A Model Optimization Approach to the Automatic Segmentation of Medical Images

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SUMMARY The aim of this work is to develop an efficient medical image segmentation technique by fitting a nonlinear shape model with pre-segmented images. In this technique, the kernel principle component analysis (KPCA) is used to capture the shape variations and to build the nonlinear shape model. The pre-segmentation is carried out by classifying the image pixels according to the high level texture features extracted using the over-complete wavelet packet decomposition. Additionally, the model fitting is completed using the particle swarm optimization technique (PSO) to adapt the model parameters. The proposed technique is fully automated, is talented to deal with complex shape variations, can efficiently optimize the model to fit the new cases, and is robust to noise and occlusion. In this paper, we demonstrate the proposed technique by implementing it to the liver segmentation from computed tomography (CT) scans and the obtained results are very hopeful.

key words: model fitting, image segmentation, kernel methods, particle swarm, shape priors

1. Introduction

The image segmentation is the first and essential process in many medical applications including analysis of anatomical structure [1], lesion detection [2], volume measurement and surgical planning [3]. This process is traditionally performed by radiologists or medical specialists who use their knowledge and experience to manually trace the objects on each image or slice. In almost all of these applications, the medical specialists have to access a large number of images which is a tedious and a time consuming process. Although the automatic segmentation is helpful in these applications, it is a demanding issue which needs a considerable amount of knowledge inclusion.

Many researchers make an effort to develop semi-automatic and automatic medical image segmentation techniques and several articles have been presented in the literature. Some of these techniques interpret the image as an undirected and weighted graph, and compute the minimal cost path between user defined seed points [4]. Although this class of segmentation techniques gives the user a full control over the segmentation process, it still requires the user interaction time and the quality of segmentation result is greatly depends on the skills of the operator. Another class of these techniques depends on the gray levels analysis and a simple or iterative thresholding to create a binary images that are usually further processed by morphological operators to separate the attached organs [5]. The techniques of this class are likely to fail when the gray levels of different organs are similar or when patients with completely different gray level characteristic are processed. To overcome these limitations, a group of researchers used the learning techniques as the neural network to learn the gray level characteristics corresponding to different tissues [6]. Unfortunately their techniques are keeping some of the original limitations and they recommend the practice of basic anatomical knowledge.

Due to the limitation of the previously mentioned techniques, more advanced techniques incorporate the prior information captured from a set of training cases in the segmentation process [7]. These techniques capture and describe prior information regarding the shape, size and position of each organ. In order to achieve this goal the researches employ deformable models, statistical shape models, and probabilistic atlases [8]. However these techniques surmount the main limitations of previously mentioned techniques they produce their own limitations as the difficulty to build a proper training set, the challenge of representing all the shape variations, and the difficulty to get the optimal model parameters which fit the new cases. Moreover different approaches to medical image segmentation employ the level set method [9] with some novel speed functions. These methods propagate the implicitly defined surface toward the object boundary according to local image characteristic and the past front history [10]. Though these techniques are able to produce a reasonable segmentation, the reliance on image information alone often lead to inaccurate segmentation results and the incorporation of prior knowledge and the parameters adjustment can greatly affect their accuracy.

The incorporation of shape priors with the segmentation techniques has been shown to be an effective way for knowledge inclusion and it is leading to more robust segmentation [11]. Many researchers integrate linear shape priors with level set methods to control the contour evolution process [12]. However these approaches are able to capture small variations of the shape of an object, they lead to unrealistic shape priors when the object undergoes complex or nonlinear deformations. In [13], Y. Rathi, et. al proved that the nonlinear shape prior obtained from kernel PCA (KPCA) space is more realistic and outperform the linear one. Additionally in [14], S. Dambreville, et. al incorporated the nonlinear shape model into a level set framework. However these techniques incorporate nonlinear shape pri-
ors, they depend on the variational level set method and they can be trapped in a local minima and a manual initialization is very essential. Furthermore, they rely on the image moments only which is unsatisfactory in the case of complex textures.

