

* 研究論文 *

Shape and Texture Priors for Liver Segmentation in Abdominal Computed Tomography Scans Using the Particle Swarm Optimization Algorithm

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Abstract

Accurate medical diagnosis requires the segmentation of a large number of medical images. Although manual segmentation provides good results, it is a costly process in terms of both money and time. Automatic segmentation, on the other hand, remains a challenge due to low image contrast and ill-defined boundaries. In this report, we propose a fully automated medical image segmentation framework in which the segmentation process is constrained by two prior models: a shape prior model and a texture prior model. The shape prior model is constructed from a set of manually segmented images using principal component analysis (PCA), while wavelet packet decomposition is used to extract the texture features. The Fisher linear discriminant algorithm is employed to build the texture prior model from the set of texture features and to perform preliminary segmentation. Then, the particle swarm optimization (PSO) algorithm is used to refine the preliminary segmentation according to the shape prior model. In this work, we tested the efficacy of the proposed technique for segmentation of the liver in abdominal CT scans. The obtained results demonstrated the efficiency of the proposed technique in accurately delineating the target objects.

Key words: Medical image segmentation, Shape priors, Particle swarm optimization, Liver segmentation

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1. Introduction

Although the medical image segmentation and the analysis of anatomical structure are very essential in medical diagnosis, it is very difficult and it requires a considerable amount of experience and knowledge. In the manual segmentation, the radiologist or the physician uses his/her experience to perform the segmentation, but when the amount of available data increased, the manual segmentation becomes a tough process and it is becoming essential to perform it automatically.

Many researchers attempt to automate the medical image segmentation process and several methods have been developed for this purpose [1, 2]. The traditional methods utilize the intensity changes in order to extract the edges and the local features of the desired objects [3] or they start with a seed point inside the region of interest and then grow the region by using the similarity measures [4, 5]. Despite these methods are helpful in some situations, they do not work well for medical applications because of noise, clutter, occlusion and the similarity between objects intensity.

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More advanced and a state of the art methods, model the segmentation problem as an optimization of energy function [6]. In these methods, a closed curve deforms until the balance is reached between the internal and the external energy. This curve is represented as a set of control points [7] or it is embedded as a zero level in a level set function [8]. Although these methods are more accurate than the traditional methods, the reliance on image information only usually leads to inadequate results. The addition of prior information to segmentation process has shown to improve the segmentation results and recently there has been an increased interest in the methods relying on prior information.

In [9~12], the authors proposed prior shape models using principle component analysis (PCA) and active shape model. In these models, the shapes are represented using the points distribution map (PDM) which needs a hard correspondence between the manually selected points and any slight misalignment of these points leads to inconsistent segmentation results. Additionally in these models, the segmenting curve is evolved locally according to the spatial intensity around these selected points which increases the dependency on the initial guess of the curve. Rueckert et al. [13] proposed a statistical deformation model of the brain using non-rigid registration. In that model, the authors applied the PCA to a set of shapes represented by manually selected landmarks and using the gradient descent algorithm to locally optimize their position. Unfortunately, this method also needs accurate correspondence between the landmark points and the final segmentation results are highly affected by the initial curve guess. In [14], Leventon et al. overcame the problem of landmarks correspondence by applying the PCA to a set of shapes represented by signed distance function which is resistant to misalignment. On the other hand, this method depends on the image gradient and the spatial intensity for local curve evolution. The most related work to our work was proposed by Tasi et al. in [15], who adopt the implicit shape representation proposed in [14] and calculate the parameters of this model to minimize a region-based energy function. In that technique, local optimization using gradient descent was performed according to the local area properties, average intensity inside and outside the segmenting curve, which leads to unrealistic segmentation in the cases of complex texture and inaccurate initialization.

In this work, we propose an automated medical image segmentation framework incorporating both shape and texture prior. In this framework the desired texture is efficiently modeled using the wavelet packet decomposition. The prior shape model is constructed by the statistical analysis of a set of training shapes describing the variation in object shape. The particle swarm optimization algorithm (PSO) is used to accurately segment the image by directly adapting the prior shape model according to image features.

After this introduction, In Section 2, we will describe in details the proposed segmentation technique. The experimental results will be presented in Section 3 and the paper will be concluded in Section 4.

