Liver Segmentation in MRI Images using an Adaptive Water Flow Model

Marjan Heidari[1], Mehdi Taghizadeh[2]*, Hassan Masoumi[3], Morteza Valizadeh[4]

[1]PhD Candidate, Department of Biomedical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran
[2]PhD, Department of Electrical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran
[3]PhD, Department of Biomedical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran
[4]PhD, Department of Electrical and Computer Engineering, Urmia University, Urmia, Iran

ABSTRACT

Background: Identification and precise localization of the liver surface and its segments are essential for any surgical treatment. An algorithm of accurate liver segmentation simplifies the treatment planning for different types of liver diseases. Although liver segmentation turns researcher's attention, it still has some challenging problems in computer-aided diagnosis.

Objective: This study aimed to extract the potential liver regions by an adaptive water flow model and perform the final segmentation by the classification algorithm.

Material and Methods: In this experimental study, an automatic liver segmentation algorithm was introduced. The proposed method designed the image by a transfer function based on the probability distribution function of the liver pixels to enhance the liver area. The enhanced image is then segmented using an adaptive water flow model in which the rainfall process is controlled by the liver location in the training images and the gray levels of pixels. The candidate liver segments are classified by a Multi-Layer Perception (MLP) neural network considering some texture, area, and gray level features.

Results: The proposed algorithm efficiently distinguishes the liver region from its surrounding organs, resulting in perfect liver segmentation over 250 Magnetic Resonance Imaging (MRI) test images. The accuracy of 97% was obtained by quantitative evaluation over test images, which revealed the superiority of the proposed algorithm compared to some evaluated algorithms.

Conclusion: Liver segmentation using an adaptive water flow algorithm and classifying the segmented area in MRI images yields more robust and reliable results in comparison with the classification of pixels.

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Keywords

Image Processing; Image Enhancement; MRI Scans; Artificial Intelligence; Image Processing; Computer-Assisted

Introduction

Medical imaging is a useful diagnostic tool for characterizing organs in the medical diagnosis and treatment process [1]. It enables the inspection of the organs of the body in a non-invasive manner and allows the specialists to view the anatomy that cannot be achieved by the other ways. Medical decisions and modern surgeries extremely rely on software and computer-aided programs such as imaging techniques [2]. One of the fundamental problems of medical image analysis is the image segmentation that some research has been conducted on it. In medical images, the quality of segmentation is affected

*Corresponding author: Mehdi Taghizadeh
Department of Electrical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran
E-mail: m.taghizadeh@kau.ac.ir

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by some factors such as overlapping of different organs contours, noises, variable shape and intensities of desire organs, and similar intensities of other organs [3]. Automatic liver segmentation in medical images, including Magnetic Resonance Imaging (MRI) and CT scan is still a challenging problem [4]. For any surgical treatment, identification and precise localization of the liver surface and segments are essential [5]. An accurate liver segmentation algorithm can simplify the treatment planning for different types of liver diseases [6].

Gloger proposed a three steps liver segmentation algorithm using the Linear Discriminant Analysis (LDA) based probability maps of multiple MRI images [7]. The algorithm is based on a thresholding algorithm and a modified region growing approach. In this study, all available MR-channel information is employed to identify the liver issue and position probability. The probability maps, which are formed by employing the multiclass discriminant analysis, are used in the segmentation stage.

Liver segmentation in the MRI images strictly suffers from intensity inhomogeneity. Liu proposed an intensity inhomogeneity correction with edge- preservation method [8]. First, the intensity inhomogeneity was corrected by local entropy. Subsequently, the image is filtered by an edge-preserving method. Finally, the detail loss is compensated by the cooperation of the original image. The intensity modification is performed on the internal energy of the level set method. Besides, external energy is affected by the edge preservation, which drives the minimum energy level toward the boundaries of liver.

Said introduced a liver segmentation based on Moth-flame optimization (MFO) algorithm [9], clustering the abdominal MRI image. The initial clusters for representing the segmented image are selected by uses. The morphological operations are used to produce the final segmented liver image. In another research, the whale optimization algorithm was utilized for clustering of MRI image [10] and used a statistical image, determining the candidate location of the liver in the image, by multiplying the binarized statistical image with the clustered image, and a great part of other organs is removed. Some clusters representing the liver area are selected by users to form the initial segmentation. Finally, the segmentation results are enhanced by the morphological operations.