Therefore in this work, we propose an efficient automatic segmentation technique by combining texture features-based classification and nonlinear shape model optimization. In this technique, the high level texture features extracted using the over-complete wavelet packet decomposition are used to accurately define the different tissues and to perform a preliminary segmentation. Additionally, the kernel PCA (KPCA) is utilized to capture the shape variations and to build a nonlinear shape model from a set of manually segmented images. The particle swarm optimization algorithm (PSO) is then applied to efficiently obtain the parameters of the shape model and to accurately fit it with the pre-segmented images.

After this introduction, in Section 2, the basic PSO algorithm is explained. In Section 3, we briefly describe the KPCA and how it is used to obtain the nonlinear shape priors. The texture prior extraction will be discussed in Section 4. In Section 5, the proposed PSO segmentation framework will be presented. The experimental results will be shown in Section 6 and the paper will be concluded in Section 7.

2. Particle Swarm Optimization (PSO)

PSO is a population based stochastic optimization technique founded by Kennedy and Eberhart in 1995 [15]. In this algorithm they mimic the social behavior of bird flocks searching for food to produce computational intelligence. There are many similarities between PSO and the other evolutionary computation techniques, but the PSO algorithm supports the idea of individuals cooperation instead of competition used in the other techniques and that provides a better search methodology and reduces the dependency on the parameters initialization. Additionally, it can achieve better results in a faster and cheaper way compared with other evolutionary computational techniques as proved in [16] and as we will clarify in the experimental results.

In PSO, a population or swarm of individuals – particles – are separated over the search space of some problem. Each particle represents a complete solution of this problem and it evaluates the objective function at its location. Additionally, the particle moves in the search space under the influence of its behavior and the whole swarm behavior. Each particle in the swarm is defined by three d-dimensional vectors; the current location \( \vec{x}_i \), the velocity \( \vec{v}_i \) and the best position it reaches \( \vec{p}_i \), where \( d \) is the dimensionality of the search space. The original version of PSO algorithm will be described in the following algorithm.

1. The position and velocities are randomly initialized from the specified range.
2. loop
   a. For each particle, evaluate the desired optimization fitness function.
   b. Compare particle’s fitness evaluation with its \( p_{best} \), where \( p_{best} \) is the fitness evaluation at particle’s best location. If current value is better than \( p_{best} \), then set \( p_{best} \) equal to the current value, and \( \vec{p}_i \) equal to the current location \( \vec{x}_i \).
   c. Identify the particle in the neighborhood with the best success so far, and assign its index to variable \( g \).
   d. Change the velocity and position of each particle according to the following equations.

\[
\begin{align*}
\vec{v}_i^{t+1} &= \vec{v}_i^{t} + \vec{U}(0, \alpha_1) \otimes (\vec{p}_i^{t} - \vec{x}_i^{t}) + \vec{U}(0, \alpha_2) \otimes (\vec{p}_g^{t} - \vec{x}_i^{t}) \\
\vec{x}_i^{t+1} &= \vec{x}_i^{t} + \vec{v}_i^{t+1}
\end{align*}
\]

where
- \( t \) refers to the iteration index.
- \( \vec{U}(0, \alpha_j), j = 1, 2 \) represents a vector of random values uniformly distributed in \([0, \alpha_j]\).
- \( \vec{v}_i \) is kept within the range \([-V_{max}, +V_{max}]\).
   e. If a criterion is met (sufficiently good fitness or maximum number of iteration), exit loop.
3. save the global best position as the problem solution.

This original PSO algorithm has been received many enhancements from its appearance till now [17]. The PSO with inertia weight [17],[18] is one from these enhancements which provides better control on the search space, so we are interested in it during this work. The following equations are the velocity and position update equations of the PSO with inertia weight.

\[
\begin{align*}
\vec{v}_i^{t+1} &= \omega \vec{v}_i^{t} + \vec{U}(0, \alpha_1) \otimes (\vec{p}_i^{t} - \vec{x}_i^{t}) + \vec{U}(0, \alpha_2) \otimes (\vec{p}_g^{t} - \vec{x}_i^{t}) \\
\vec{x}_i^{t+1} &= \vec{x}_i^{t} + \vec{v}_i^{t+1}
\end{align*}
\]

where, \( \omega \) is the inertia weight.

