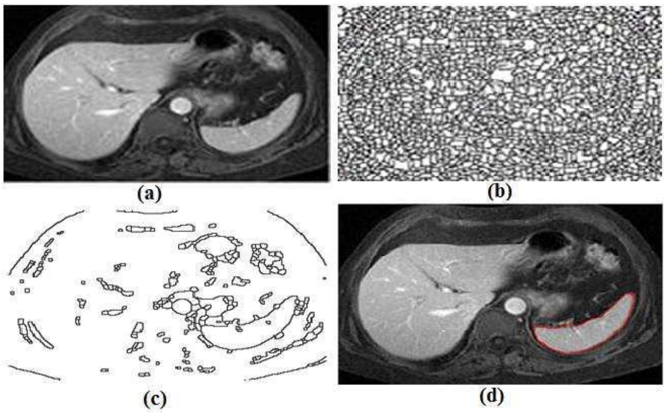

Fig 3. Results of segmentation using watershed transform (a) original image (b) Applying watershed transform directly to the original image (c) Applying watershed transform directly to preprocessed image (*SC*=1) (d) spleen segmentation using proposed algorithm (optimum *SC*=0.1612

TABALE I
The Effect of *SC* Parameter on the Number of Regions Detected by Watershed Transforms

Scaling parameter (SC)	Number of detected regions
0.10	120
0.15	411
0.20	724
0.30	1404
0.60	1654

TABLE II
Results of Feature Extraction using Neural Network

Image	A	P	CMx	CMy
1	0.0330	0.2614	0.6990	0.7675
2	0.0463	0.2783	0.6908	0.7901
3	0.0581	0.2841	0.5501	0.7990
4	0.0644	0.3371	0.6257	0.8182
5	0.0614	0.2808	0.5158	0.8347

TABLE III
THE CALCULATED FEATURES USING WATERSHED TRANSFORM WITH OPTIMUM *SC* VALUE

Image	A	P	CMx	CMy	E
1	0.0291	0.3219	0.6733	0.8001	3.9×10^{-14}
2	0.0349	0.2153	0.6402	0.7211	6.28×10^{-12}
3	0.0618	0.2711	0.5911	0.7881	4.61×10^{-16}
4	0.0522	0.2688	0.6701	0.8239	6.84×10^{-5}
5	0.0743	0.2603	0.5926	0.7981	4.47×10^{-13}

TABLE IV
ACCURACY OF ACTIVE CONTOUR AND PROPOSED METHOD FOR SPLEEN AREA EXTRACTION

Image	Active contour	Proposed method
1	0.8533	0.8647
2	0.8909	0.9075
3	0.9071	0.9217
4	0.8631	0.9135
5	0.8134	0.8277

IV. CONCLUSION

In this paper, we proposed a new algorithm for spleen segmentation in abdominal MRI images. The proposed algorithm is automatic and use a combined neural network and recursive watershed transform for obtaining optimum parameter and spleen segmentation. The proposed algorithm tested with different abdominal MRI and results showed the efficiency of proposed algorithm. In the future, we are going to complete the proposed algorithm for the segmentation of kidney in abdominal MRI.

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