2. The proposed framework

The proposed segmentation framework consists of two stages; offline training and online segmentation as shown in **Fig. 1**. In the training stage we apply the level set method [16] on a set of manually segmented images to represent the desired objects and then the prior shape model is derived using the principle component analysis. Additionally, in this stage we extract the wavelet-based textural features and employ the linear fisher discriminate algorithm [17] to build the textural prior model. In the segmentation stage, the PSO algorithm with inertia weight [18, 19] is utilized to segment the desired object from new CT scans according to its features and the previously constructed models. In this work, we benefit from the redundancy of organ shape to segment the whole patient using selected key frames. The usage of 2D key frames reduces the memory utilization and the need of accurate correspondence between different 3D images.

1) The training stage

(1) Prior shape model formulation

Motivated by the pioneering work of Andy Tasi [15] et al., we derive the prior shape model from a set of n training images according to the following algorithm.

1. Derive the level set functions that describe the desired object from the n training images and denote it as $\Psi_i(x, y), i = 1, 2, \dots, n$.

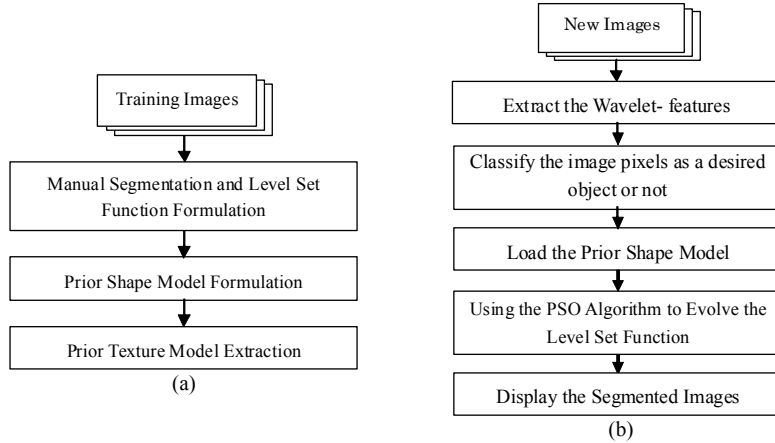


Fig. 1 The Proposed Technique; (a) the offline training stage, and (b) the online segmentation stage.

2. Compute the mean level set function $\bar{\Phi}$ from the set of level set functions Ψ_i as

$$\bar{\Phi}(x, y) = 1/n \sum_{i=1}^n \Psi_i(x, y) \quad (1)$$

3. Derive the shape variability functions $\bar{\Psi}_i, i = 1, 2, \dots, n$ as

$$\bar{\Psi}_i(x, y) = \Psi_i(x, y) - \bar{\Phi}(x, y) \quad (2)$$

4. Construct a column vectors $\psi_i, i = 1, 2, \dots, n$ consisting of N samples of each $\bar{\Psi}_i$, $N = N_1 \times N_2$ is the image size, by stacking the N_2 columns of $\bar{\Psi}_i$.

5. Define the shape variability matrix S as $S = [\psi_1 \ \psi_2 \ \dots \ \psi_n]$.

6. Employ the eigenvalue decomposition to the shape variability matrix S to compute the variance in shape as

$$1/n S S^T = U \Sigma U^T, \quad (3)$$

where U is $N \times n$ matrix whose columns represent the n orthogonal modes of variation in shapes and $\Sigma = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$ is an $n \times n$ diagonal matrix whose diagonals elements represent the corresponding eigenvalues.

7. Arrange back the N elements of each column of U to yield a vmaximum of n eigenshapes or principle modes $\Phi_i, i = 1, 2, \dots, n$.

8. Select the k – largest Eigenvectors which represent the dominant shape variations. The percentage of variation can be computed from the corresponding Eigenvalues according to the following equation.

$$\text{Variations} = 100 \times \sum_{i=1}^k \lambda_i / \sum_{j=1}^n \lambda_j, \quad (4)$$

Sample training images and its level set representation are shown in **Fig. 2**. The mean shape and the first three eigenshapes are illustrated in **Fig. 3**.

