

Exploiting User Labels with Generalized Distance Transforms Random Field Level Sets

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Abstract

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EXPLOITING USER LABELS WITH GENERALIZED DISTANCE TRANSFORMS RANDOM FIELD LEVEL SETS

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ABSTRACT

We present an approach for exploiting user labels with random field level sets in image segmentation. A sparse set of user labels is propagated to the rest of the image by computing a generalized distance transform which takes into account image intensity information. The region-based level set formulation is modified to use random field level sets whose range is restricted to the probability values. These two ideas are combined in a single level set functional. Improved results are shown on a liver segmentation task.

Index Terms— segmentation, level set, semi-automatic, user interaction, medical imaging.

1. INTRODUCTION

Segmentation is an important problem in medical imaging, and is crucial for applications such as target delineation in radiation therapy planning and treatment. This task is often performed manually, which is time-consuming and tedious, even for a trained expert. Although there is a large body of work on automatic segmentation [1], the results of complete automation are often unreliable. An alternative approach is to incorporate user guidance in a semi-automatic framework.

The level set method [2, 3] is a popular approach for segmentation; however, user interaction is often limited to only providing an initialization for an iterative algorithm. Here we show how exploiting user information (beyond just initialization) in a random field level set framework can both increase segmentation accuracy and decrease computation time.

The region-based level set method represents the segmentation of a domain Ω with a function $f : \Omega \rightarrow R$, such that

$$\Omega_1 = \{(x, y) : f(x, y) > 0\}, \quad (1)$$

$$\Omega_2 = \{(x, y) : f(x, y) < 0\}, \quad (2)$$

$$C = \{(x, y) : f(x, y) = 0\}, \quad (3)$$

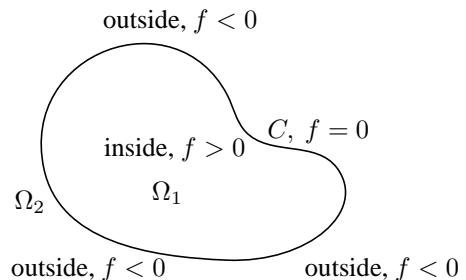


Fig. 1. Chan-Vese level set model.

where Ω_1 and Ω_2 are the object and background, respectively, and C is the boundary between these two regions (see Figure 1). This avoids an explicitly parameterization of the boundary contour, and seamlessly handles topological changes. The level set function is evolved until it reaches a local minimum of some cost function, such as the one proposed by Chan and Vese [3]:

$$J_0 = \sum_{i=1}^2 \int_{\Omega} (u(x, y) - \bar{u}_i)^2 \chi_i(f(x, y)) dx dy \quad (4)$$

where u is the image intensity function, and

$$\bar{u}_i = \frac{\int_{\Omega} u(x, y) \chi_i(f(x, y)) dx dy}{\int_{\Omega} \chi_i(f(x, y)) dx dy}, \quad (5)$$

are the mean image intensities of each region, and

$$\chi_1(z) = H(z) \quad (6)$$

$$\chi_2(z) = 1 - H(z), \quad (7)$$

where

$$H(z) = \begin{cases} 0 & \text{if } z < 0, \\ 1 & \text{if } z \geq 0, \end{cases} \quad (8)$$

is the Heaviside function step function. This cost function minimizes the sum of the image intensity variances of the object and background.

*This work was performed while at Mitsubishi Electric Research Laboratories.

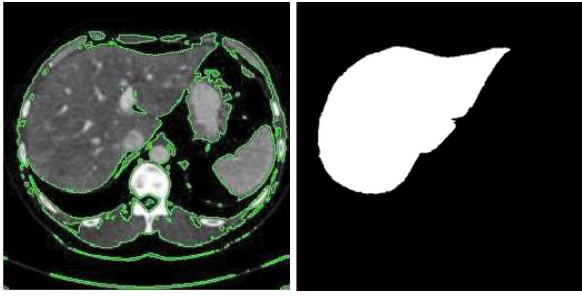


Fig. 2. The level set can separate tissue from background, but cannot segment the liver (ground truth on the right) from the rest of the image.

Although this model is well-suited for coarse object-background segmentation, it does not give the desired result for more specialized segmentation tasks, such as that shown in Figure 2. The level set is able to separate tissue from air, but cannot isolate a particular object, such as the liver.

2. EXPLOITING USER LABELS

In semi-automatic segmentation, it is intuitive and easy for a user to scribble both object and background regions; indeed, this approach has been successfully used in other segmentation methods [4]. However, the cost function in (4) does not use any user interaction beyond an initialization for f . Recently, there has been work on incorporating user labels in the level set method by explicitly adding a user term in the cost function [5, 6]. User information is represented by a label function

$$L(x, y) = \begin{cases} +1 & \text{if } (x, y) \text{ is marked as object,} \\ -1 & \text{if } (x, y) \text{ is marked as background,} \\ 0 & \text{otherwise,} \end{cases} \quad (9)$$

and the cost function includes a term penalizing deviations from the user labels:

$$J_{U_0} = - \int_{\Omega} L_{\sigma}(x, y) \text{sign}(f(x, y)) dx dy, \quad (10)$$

where L_{σ} is the user label function after spatial smoothing with a Gaussian kernel. This encourages the level set to respect the user object/background labels, exponentially weighted by geometric distance to the labels.

