A Novel Level Set Based Shape Prior Method for Liver Segmentation from MRI Images

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Abstract. Liver segmentation in MR Image is the first step of our automated liver perfusion analysis project. Traditional Level Set methods and active contours were often used to segment the liver, but the results were not always promising due to noise and the low gradient response on the liver boundary. In this paper we propose a novel level set based variational approach that incorporates shape prior knowledge into the improved Chan-Vese's model [1] which can overcome the leakage and over-segmentation problems. The experiments are taken on abdomen MRI series and the results reveal that our improved level set based shape prior method can segment liver shape precisely and a refined liver perfusion curve without respiration affection can be achieved.

Keywords: Liver Segmentation, Level Set, Shape Prior.

1 Introduction

Medical image segmentation is a fundamental research topic, for which numerous approaches have been proposed during the past several decades. Among them, level set methods, which were first introduced by Osher and Sethian[2] for capturing moving fronts, plays an important role. They model the propagating curve as a specific level set of a higher dimensional surface. So as time progresses, the surface can change to take on the desired shape.

In 1989, D.Mumford and J.Shah gave the famous Mumford-Shah's functional which was discussed comprehensively in [3,4]. In this approach, the segmentation problem is to find a piecewise smooth function which approximates the image and also prohibit the excessive length of the boundaries between any two contiguous regions. Later in 2001, Chan and Vese proposed a new model that combines the Mumford-Shah's functional and level set methods, which can handle curves, surfaces with topological changes conveniently. Besides this, Kass, Witkins and Terzopoulos [5] introduced the classic snake model for segmenting objects in images.

However, all of these models above fail to segment objects from images when the objects are occluded by other objects or some parts of them are in low gray contrasts

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or even missing, because they are all gray intensity based. Actually, these situations always happen in our abdomen MRI images. Therefore, making use of the prior shape information makes sense. In recent years, there has been much effort in trying to integrate prior shape knowledge into level set based segmentation. For example, In [6], Cremers et al. introduced statistical shape knowledge into the Mumford-Shah's functional. In [7], Cremers et al. incorporates a level set based shape term into Chan-Vese's segmentation model [1].

But in our practical experiment, we found that these models still have some defects. They do not allow for the translation, rotation and scaling of the prior shapes. The prior shapes have to be placed exactly at the locations of the desired objects, with exactly the same poses and scales, which is too ideal to be met in real applications.

In this paper, a novel shape prior segmentation approach based on Chan-Vese's model [1] is proposed. It not only allows translation, rotation and scaling of prior shapes, but also performs object supervision before segmentation to achieve better segmentation result and high performance. Moreover, some statistical methods are introduced to get a suitable initial prior shape.

The outline of this paper is as follows: In section 2, a brief review of level set and CV model will be discussed. In section 3, we will detail our novel variational model. In section 4, our method will be validated in several experiments. Finally we conclude the paper in section 5.

2 Level Set and CV Model

Firstly we want to declare that although this work is built on the region-based level set scheme introduced by Chan and Vese, other data-driven level set schemes should also be employed. Essentially, the level set method is a moving interface problem. Its main idea is to embed the propagating curve as the zero level set of a higher dimensional function, such as the signed distance to the interface. For example, given an object $\Omega \subset R^2$, which is assumed to be closed and bounded, and $\partial\Omega$ is its boundary. We define the function as follows:

$$\phi(x, y, t = 0) = \pm d \tag{1}$$

Where d is the distance from (x,y) to $\partial\Omega$ at t = 0, and the plus (minus) sign is chosen if the point (x,y) is outside (inside) the subset Ω.

In [1], Chan and Vese propose to generate a segmentation of an input image f(x) by minimizing the functional:

$$E_{cv}(c_1, c_2, \phi) = \int_{\Omega} \left\{ (u - c_1)^2 H(\phi) + (u - c_2)^2 (1 - H(\phi)) + \mu \left| \nabla H(\phi) \right| \right\} dx \tag{2}$$

Where: u: $\Omega \to R^2$ is an image defined on Ω, c_1 and c_2 are two scalar variables. Hence, H denotes the Heaviside function. The last term in (4) $\int_{\Omega} \left| \nabla H(\phi) \right|$ measures the length of the zero-crossing of ϕ, and $\mu > 0$ is a parameter that describes how large

the length of the boundaries is permitted. The Euler-Lagrange equation for this formula is implemented by gradient descent:

$$\frac{\partial \phi}{\partial t} = \delta(\phi)\left[\mu div(\frac{\nabla \phi}{|\nabla \phi|}) - (u - c_1)^2 + (u - c_2)^2\right] = 0 \tag{3}$$

c_1 and c_2 are updated in alternation with the level set evolution to take on the mean gray value of the input image u in the regions defined by $\phi > 0$ and $\phi < 0$ respectively:

3 The Improved Model

3.1 Feature Image

In the MR images of liver, due to the liver movement and the blood flow, part of the boundary is usually not clear and intensity inhomogeneity exists, where the CV model does not work well. Consequently, borrowing the idea of Xianhua Duan, Deshen Xia in [8], we here introduce the feature image according to the object intensity, which brings in better result and less iterations. The feature image function can be described as below:

$$f = |u - m|^p \tag{4}$$

Here u is the input image, and m represents the intensity of the manually defined seed point. The scalar variable p has a value range from 0.001 to 2.5, which can has different values in different images. We choose this manual contrast enhancing method because it's simple but can meet our requirement well. To make it shown as a binary image, we need to normalize it:

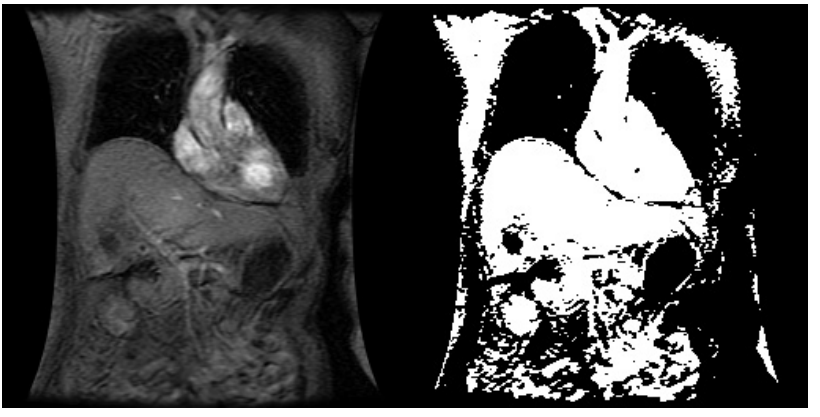
$$f = 255 * \frac{f - \min(f)}{\max(f) - \min(f)} \tag{5}$$

Where min(f) is the minimal intensity value of image f which is obtained from functional (4), and max(f) is the maximal intensity value. Functional (5) encourages enhancing gradient where the boundary is not very clear, with which the number of iterations can be reduced.

Figure 1(a) is an example of MRI liver image, showing relatively low gray contrast when Figure 1(b) shows the feature image we got by formula (5).

3.2 Labeling Function and Initial Result

The proposed model requires an initial segmentation result which could be achieved by implementation of CV model. However, because of the low quality of liver MRI, there are some flaws such as leakage and over segmenting, which are shown in Fig.2.



(a) (b)

Fig. 1. (a) is a MRI image of liver with low gray contrast and (b) is the feature image we got by functional (12). Here we make p = 1.0, and set seed point at (137, 73). From the images above, the gradient has been enhanced, and the intensity inhomogeneity of target region has been reduced.

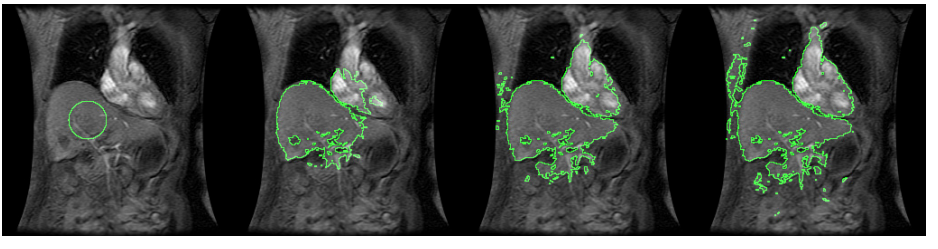


Fig. 2. Active contours procedure. The propagation starts from left to right.

To solve these problems, the labeling function L is introduced. We define L(x, y) = 1 if point (x, y) is in the target region; while in the region we are not interested, set L(x, y) = -1. From formula (3) we can get the iterative function of ϕ, and then define that in each step of curve evolution, the function ϕ only works when L > 0. Consequently, a better initial result for matching can be obtained (Fig.3).