(2) Prior texture model extraction

We utilize the over-complete wavelet packet transform [20] to extract the high-level features vector for each pixel in the training images. The over-complete wavelet packet transform doesn't perform the down-sampling as in standard wavelet packet transform, so it ensures the translation invariance property which is indispensable for textural analysis. In addition, it provides robust texture features at the expense of redundancy [21]. Feature extraction using over-complete wavelet packet transform can extract all band-pass information about texture. In this work, we extract the wavelet packet feature set by employing the following algorithm.

1. Apply a two-level over-complete wavelet packet decomposition on the input image.

2. At level-1, select the four sub-bands as feature sub-images.
3. At level-2, in each sub-channel, select the sub-band with the maximum variance to be a feature sub-image
4. Calculate the local energy around each pixel of the feature sub-images as

$$E(x, y) = 1/(2m + 1)^2 \sum_{i=-m}^m \sum_{j=-m}^m F(x + i, y + j), \quad (5)$$

where $F(x + i, y + j)$ is the wavelet coefficient of a feature sub-image in the $(2m + 1) \times (2m + 1)$ window centered at pixel (x, y) .

5. Construct the feature vectors of each pixel in the image from the energy of the corresponding feature sub-images.

After the construction of the high level features vector, we assign a label to each pixel to indicate whether this pixel is a desired object pixel or not and finally, we use the linear fisher discriminate algorithm [17] to build the textural prior model. The energy, $l_2 - norm$, of each feature sub-image is a favorable feature of texture because it indicates dominant spatial-frequency channels of the original image and it leads to better classification results than the spatial domain methods as shown in **Fig. 4**. Linear fisher discriminate algorithm is a classification method that project high-dimensional data onto a line and performs classification in this one-dimensional space. This projection maximizes the distance between the means of the two classes while minimizing the variance within each class.

2) The segmentation stage

The first step in the segmentation stage is to extract the wavelet packet based feature set of the new image and then classify each pixel in this image as a desired object pixel (true) or undesired object pixel (false) according to the prior textural model. This classification processes is carried out by using the linear fisher discriminate algorithm. Finally, this stage is completed by applying the PSO algorithm to get the level set function that truly segments the image as we will clarify in the next sections. The PSO algorithm provides global shape parameters and reduces the dependency on the contour initialization. Additionally, it can achieve better results in a faster and cheaper way compared with other evolutionary computational techniques as proved in [23] and as we will clarify in the experimental results.

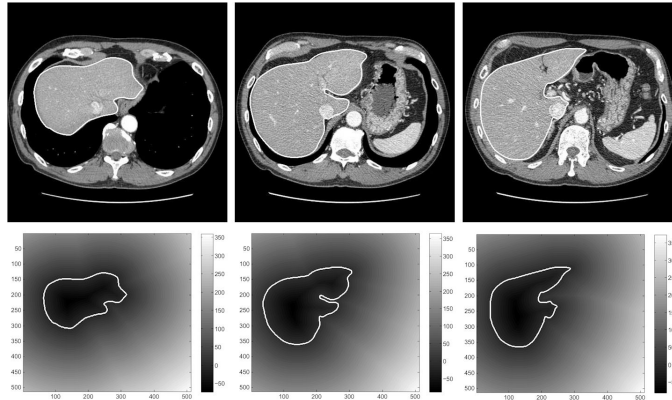


Fig. 2 Sample training images, the manual segmentation on the top and its corresponding level set representation on the bottom.

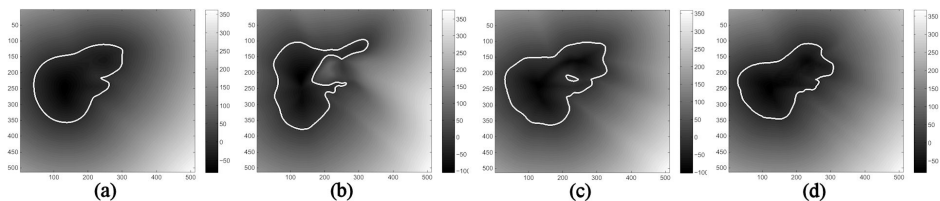


Fig. 3 Shape model; (a) the mean shape (ms), (b) $ms + \sigma_1 \Phi_1$, (c) $ms + \sigma_2 \Phi_2$, (d) $ms + \sigma_3 \Phi_3$, and $\sigma_i = \sqrt{\lambda_i}$.