The researchers have found that the large value of \( \omega \) allows the particles to perform extensive exploration and the small value of \( \omega \) increases the chance to get local optima. So they have found that the best performance could be achieved by using a large value of \( \omega \) (e.g., 0.9) at the beginning and gradually decrease it until reach another small value of \( \omega \). In addition, the velocity of each particle is kept within a specified range of \([-\text{maximum velocity}, \text{maximum velocity}]\).

3. Nonlinear Shape Priors

The nonlinear shape priors have been proven to be an efficient way for the representation of complex object deformation [13]. Additionally, the KPCA has been shown as a
The kernel is a function feature space without explicitly mapping the dataset [19]. The dimension of this mapping is very high and may be infinite and it increases the computational cost. Therefore, the KPCA benefits from the kernel trick to perform PCA in the feature space without explicitly mapping the dataset [19]. The kernel is a function \( k (.,.) \) such that, for all data points \( x_i \), the kernel matrix \( K(i,j) = k(x_i,x_j) \) is symmetric positive definite. In addition, the kernel function gives the inner product between two points in the feature space, i.e., \( k \left( x_i, x_j \right) = \langle \varphi (x_i), \varphi (x_j) \rangle \).

Let \( \tau = \{x_1, x_2, \ldots, x_N\} \) be a set of training data. The kernel trick can be used to obtain the eigenvectors in the feature space from the following Eigen decomposition:

\[
HKH = \Sigma \Psi^T, \tag{5}
\]

where \( H \) is the centering matrix defined as \( H = I - \frac{1}{N} 11^T \), \( I \) is the \( N \times N \) identity matrix, \( 1 = [1, 1, \ldots, 1]^T \) is \( N \times 1 \) vector, \( \Psi = [a_1, a_2, \ldots, a_N] \) with \( a_i = [a_{i1}, a_{i2}, \ldots, a_{iN}] \) is the matrix containing the eigenvectors and \( \Sigma = \text{diag}(\lambda_1, \lambda_2, \ldots, \lambda_N) \) contains the corresponding eigenvalues. Denote the mean of the \( \varphi \)-mapped data by \( \bar{\varphi} = \frac{1}{N} \sum_{i=1}^{N} \varphi (x_i) \) and as described in [13], [14], [19], the centered map \( \bar{\varphi} \) can be defined as:

\[
\bar{\varphi} (x_i) = \varphi (x_i) - \bar{\varphi}, \tag{6}
\]

The \( k^{th} \) orthonormal eigenvector of the covariance matrix in the feature space can then be computed as:

\[
V_k = \sum_{i=1}^{N} a_{ik} \bar{\varphi} (x_i) \tag{7}
\]

In addition, the projection of the \( \varphi \)-image of a test point \( x \) onto the subspace spanned by the first \( n \) eigenvectors is given by:

\[
P_\varphi (x) = \sum_{k=1}^{n} \beta_k V_k + \bar{\varphi}, \tag{8}
\]

where, \( \beta_k \) is the projection of \( \varphi (x) \) onto the \( k^{th} \) component and it is computed as:

\[
\beta_k = \frac{1}{\sqrt{\lambda}} \sum_{i=1}^{N} a_{ik} \bar{k}(x_i), \tag{9}
\]

\( \bar{k}(.,.) \) is the centered kernel function and it is given by:

\[
\bar{k}(x,y) = \langle \bar{\varphi}(x), \bar{\varphi}(y) \rangle = k(x,y) - \frac{1}{N} 1^T k - \frac{1}{N} 1^T k y + \frac{1}{N^2} 1^T K 1 \tag{10}
\]

with \( k_i = [k(x_1,x_1), k(x_1,x_2), \ldots, k(x_N,x_N)]^T \)

3.2 Shape Priors Using KPCA

As a first step in the shape modeling, a set of CT slices must be segmented manually and its corresponding level set have to be formulated. In order to simplify this process, we built an interactive system that allows the medical doctor to segment the objects by selecting some points around it and then, the cubic Spline interpolation [20] is employed to estimate the segmenting curve from these points as shown in Figure 1 (a). Additionally, the level sets which describe the segmented objects are formulated according to the following procedure.