Huynh proposed a 3D liver segmentation scheme in [11]. In this method, an anisotropic diffusion filter is used to reduce the noise by preserving the liver boundaries. After that, an edge enhancer and a nonlinear gray-scale transfer function are used to enhance the liver boundaries. In addition, a fast marching algorithm generates an initial surface that approximates the liver shape. Finally, an active contour segmentation algorithm refines the initial surface to determine liver boundary precisely.

An automated 3D liver segmentation scheme has been proposed in [11] and uses an anisotropic diffusion filter to reduce the noise while preserving the liver boundaries. Then an edge enhancer and a nonlinear gray-scale transfer function are used to enhance the liver boundaries and a fast marching algorithm generates an initial surface that approximates the liver shape. Finally, an active contour segmentation algorithm refines the initial surface for precise determination of the liver boundary.

A fusion of watershed and the neural network has been proposed for liver segmentation [12]. Traditional watershed transform generally leads to the over-segmentation of medical images. Therefore, a neural network was trained based on the features of the liver to adjust automatically the parameters of the watershed, enhancing the segmentation quality.

In [13], fuzzy theory and the level set were used for liver segmentation. A level set and probabilistic map were used in [14], using some manually segmented images for training the algorithm. In [15], active contours were used to segment the liver in MRI. The initial boundary was defined based on the knowledge of radiologists.

Recently, a liver segmentation algorithm in Gd-EOB-DTPA-enhanced MRI based on the fully convolutional residual network was proposed [16]. The main disadvantage of segmentation algorithm-based on deep learning is their need to the training sample, which is not easily available in many research areas.

The water-flow algorithm was used to segment document images [17-18], in which the image is regarded as area and drops of water are poured image. The poured water flows down the low altitude area representing the black objects. Therefore, the level of water at valleys rises. By thresholding the water amount on the image surface, the image is segmented. Proper controlling of the rainfall process is essential for the success of these segmentation algorithms.

In this paper, an algorithm of reliable liver segmentation based on an adaptive water-flow model is introduced. To avoid over-segmentation of MR images, the rainfall process is controlled with the intensity distribution of liver area in the training images and statistical map of the liver. The proper features, which are extracted from candidate liver segments, are classified by MLP neural network. Classifying segments instead of pixels leads to robust and accurate liver segmentation results.

Material and Methods

In this experimental study, the proposed algorithm enhances the MRI image and segments the liver area using an adaptive water flow method. The candidate liver segments are classified by MLP neural network, trained by some manually segmented images.

MRI images description

The proposed algorithm was trained and evaluated by a dataset from the imaging center of Namazi hospital, Shiraz, Iran. It contains 500 MRI images with the size of 320×320 pixels captured using A 1.5 tesla Philips MRI (INTERA, PHILIPS MEDICAL SYSTEMS, EINDHOVEN, NETHERLANDS). The slice thickness, magnetic field strength, and flip angle were set to 5.0 mm, 1.5 T, and 50°, respectively. The MRI images were manually segmented by a radiologist to train the system and evaluate the segmentation algorithm. The training dataset includes 250 MRI images and the remaining 250 MRI images, named test dataset, was used for evaluating the performance of the liver segmentation algorithm.

Enhancement of Liver region

The similar intensities of different organs in the MRI and the variable intensities of the liver cause segmentation to be a challenging problem. Therefore, some enhancement algorithms are used to map the liver area into a certain interval of gray levels to facilitate liver segmentation. In this research, the probability distribution function of the liver gray levels is used to design the transfer function. Also, three-channel MRIs are used to eliminate the blood vessels of the liver, hence reducing the intensity variability of the liver.

Elimination of blood vessels

Most blood vessels of the liver commonly appear in a specific MRI channel and disappear in the previous or next channel. Thus, the blood vessels can be eliminated by three-channel processing of MRI images. Suppose I_{t-1}, I_t, I_{t+1} are three consecutive MRI channels and the channel I_t processes to eliminate its blood vessels. Figure 1 shows three channel MRIs and the result of the proposed method. Red rectangular boxes reveal that the blood vessels of the channel I_t rarely appear in both I_{t-1}, I_{t+1} channels. Therefore, a simple three-channel processing the operations according to Equation (1) can reduce the effect of blood vessels in the segmentation process.

$$I(x,y)=\begin{cases} min\left(I_{t+1}(x,y), I_t(x,y), I_{t-1}(x,y)\right) I_t(x,y)>T_1 \\ I_t(x,y)>T_1 \;\; I_t(x,y)\leq T_1 \end{cases} \quad (1)$$