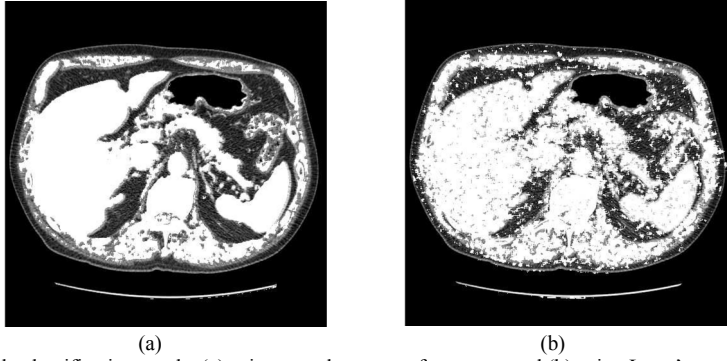


Fig. 4 Sample classification results (a) using wavelet texture feature set and (b) using Laws' texture energy [22].

(1) The model description

Each particle in the PSO population consists of the set of parameters that control the shape of the segmenting curve. As Tasi et al. did in [9], we use the mean shape and the shape variability derived from the training stage to define the level set function that implicitly represents the segmenting curve as in the following equation.

$$\Phi(x, y) = \bar{\Phi}(x, y) + \sum_{i=1}^k w_i \Phi_i(x, y), \quad (6)$$

where, k is the number of principle eigenshapes, $w_i, i = 1, 2, \dots, k$ are the weights for these eigenshapes and these weights are ranged from $-\sigma_i$ to σ_i (where σ_i^2 are the eigenvalues corresponding to these i^{th} eigenshape). In addition, we consider the pose parameters; a, b for translation, h for scaling, and θ for the rotation angle, which incorporated in this framework using an affine transform. Therefore each particle P in the PSO population is represented as $P = [(w_i, i = 1, 2, \dots, k), a, b, h, \theta]$ and it represents a segmenting curve. This segmenting curve can be expressed as the zero level of the level set function

$$\Phi(\tilde{x}, \tilde{y}) = \bar{\Phi}(\tilde{x}, \tilde{y}) + \sum_{i=1}^k \Phi_i(\tilde{x}, \tilde{y}), \quad (7)$$

where, $(\tilde{x}, \tilde{y})$ is the new coordinate system obtained using the affine transformation.

The fitness of each particle in this work represents how the corresponding curve segments the image. So in the proposed technique, we tend to maximize the fitness function proposed in [16]. This fitness function is formulated as:

$$FT = 500(A + (1 - B)), \quad (8)$$

where, A is the fraction of pixels inside the segmenting curve that are labeled "true" and B is the fraction of the pixels outside the segmenting curve that are labeled "true". The maximization of this fitness function means that more desired pixels are gathered inside the segmenting curve. The constant value 500 is a scaling factor to magnify the difference among the particles and to reduce the effect of software rounding.

(2) The PSO algorithm configuration

In this work, we are employing the PSO algorithm with inertia weight described in [18, 19]. The PSO algorithm includes an inertia term and acceleration constants which give us more control on the segmenting curve. The PSO algorithm configuration is shown in **Table 1** and the curve parameters configuration is provided in **Table 2**. The parameters in **Table 1** control how fast the PSO converge to the correct segmentation and make the balance between the global and local search, however the PSO is robust to initialization. The parameters in **Table 2** control the shape formulation and its transformation. Among these parameters, w_i have fixed ranges and the other parameters are selected practically according to the characteristic of the cases and the selection of these parameters have to guarantee that all possible variations and transformations are considered.

Table 1 PSO algorithm configuration.

Swarm Size (the number of segmenting curves)	25
The Maximum Number of Epochs	100
Local Best Influence	2
Global Best Influence	2
Initial Inertia Weight	0.9
Final Inertia Weight	0.4
Epoch When Inertial Weight at Final Value	80

Table 2 Curve parameters configuration.