1. Construct a binary mask from the segmenting curve with the value of 1 inside the curve and the value of 0 outside it.
2. Use the binary mask generated in the previous step to generate a mask with the value of -1 inside the object and the value of 1 outside it. This mask is regarded as a sign function and denoted as \( s \) as shown in Figure 1 (b).
3. Compute the Euclidian distance transform between each pixel and the segmenting curve and denotes it as \( D \) as shown in Figure 1 (c).
4. Formulate the level set function as \( \Psi(x,y) = s(x,y) \cdot D(x,y) \) as shown in Figure 1 (d).

Furthermore, the process of shape modeling is completed according to the following algorithm:

1. Load the \( N \) level set functions \( \Psi_i(x,y), i = 1, 2, \ldots, N \) which had been constructed from the training images.
2. Constructing a column vectors \( \psi_i, i = 1, 2, \ldots, N \) consisting of \( M \) samples of each \( \Psi_i \). \( M = m_1 \times m_2 \) is the image size, by stacking the \( m_2 \) columns of \( \Psi_i \).
3. Defining the shape matrix \( S \) as \( S = [\psi_1, \psi_2, \ldots, \psi_N] \).
4. Using the Gaussian kernel \( k(\psi_i,\psi_j) = e^{-\frac{d(\psi_i,\psi_j)}{\sigma^2}} \), with \( \sigma^2 = \frac{1}{N} \sum_{i=1}^{N} \min_{j=1}^{M} d^2(\psi_i,\psi_j) \) to build the kernel matrix \( K \).
5. Applying KPCA as described in the previous section and selecting the eigenvectors that have eigenvalues greater than one as a shape representation.

4. Texture Priors

We utilize the over-complete wavelet packet transform to extract the high-level feature vectors for each foreground pixel in the training images. As illustrated in Figure 2 the over-complete wavelet packet transform does not 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 bandpass information about the texture. In this work, we extract the wavelet packet feature set according to the following procedure:
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
   \[
   E(x, y) = \frac{1}{2m + 1} \sum_{i=-m}^{m} \sum_{j=-m}^{m} F(x + i, y + j)^2, \tag{11}
   \]
   where, $F(x + i, y + j)$ is the wavelet coefficient of a feature sub-image in $(2m + 1) \times (2m + 1)$ 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 feature vectors, we assign a label for each pixel to indicate whether this pixel is a desired object pixel or not and finally, we use the linear fisher discriminate algorithm [22] 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 the dominant spatial-frequency channels of the original image and it leads to better classification results than the spatial domain methods as shown in Figure 3. 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.

5. PSO-Based Segmentation

In order to segment a new image, its wavelet packet based feature set is extracted and each foreground pixel in this image is classified as a desired object pixel (true) or undesired object pixel (false) according to the prior textural model as shown in Figure 4. This classification process is carried out by using the linear fisher discriminate algorithm. Finally, this stage is completed by applying the PSO algorithm [17] to get the level set function that truly segments the image as shown in Figure 5 and described in the following sections.

5.1 The Model Description

Each particle in the PSO population consists of the set of parameters that control the shape and the pose parameters of the segmenting curve. In this framework, the level set function $\phi(x, y)$ that implicitly represents the segmenting curve is defined as the pre-image of feature vector $\nu = \sum_{i=1}^{l} w_i \alpha_i, l$.
is the number of KPCA principle components, \( a_i \) and \( w_i \), \( i = 1, 2, \ldots, l \) are the normalized KPCA principle components and its weights respectively. The pre-image of this feature vector is computed according to the direct method proposed in [23].

Furthermore, we consider the pose parameters, \( a, b \) for translation, \( h \) for scaling and \( \theta \) for rotation, which incorporated in this framework using an affine transform. According to above considerations, each individual, particle, \( P \) in the PSO population is defined as \( P = [(w_i, i = 1, 2, \ldots, l), a, b, h, \theta] \) and it represents a segmenting curve.

The fitness of each particle in this work represents how the corresponding curve segments the image. Accordingly in the proposed framework, we tend to maximize the fitness function used in [24]. This fitness function is formulated as:

\[
FT = 500(A + (1 - B)),
\]

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.

5.2 The PSO algorithm configuration

In this work, we are employing the PSO algorithm with inertia weight described in Section1. 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 Table1 and the curve parameters configuration is provided in Table2. The parameters in Table1 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 Table2 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.