Transfer function design

The liver is surrounded by other organs that some are brighter than the liver and the oth-

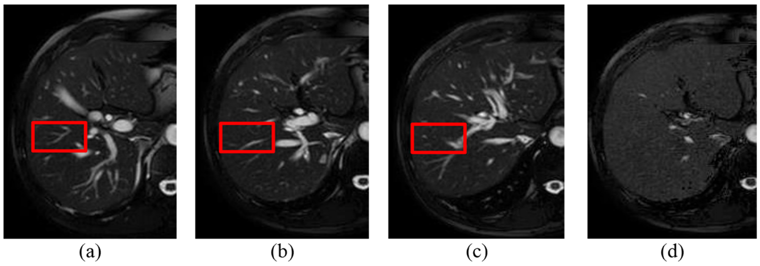

Figure 1: Three consecutive Magnetic Resonance Imaging (MRI) channels (a) I_{t-1}, (b) I_t, (c) I_{t+1} and (d) blood vessel elimination result

ers are darker. In addition, the gray levels of the surrounding organs and liver are close, the iver-regmentation process faces more difficulty. In this paper, a transfer function will be introduced based on the probability distribution of the liver, mapping the liver area into a specific gray-scale interval and the other organs can approximately be distinguished from the liver. To form the probability distribution of the liver, 500 MRI images were manually segmented by the radiologist, and the liver areas were labeled. The occurrence of the gray levels in the liver area was calculated and normalized. Then, the probability distribution, named p_L, was obtained. The transfer function was designed in a way that the liver area is mapped to the dark gray levels and the other organs as much as possible are mapped to the bright gray levels. The transfer function represented by Equation (2) significantly satisfies our requirements. Figure 2 shows the probability distribution of the liver gray levels and the designed transfer function.

$$f(l) = 255\left(1 - \frac{p_{L(l)}}{\max\limits_{0 \le l \le 255}\left(p_{L(l)}\right)}\right) \qquad (2)$$

Appling the proposed transfer function to the MRI image properly enhances the liver area. The fine details of the enhanced MRI image are neglected by a Gaussian low pass filter to increase the performance of segmentation. The enhanced liver area and its filtered version are shown in Figure 3.

Image segmentation by Adaptive water flow algorithm

In a water-flow algorithm, water drops are poured on the image surface, which can be imagined as a mountainous area. The water flow model directs the drops of rain toward valleys by finding the minimum value inside a small searching, and shifting its center into the minimum point. In a water-flow algorithm, the rain-drops are poured on the image surface, which can be imagined as a mountainous area. The water flow model directs the drops of rain toward valleys by finding the minimum value inside a small searching, and shifting its center into the minimum point. The process is continued till the minimum value inside the searching mask is found at its center, where the drop is placed. Therefore, the poured water finds

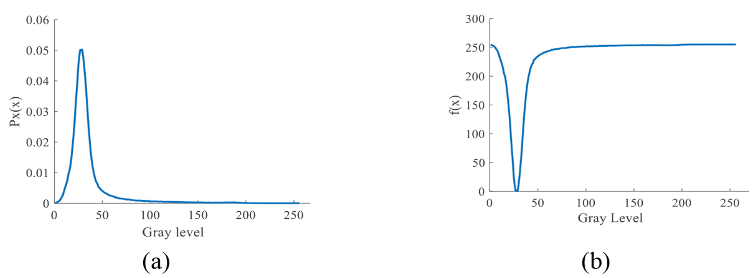

Figure 2: Illustration of (a) probability distribution function of liver gray levels, (b) designed transfer function.

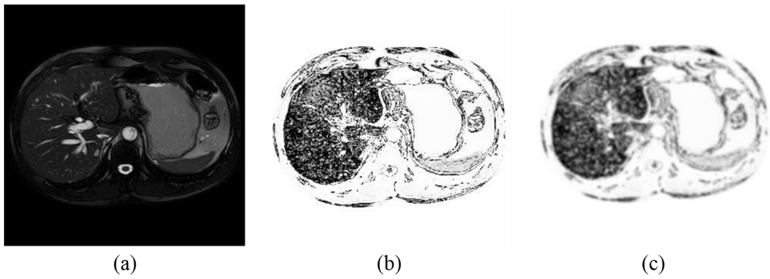

Figure 3: Enhancement of liver area (a) original image (b) image after applying the designed transfer function and (c) smoothed version of image

and fills the valleys; hence low altitude region can be distinguished from the others by thresholding the water amount on the surface. This algorithm may result in an over-segmentation problem if the stopping of the rainfall process exceeds the optimal value of rainfall. Also, the liver region may break into several small segments if the rainfall stops before reaching the optimal value of the rainfall process. Therefore, adaptive control of the rainfall process is necessary for appropriate segmentation.