Parameter Name	Parameter Range	Maximum Velocity
$w_i, i = 1, 2, \dots, k$	$-\sigma_i \sim \sigma_i$	$\sigma_i/5$
a, b	$-20 \sim 20$	2
h	$0.5 \sim 2$	0.5
θ	$-90 \sim 90$	10

(3) The PSO algorithm implementation

After we configure the PSO algorithm and adjust the curve parameters according to the desired object, we carry out the segmentation process according to the following sequence:

1. Select the curve parameters randomly from the range specified in **Table 2** and create the corresponding level set functions.
2. Segment the image by using the curves derived from the generated level set functions.
3. Measure the fitness of each curve by computing the fitness function described in Section 2.2(1) and determine the best curve.
4. Update the curves parameters according to the PSO algorithm equations.
5. Create the level set functions from the new parameters and repeat Step-2.
6. Repeat Step-3.
7. If the best curve is not changed for more than 10 epochs, produce the segmentation results; else go to Step-4.

3. Experimental results

In this work, we use a portal phase of computed tomography (CT) images of resolution 512×512 pixels and of 1mm slice interval to perform two experiments of liver segmentation. The used datasets contain normal cases as well as cases with liver tumors and they are interpreted by one medical doctor. In the first experiment, a dataset of five CT images of different patients were used. Each CT image consists of about 150 slices stacked together and the liver fully appears in about 100 slices. In this experiment, 34 key slices were extracted from one patient in the dataset and were manually segmented. The resulting level sets of manually segmented images were used to build the shape prior and textural prior models as described in Section 2 and we select 8 principle modes, represent 85% of shape variation according to Equation 3, to represent the shape variations ($k = 8$). After we had built the shape and textural prior models, we employed the proposed PSO segmentation technique on a set of test slices extracted from the patient used in the training stage as well as a set of test slices extracted from the other patients. Sample results of this experiment are shown in **Fig. 5** and **Fig. 6**.

In the second experiment, a dataset of ten CT images of different patients were used for cross validation; nine patients were used for training and one patient were used for testing. Each CT image consists of about 170 slices stacked together and the liver fully appears in about 140 slices. In this experiment, key frames were extracted from different patients at interval of 5 slices and all extracted frames were manually segmented. The level sets constructed from corresponding frames were used to build multi shape and texture models. In this work, we use 27 slices to build each model and select 7 principle modes, represent 91% of shape variation according to Equation 3, to represent the shape variations ($k = 7$). Sample results of this experiment are shown in **Fig. 7** and **Fig. 8**.

To validate the superiority of the proposed segmentation technique, three competitive techniques were utilized to segment the liver in the same set of slices and all results were compared. The first implemented technique is the active contour without edges [25] with a manual initialization inside the liver, the second technique performs the segmentation using the wavelet packet decomposition feature set and the fisher linear discriminate algorithm, and the third technique utilizes the genetic algorithm (GA) to fit the pre-constructed shape model as proposed in [24].

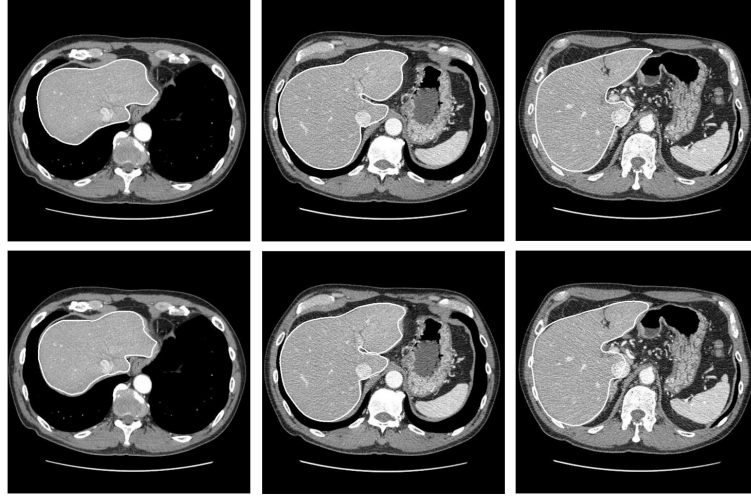


Fig. 5 Samples of the proposed technique results, the first experiment, on slices of the same patient used in the training stage, the manual segmentation on the upper row and the results on the bottom row.