3.3 Getting Initial Shape Model

To complete our variational model, a suitable shape model as prior knowledge is needed. We choose to use some statistical methods to get the initial shape model, 30 abdomen MRI images were segmented manually by experienced radiologists, the initial shape model can be achieved by follow steps:

At first, 20 points on the contour of the 1st image are chosen as the feature points which can represent the segmentation contour. Therefore we use registration method to find the corresponding 20 points on the 2nd, 3rd … 30th images to get 20 groups of points.

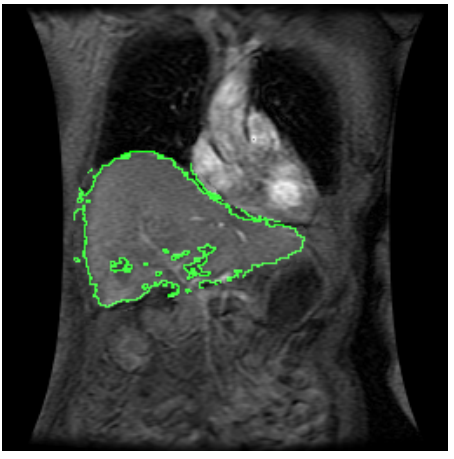


Fig. 3. Initial segmentation result with labeling function, where most extra parts are removed

In the second step, we target at finding a coordinate with the highest probability in each group, where the Mean Shift [9], a classical method to find the densest region in distribution of identical sample points, is employed. After the initial point x is chosen, the Mean Shift vector of point x can be defined as:

$$M_h(x) \equiv \frac{1}{k} \sum_{x_i \in s_h} (x_i - x) \tag{6}$$

Here s_h is a circle with center point x and radius h, k is the number of points falling within the region s_h. Obviously, the average mean shift should point in the direction of most rapid increase of the probability density function, and have a length proportional to the magnitude of the gradient. Therefore in each iteration, point x is moved a step along the Mean Shift vector direction, and the Mean Shift Vector of the new coordinate will be recalculated. After enough iterations, s_h will finally converge to the densest region, and the final center point will be what we want. The Mean Shift vector moving process is show in (Fig.4) below.

Consequently, a most probable point position is calculated in each group, so 20 feature points are achieved. Afterwards we use cubic spline curve algorithm to outline the contour, which is treated as the initial shape model contour.

3.4 Training of Shape Model

In [7], Cremers et al. incorporates a level set based shape term into Chan-Vese's segmentation model. But in real applications, we found that their model has a shortcoming which cannot be overlooked. Their model does not allow for the translation, rotation and scaling of the prior shapes. In fact, the prior shapes usually cannot be exactly located on target objects, with the same poses and scales. Therefore, we propose that

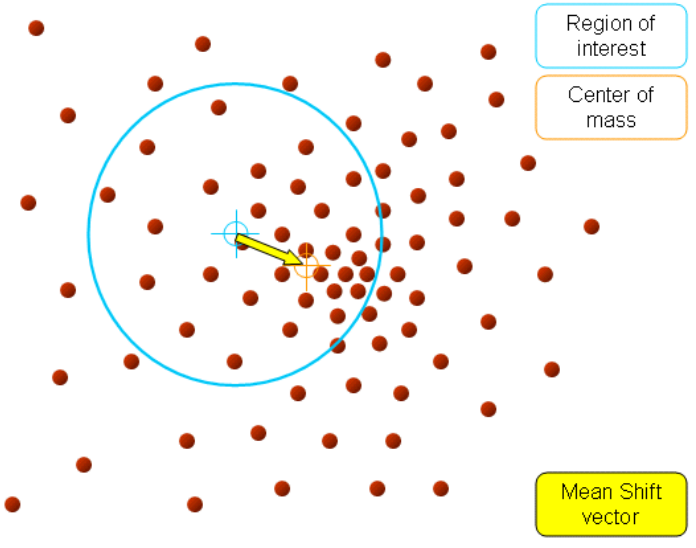


Fig. 4. The Mean Shift Vector movement

we can match the shape models to the initial segmentation results, which can regularize their positions, poses and scales. This key step allows affine transformation of the prior shapes.

The gradient descent method is employed in object matching. Firstly, we define the transformation of shape model as rigid-body transformation, which means our transformation matrix only includes translation, rotation and scaling parameters.

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} * \begin{bmatrix} s_x \cos\theta & -s_y \sin\theta & x_c(1-s_x\cos\theta)+y_c s_y \sin\theta + t_x \\ s_x \sin\theta & s_y \cos\theta & y_c(1-s_y\cos\theta)-x_c s_x \sin\theta + t_y \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} \quad (7)$$

Here (x_c,y_c) is the central coordinates, s_x and s_y are the scale parameters in the x axis and y axis respectively. Moreover, θ represents the shape model turn angle; t_x and t_y are the translation parameters.