A locally rainfall stopping criterion

The rainfall process is locally controlled at each point based on gray level and location of the pixels in the MRI image. A statistical liver map (SLM) is generated by counting the frequency of belonging each point into the liver area in the manually segmented MRI. Here T_i represents the i^{th} manually segmented MRI image, in which the pixels representing the liver area are marked with one, other pixels are marked with zero, and SR is an image determining the stopping of rainfall. The SLM and SR images are formed according to Equations (3) and (4), respectively.

$$SLM(x,y)=\frac{1}{500}\sum_{i=1}^{500}T_i(x,y) \tag{3}$$

$$\mathrm{SR}(\mathrm{x},\mathrm{y})=\frac{255\times p_L(I_t(x,y))}{\max\limits_{0\le l\le 255}[p_L(l)]}\times SLM(x,y)^{\gamma} \tag{4}$$

Where I_t (x,y) denotes the intensity of pixel located at (x,y) in the original MRI image and γ is a parameter experimentally set to 0.3. The rainfall continues at pixel (x,y) until the number of droplets poured on that pixel is smaller than the value of $SR(x,y)$.

Candidate liver segments extraction

After stopping the rainfall process at all pixels of the image, the water amount (WA) is calculated using Equation (5).

$$WA(x,y)=G(x,y)-I(x,y) \tag{5}$$

Where $G(x,y)$ and $I(x,y)$ are the images after and before applying the water flow algorithm, respectively. The water amount is thresholded using Equation (6) to find the candidate liver segments.

$$CL(x,y)=\begin{cases}1 & if\ \ WA(x,y)\ge T\\ 0 & if\ \ WA(x,y)<T\end{cases} \tag{6}$$

Where T is a threshold computed using the Otsu algorithm, maximizing the intra distance between two classes to find the optimal threshold value [19]. Figure 4 (a-d) shows the statistical liver map, stopping of rainfall, water amount, and candidate liver images for the MRI image shown in Figure 3(a).

Classification of candidate liver segments

Each candidate segment is classified as either liver or non-liver to obtain the final segmentation of MRI. First, the segments are mapped to the proper feature space and finally classified by MLP neural network.

Feature extraction from candidate liver segments

To discriminate liver segments and the other organ's segments, eight features are extracted

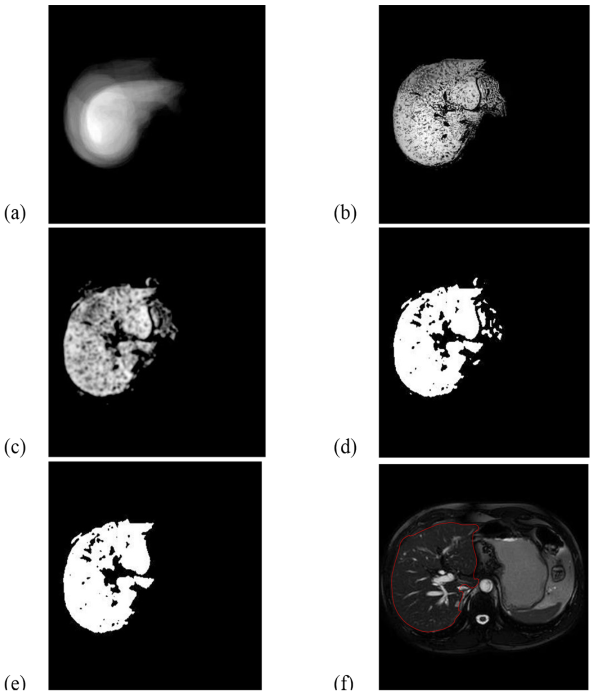

Figure 4: Different stages of liver segmentation (a) statistical liver map (b) stopping of rainfall (c) water amount (d) candidate liver (e) output of classification (f) final boundary of the liver.

from the candidate livers. The texture features are extracted using Grey-Level Co-occurrence Matrix (GLCM), revealing the occurrence of the pair of pixels with a specific value and distance in the image or sub-image [20].