To generalize the idea above, which basically performs isotropic smoothing of the user labels, we extend it to take into account for image intensity information. This is done by computing the generalized distance transform as the distance of the shortest path (geodesic) from an unlabeled location to a labeled point [7]. The idea is to consider image locations as nodes on a grid graph, where the edge weights on the edges are proportional to image intensity difference:

$$w_{ij} = |u(x_i, y_i) - u(x_j, y_j)|. \quad (11)$$

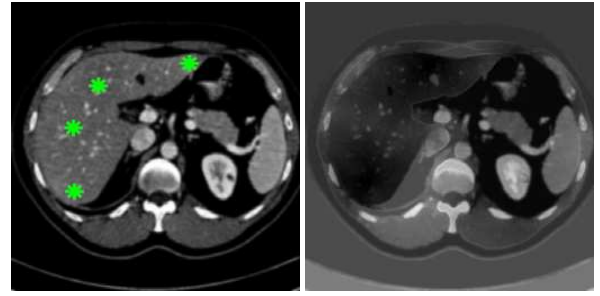


Fig. 3. User selected points (left) and the corresponding geodesic distance transform (right).

The generalized distance for an unlabeled node i is then the distance of the shortest path to any labeled node ℓ :

$$D(x_i, y_i) = \min_{\ell} w_{ik_0} + \left(\sum_{k=0}^{m-1} w_{j_k, j_{k+1}} \right) + w_{k_m, \ell}. \quad (12)$$

This propagates the user labels across homogeneous regions, while respecting edge boundaries, as shown in Figure 3. Thus, instead of fixed-radius spherical geometry, we use appearance-based geometry. We can also view this as using edge-based level sets [8] to propagate user labels.

3. RANDOM FIELD LEVEL SETS

Let $D(x, y)$ represent the generalized distance transform described above; a pixel with smaller geodesic distance will be closer to a labeled pixel, *i.e.*, it has a larger probability belonging to the object, so the initial probabilities can be a function of the distance:

$$f^{(0)} = 1 - \frac{D}{\max_{(x, y)} D}. \quad (13)$$

This motivates the restriction of level set function f values to the probability interval $[0, 1]$, and the interpretation of f as a random field of object probabilities. In particular, the locations with object user labels have probability one, while those with background labels have probability zero. Given a random field level set, we can threshold the probabilities (e.g., at 0.5) to obtain a segmentation. The basic idea is to exploit both the sign and the value of the region-based level set function.

3.1. Mean Belief Cost

Since a location is labeled as object if the corresponding belief (probability) is above a threshold p , we design a cost based on the average belief inside the object:

$$J_B = \frac{\int_{\Omega} f(x, y) H(f(x, y)) dx dy}{A(f)}, \quad (14)$$

where $A(f) = \int_{\Omega} H(f(x, y)) dx dy$ is the area of the object. Intuitively, all locations in the object region should have high confidence. Empirically, we found that this cost encourages segmentations corresponding to a single compact region.

3.2. Prior Segmentation Cost

For 3-D segmentation, a common approach is to first segment one slice, and then to propagate the level set across slices. To this end, we design a prior segmentation cost:

$$J_P = \int_{\Omega} (H(f(x, y)) - H(f'(x, y)))^2 dx dy, \quad (15)$$

where $f'(x, y)$ is the level set of the adjacent slice. This term can also be used to handle the propagated user labels by letting $f' = f^0$. In either case, a previous result from an adjacent slice or the propagated user labels is used as a prior segmentation. This term is similar to the one used by [5, 6], except that f' uses the generalized distance transform label propagation, as opposed to an isotropic propagation. In general, this term can be used to penalize a segmentation from a prior shape model.

3.3. Level Set Functional

Our overall cost function combines the previous terms:

$$J = J_0 + \lambda_P J_P + \lambda_B J_B, \quad (16)$$

and gives the Euler-Lagrange update:

$$\begin{aligned} \frac{\partial J}{\partial t} = \delta(f) & \left[\mu \operatorname{div} \left(\frac{\nabla f}{\|\nabla f\|} \right) \right. \\ & - \lambda_1 (u(x, y) - \bar{u}_2)^2 + \lambda_2 (u(x, y) - \bar{u}_1)^2 \\ & \left. - \lambda_P (H(f) - H(f')) \right] \\ & + \lambda_B \frac{H(f) + f \delta(f)}{A(f)}, \end{aligned} \quad (17)$$

where δ is the Dirac measure, and the $\lambda_{()}$ parameters are designed to weight the corresponding costs. After each update step, the level set function is normalized to the range $[0, 1]$.

In our numerical implementation, we use a smooth Heaviside function $H_{\epsilon}(z) = \frac{1}{2} \left(1 + \frac{2}{\pi} \arctan\left(\frac{z}{\epsilon}\right) \right)$, with $\epsilon = 1$ (and corresponding smooth Dirac measure). The level set is evolved with time step $\Delta t = 0.1$ and unit spatial spacing.