Thereafter, we need a distance map which is formed by assigning each pixel a value to the nearest edge pixel. In our application, the CV model's evolving result (Fig 3) is naturally a signed distance map. However, because of the low quality of our MRI image series, it is always difficult to distinguish liver's boundary region with others, which makes our signed distance map noisy.

To solve this problem, we choose to remove the noise part in our initial segmentation result (Fig 3), and then recalculate the distance map. We define the points on the contour of that image (green curve) as feature points. The distance values can be determined in two passes through the image by a process known as "chamfering". The

image points array (D[i, j] i, j = 1 to n) is initially two valued: 0 for feature points and infinity otherwise. The forward pass modifies the array as follows:

```
FOR i = 2 STEP 1 UNTIL n DO
   FOR j = 2 STEP 1 UNTIL n DO
     D[i, j] = MINIMUM( D[i, j], D[i-1, j]+2, D[i-1,
     j-1]+3, D[i, j-1]+2, D[i+1, j-1]+3);
```

Similarly, the backward pass operates as follows:

```
FOR i = (n-1) STEP -1 UNTIL 1 DO
   FOR j = (n-1) STEP -1 UNTIL 1 DO
     D[i, j] = MINIMUM( D[i, j], D[i+1, j]+2,
    D[i+1, j+1]+3, D[i, j+1]+2, D[i-1, j+1]+3);
```

The incremental distance values of 2 and 3 provide relative distances that approximate the Euclidean distances 1 and the square root of 2.

After transforming the shape model, we overlap the initial shape model (obtained in step 3.3) on the distance map to calculate the sum of the distance values as the measure of similarity, which can be described as the follow formula:

$$F(t_x, t_y, \theta, s_x, s_y) = \sqrt{\frac{\sum_{i=1}^{N} D^2(p_i)}{N}} \tag{8}$$

Where the meanings of shape parameters t_x, t_y, θ, s_x and s_y have been explained in functional (7), p_i represents the *ith* point which was overlapped by the shape model contour, and N is the total number of this kind of points. In addition, $D(p_i)$ is the distance value of p_i, which can be looked up in the distance map.

At each step of the curve evolution, we seek to estimate the shape parameters by gradient descent method, with the target of finding the proper t_x, t_y, θ, s_x and s_y so that $F(t_x, t_y, \theta, s_x, s_y)$ is minimized. Consequently, the transformation functional (7) can be used to get the final shape model curve.

3.5 Shape Prior Segmentation

To cope with the problem of unsuccessfully segmentation on low quality images, prior shape knowledge is introduced into the level set scheme. The basic idea is to extend the image-based cost functional by a shape energy which favors certain contour formations:

$$E_{total}(\phi) = E_{cv}(c_1, c_2, \phi) + \alpha E_{shape}(\phi) \quad (\alpha > 0) \tag{9}$$

The shape comparison term should reflect the difference between two shapes. Therefore we choose to borrow the idea of Tony Chan and Wei Zhu in [10], and define it as follows:

$$E_{shape}(\phi, \psi) = \int (H(\phi) - H(\psi))^2 dx \tag{10}$$

Here, H(x) is the Heaviside function, φ is the signed distance function (SDF) mentioned in (1), and ψ is the SDF of final shape model obtained in step 3.4. With combination of formula (9) and (10), the liver can be segmented with shape prior knowledge successfully.

4 Experiment Result

To evaluate our novel method, a series of 2D 256* 256 abdomen MRI images are used in experiment, which are taken with a GE Genesis Signa HiSpeed CT/I system at the Shanghai First People's Hospital, and the parameters are: slick thickness 15.0, repetition time 4.7, echo time 1.2, magnetic field strength 15000, flip angle 60 degrees.

The experiments are performed on a PC with Pentium D 2.8Ghz, 1G RAM. We will show the result with two images. One is the abdomen MRI (Fig.5), and the other is the same image with some missing parts (Fig.6). The initial prior shape is a similar but not exactly fit liver. In addition, the parameters chosen are: $\mu = 0.1$, $\varepsilon = 1$, $\alpha = 1$, $\nabla t = 0.1$.