In this paper, the GLCM matrix was obtained for each candidate liver segment in the directions 0 and 90 degree and distance offset of 1 pixel. The two GLCMs were averaged before the feature extraction. Five texture features, including contrast, energy, homogeneity, correlation and entropy [20] were extracted using the averaged GLCM. Beside the texture features, three features including average gray level (AGL), average water amount (AWA), and the area of segments were computed. Here S_i presents the pixels belonging to the i^{th} candidate liver segment. The aforementioned features are computed by equations (7-9).

$$Area_i = \sum_{(x,y)\in S_i} 1 \tag{7}$$

$$AGL_i = \frac{1}{Area_i} \sum_{(x,y)\in S_i} I(x,y) \tag{8}$$

$$AWA_i = \frac{1}{Area_i} \sum_{(x,y)\in S_i} WA(x,y) \tag{9}$$

Classification of segments by MLP

Each candidate liver segment is represented by eight features. In this research, an MLP neural network is used to classify the candidate liver segment as either liver area or non-liver area. The MLP is a well-known artificial neural network for classification purposes. An artificial neural network consisst of some layers. Each layer is composed of some interconnected units that serve as model neurons. The output of each neuron is only passed to the neurons of the next layer. The feature vector is given to the input layer and the final output is received from the output layer. The MLP network can classify the input feature vector accurately if its parameters, including weights and biases, are adjusted properly by a learning algorithm with a minimum error function. The error back-propagation is a well-known learning algorithm, iteratively changing the network parameters and the negative gradient of the error function and the learning process is stopped when the predefined criteria are met.

An MLP network with one hidden layer, containing enough neurons and utilizing an appropriate nonlinear transfer function is, typically sufficient for classifying objects [21]. Therefore, a 3-layer network was selected for our application and the number of units in the hidden layer was experimentally set to 12. The candidate liver segments of 250 liver images were labeled according to the ground-truth images generated by a radiologist and 261 liver segments and 2531 non-liver segments were annotated and used to train the MLP. The remaining ground truth images were used to evaluate the network and segmentation algorithm. The trained MLP resultes in the accuracy of 98.7% for test candidate liver segments.

Liver boundary extraction

In this step, the boundary of the liver is extracted as follows: a binary image is generated in which the liver area pixels are labeled as 1 and the remaining pixels are labeled 0. Consequently, a morphological operator is applied to the image to process the image by a disk shape structuring element filling the remaining holes in the liver area and find the white area boundary. Finally, the boundary is smoothed using an averaging filter.

Results

The performance of the introduced liver segmentation method was evaluated over the test dataset, including 250 MRIs with accuracy of 97%. Figure 4(e-f) shows the results of liver area classification and the extracted liver boundary for the image shown in Figure 3(a).

Discussion

Results were compared to those of three liver segmentation the algorithm including, liver segmentation by whale optimization [10], multi-variability model-based liver segmentation algorithm [4], and liver segmentation based on watershed and neural network [12] to evaluate the performance of the introduced method. The evaluation criteria, including similarity index, precision, and accuracy [10], defied according to Equations (10-12), were calculated over the test set (Table 1).

$$\text{Similarity index} = \frac{I_{auto} \cap I_{man}}{I_{auto} \cup I_{man}} \tag{10}$$

Table 1: Comparison of proposed method and three other methods.

	Similarity index	Precision	Accuracy
Whale optimization [10]	0.94±0.06	0.91±0.03	0.92±0.04
Multi-variability [4]	0.92±0.03	0.88±0.06	0.90±0.02
Watershed [12]	0.90±0.05	0.87±0.03	0.89±0.04
Proposed method	0.96±0.03	0.93±0.06	0.97±0.04

$$\text{Accuracy} = \frac{TP + TN}{N} \tag{11}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{12}$$

The experimental results of the proposed method showed good efficiency and performance in comparison with the other algorithms that are evaluated in Table 1.

The main reasons in the proposed algorithm's high efficiency can be summarized as follow: (I) employing a new transfer function for discrimination of liver pixels from others, (II) using an adaptive water flow model which controls the rainfall process based on some knowledge about the statistical position of liver and its gray levels, and (III) Classifying segments instead of classifying the isolated pixels.

Conclusion

Liver segmentation is a challenging problem in medical image processing. In this paper, an algorithm based on an adaptive water flow model was presented, enhancing the liver area by the probability distribution function in the liver pixels and segmenting the enhanced image using an adaptive water flow model. The candidate liver segments are classified by an MLP neural network considering some texture, area, and gray level features. Since the segments are classified instead of classifying the pixels, the algorithm yields robust results. Experimental results revealed the superiority of the proposed algorithm compared to the evaluated algorithms.

Conflict of Interest

None

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