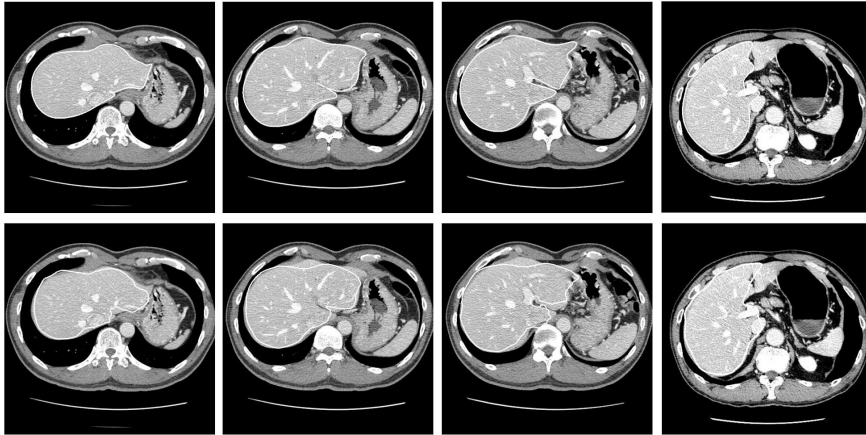


Fig. 6 Samples of the proposed technique results, the first experiment, on slices of patients other than the one used in the training stage, the manual segmentation on the upper row and the results on the bottom row.

Fig. 9 shows sample results GA-based technique. The goodness of fitness, G , of the segmentation results of all competitive techniques are computed with our experiments and illustrated in **Table 3** and **Table 4** respectively.

To calculate the goodness of fitness, we generate two binary masks to represent the manual and the computerized segmentation results. These masks have a value of 1 inside the object and a value of 0 outside. Then the goodness of fitness is calculated according to the following equation.

$$G = \frac{|Am \cap Aa|}{|Am \cup Aa|}, \quad (9)$$

where, Am represents the area of manually segmented object and Aa represents the area of automatically segmented object. A score of 1 represents a perfect match with the manual segmentation. As illustrated in **Table 3**, we note that the proposed PSO segmentation technique gives the best segmentation results. In addition, the proposed technique did not produce any overlap with the other objects as in the other methods. In the results of the second experiment, we notice the accuracy enhancement due to the high amount of shape variation included in the training data. Additionally, the results of the proposed technique are not affected by the existence of abnormalities in the liver and it is resistance to the weak segmentation results.

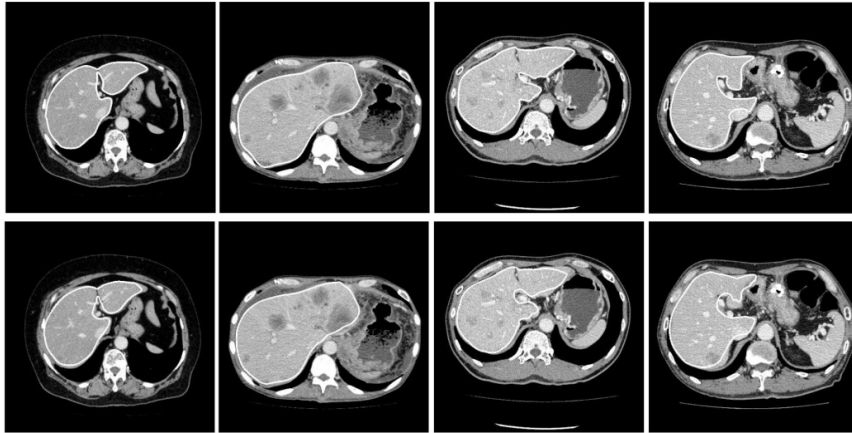


Fig. 7 Samples of The proposed technique results, the second experiment, on test slices extracted from the patients used in the training stage, the manual segmentation on the upper row and the results on the bottom row.