Compare the experiment result below to result segmented by CV model (Fig.2), it shows that if the low-level segmentation criterion is violated due to unfavorable lighting conditions, background clutter or partial occlusion of the objects of interest, then the purely image-based segmentation scheme such as CV model will fail to converge to the desired segmentation result. However, our novel method can deal with it and end up with a satisfied result, besides, different positions and poses of prior shapes are also allowed.

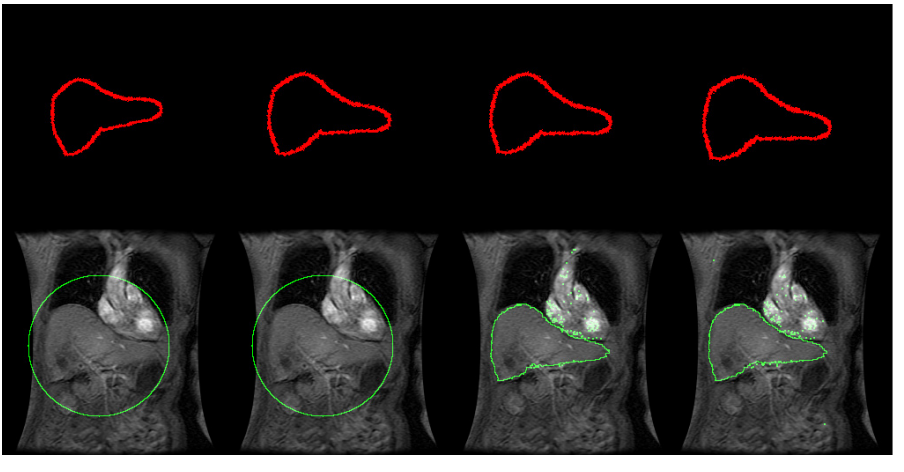


Fig. 5. The first row is the evolution of prior shape training, and the last image in the first row is the final prior shape. With the help of that shape, the second row shows the process of active contour evolution and our segmentation result.

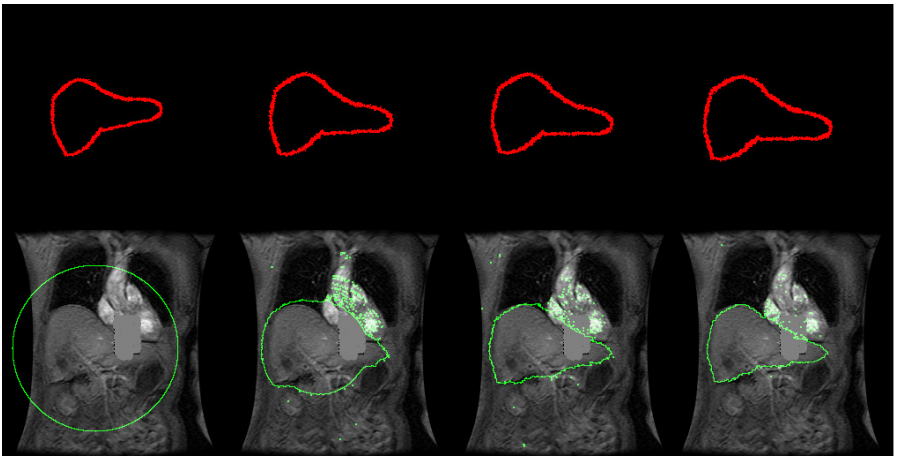


Fig. 6. The first row is the evolution of prior shape training, and the last image in the first row is the final prior shape. With the help of that shape, the second row shows the process of active contour evolution and our segmentation result. In this segmentation, even there are some missing parts, the result is still reliable.

The segmented liver shape we got here can be used as input of the liver perfusion mechanism in our lab. For certain illnesses related to the liver, the blood flow to the liver has to be studied. By injecting a contrast agent into the patients' body while taking MRI images in fixed time intervals, the concentration of the contrast agent can be studied while it flows through the patients' body. A short time after the injection the contrast agent reaches the liver and the MRI images at that time can reveal important information about the blood supply condition of the liver for the patient. The information can lead to a more accurate diagnosis. The overall procedure is called liver perfusion.

5 Conclusion

In this paper, we introduce a novel level set based variational model for segmentation using prior shapes, which helps us detect the liver perfusion position and measure the intensity. Feature image was employed to get better result and faster speed, and we propose a new measure which help to perform the training of given shapes. All of these make our model permits translation, scaling and rotation of the prior shape. The experiment results reveal that even if some part of the given image is missing or occluded, we can still get a reliable segmentation result.

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