5.3 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. Initialize the curve parameter randomly from the range specified in Table1.
2. Create the level set function from the curve parameters.
3. Segment the image by all segmenting curves derived from the level set.
4. Measure the fitness of each curve by computing the fitness function described in Section5.1.
5. Determine the best segmenting curve and the best segmentation results for each curve.
6. If the best curve is not changed for more than 30 iterations, produce the segmentation results; else go to Step-6.
7. Update the curves parameters according to the PSO algorithm equations and go to Step-2.

6. Experimental Results

In this work, we use a portal phase of computed tomography (CT) images of resolution 512 × 512 pixels and of 1 mm slice interval to perform two experiments of liver segmentation. The used datasets contain normal cases as well as cases with liver abnormalities, tumors and cysts. In the first experiment, a set 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

| 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   | 70 |

| Parameter Name | Parameter Range | Maximum Velocity |
|----------------|-----------------|------------------|
| \( w_i, i = 1, \ldots, l \) | \(-\sqrt{l} \rightarrow \sqrt{l}\) | 0.5 |
| \( a, b \) | \(-10 \rightarrow 10\) | 2 |
| \( h \) | \(0.5 \rightarrow 2\) | 0.5 |
| \( \theta \) | \(-90 \rightarrow 90\) | 10 |
experiment, two datasets were extracted and used; dataset1 consists of 34 slices of one patient with low shape variations and dataset2 consists of 33 slices of the same patient with high shape variations. These slices were manually segmented to build the nonlinear shape prior and textural prior models as described in Section 2 and Section 3. We select 8 and 10 principle modes to represent the shape variation in dataset1 and dataset2 respectively. Figure 6 shows that every principle mode expresses a variation in some object parts. After we had built the shape and textural priors, we employed the proposed PSO segmentation technique on a set of slices of the patient used in the training stage and a set of novel slices for other patients. The resulting images shown in Figure 7 and Figure 8 illustrate the effectiveness of the proposed technique in liver segmentation from the CT images.

In the second experiment, a set of ten CT images of different patients was used for cross validation; nine patients were used for training and one patient was 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, a set of 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 to represent the shape variations. Sample results of this experiment are shown in Figure 9 and Figure 10.

To validate the superiority of the proposed segmentation technique, five 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, the third technique utilizes the genetic algorithm (GA) to fit the pre-constructed shape model as proposed in [24], the fourth technique incorporate the linear shape priors of [12] in the segmentation framework, and The fifth technique is the technique proposed in [14] which incorporates nonlinear shape model and intensity-based model and it requires a manual initialization. Figure 11 shows the effectiveness of the proposed technique in the case of high shape variations, Figure 12 shows sample results of GA-based technique and Figure 13 demonstrates sample results of the fifth competitive technique. As shown in Figure 13, the balance between the shape model and the intensity-based model greatly influences the final results and keeping this balance manually is very difficult in the case of abdominal CT images. The goodness of fitness, $G$, of all techniques were computed for all datasets and compared in Table 3, Table 4 and Table 5.

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.

$$G = \frac{|A_m \cap A_a|}{|A_m \cup A_a|},$$  \hspace{1cm} (13)

where, $A_m$ represents the area of manually segmented object and $A_a$ represents the area of automatically segmented object. A score of 1 represents a perfect match with the manual
segmentation.

7. Conclusion and Future Work

In this work, the high level features extracted using the over-
complete wavelet decomposition allows the technique to ac-
curately discriminate the desired tissue. Also, the incorpo-
ration of nonlinear shape priors increases the ability to capture
the desired object accurately. In addition, the utilization of
the particle swarm optimization algorithm to adapt a region

| Segmentation technique         | Training Patient | Test Patients |
|-------------------------------|------------------|---------------|
| The proposed Technique        | 0.95             | 0.88          |
| Linear shape priors           | 0.94             | 0.83          |
| Active contour without edges  | 0.70             | 0.75          |
| Wavelet packet decomposition  | 0.52             | 0.45          |
| GA-based technique            | 0.84             | 0.80          |
| The technique proposed in [14]| 0.94             | 0.85          |
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.

In the future, we intend to enhance this PSO segmentation technique by employing the parallel PSO algorithm and utilize it for volume segmentation and visualization and as a primary step in automatic segmentation of liver tumors.

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