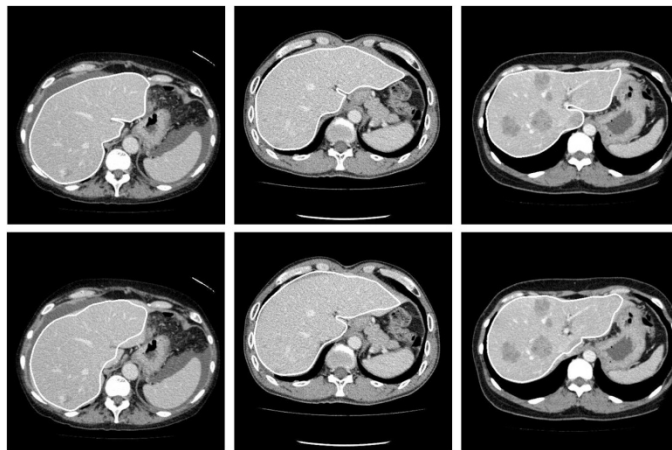


Fig. 8 Samples of The proposed technique results, the second experiment, on novel test slices extracted from the test patients, the manual segmentation on the upper row and the results on the bottom row.

The computational time for 512×512 image is about 10 min on a cor2duo PC with 2GB of memory and by using a matlab code. This time is not optimal because we used a non optimized matlab code and a basic version of PSO. In the future, we are planning to greatly reduce this time by using the parallel PSO.

Table 3 Goodness of fitness of the final segmentation results obtained using the different techniques (first experiment).

The segmentation technique	<i>G</i> of the training slices	<i>G</i> of the test slices
The proposed technique	0.94	0.88
Active contour without edges	0.70	0.75
Wavelet packet decomposition	0.52	0.45
GA-based technique	0.83	0.78

Table 4 Goodness of fitness of the final segmentation results obtained using the different techniques (second experiment).

The segmentation technique	<i>G</i> of the training slices	<i>G</i> of the test slices
The proposed technique	0.94	0.92
Active contour without edges	0.72	0.74
Wavelet packet decomposition	0.50	0.48
GA-based technique	0.85	0.79

4. Conclusion and future work

In this work, the high level features extracted using the over-complete wavelet decomposition allows the technique to accurately discriminate the desired tissue. Also, the incorporation of prior shape model in the form of mean shape and shape variability as described in Section 2 increases the ability to capture the desired object variations without overlapping with the other objects.

Furthermore, the utilization of the particle swarm optimization algorithm to evolve a region based level set function eliminates the need for deriving gradient of energy or solving complicated differential equations and it doesn't need level set re-initialization. Moreover, the PSO algorithm can efficiently explore the search space to converge to the desired object and its parameters can be easily adapted for any object. So the proposed PSO segmentation technique is very suitable for the segmentation of abdominal CT scans and it shows promised results. The comparison with other techniques shows the superiority of the proposed technique.

On the other hand, the proposed technique is computationally expensive and we tend to enhance it by employing the parallel PSO algorithm and extending the technique to the 3D cases.

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Shape and Texture Priors for Liver Segmentation in Abdominal Computed Tomography Scans Using the Particle Swarm Optimization Algorithm

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要旨：画像診断においては目的の臓器などを特定する作業が伴う、つまり多数枚の医用画像からの形状抽出が必要である。医師が手作業で抽出することができればもっとも正確な結果が得られるのだが、経済的・時間的コストの増大により実質的に困難である。一方、計算機による自動抽出手法はさまざま提案されているが、医用画像の不鮮明さゆえに、いまだ未解決の問題とされている。そこで本論文では完全自動処理による新しい医用画像抽出フレームワークを提案する。このフレームワークは事前形状モデルと事前テクスチャモデルという二種類の事前知識モデルを用いている。事前形状モデルは手動抽出されたデータセットを主成分分析することで構築し、またウェーブレット分解を用いてテクスチャ特徴を算出する。本フレームワークは二段階で処理を行っており、前段の抽出処理においては、事前テクスチャモデルと算出したテクスチャ特徴からフィッシャーの線形判別子によって抽出を行う。後段の処理では事前形状モデルと粒子群最適化手法 (Particle Swarm Optimization) を用いて前段の抽出結果をさらに向上させる。腹部 CT 画像からの肝臓抽出を目的として提案手法の検証を行った結果、目的の臓器をより正確に抽出できることがわかった。

キーワード：肝臓抽出, 事前形状モデル, 事前テクスチャモデル, 粒子群最適化手法

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