4. RESULTS

4.1. Liver Segmentation

The liver segmentation data [9] used in our experiments has $512 \times 512 \times 64$ voxels with voxel spacing 0.63mm in the x/y -direction, 3mm in the z direction. In general, without using user information, segmentation result of a liver dataset

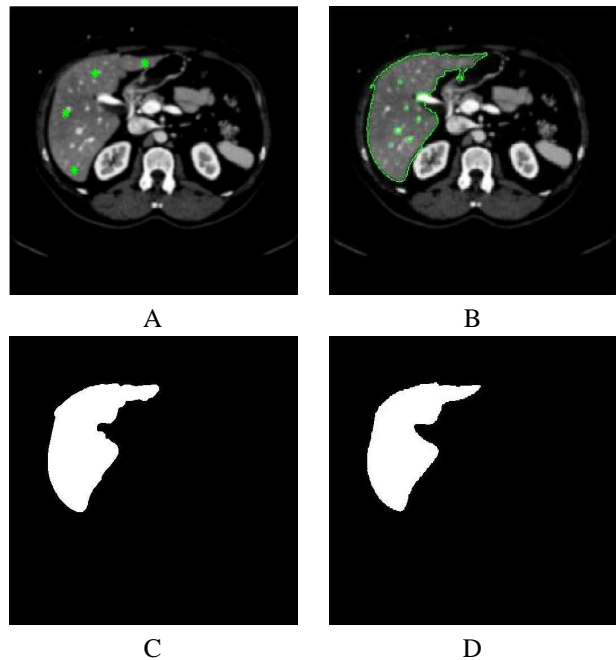


Fig. 4. User selected points (A) and the corresponding segmentation (B,C) compared to the ground truth (D) in the middle slice of the liver data.

includes other objects, *e.g.*, heart and stomach, while the results using user information as in [5, 6] lose the tip of the liver. In order to completely separate the liver from other internal organs, we use the random field level set and user label propagation described above.

The user labels a few of points inside the liver in one of the slices, *e.g.*, the middle slice. The algorithm generates the initial level set by propagating the user labels, segments the slice, and then propagates the segmentation between slices and across the entire volume. The cost function parameters are listed in Table 1, and its belief threshold is $p = 0.84$. The result is also post-processed with morphological hole-filling and opening. The segmentation result of the middle slice with user labels is shown in Figure 4. We achieve approximately 86% volumetric overlap, as between-slice propagation errors tend to accumulate towards the first and last slices.

In Figure 5 and Table 2, we different user labeling scenarios and the associated segmentation results and user/computation time on an example slice of the liver data. In general, more labeled points tends to improve the results, and a good initial label propagation also speeds up level set convergence. However, precise user labeling also tends to take more time than scribbling.

λ_1	λ_2	λ_P	λ_B
0.1	0.1	0.1	10

Table 1. Parameters for liver dataset

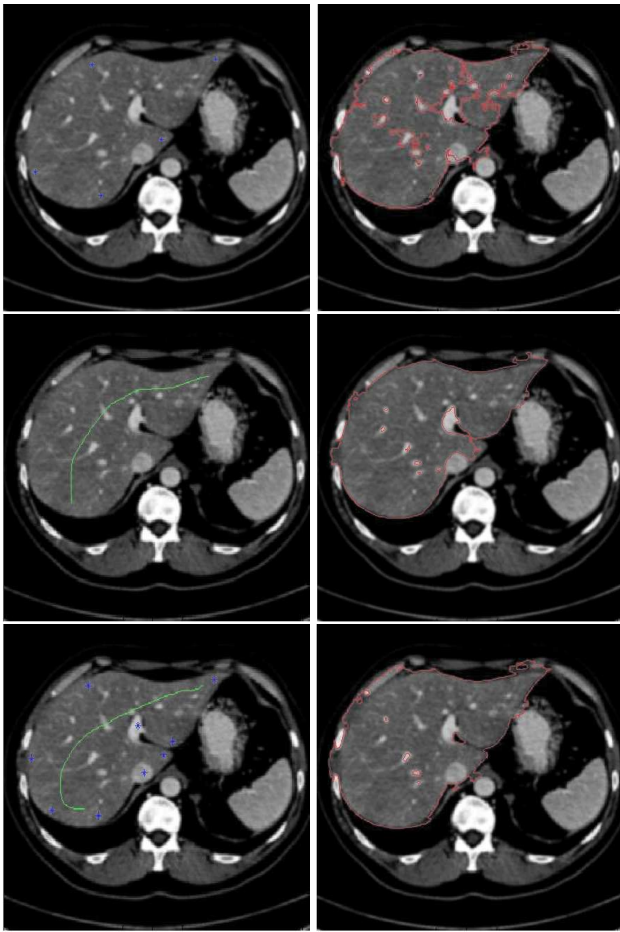


Fig. 5. Random field level set segmentation with user label points (top), scribble (middle), and both (bottom).

5. SUMMARY

We proposed a method to exploit user information in region-based level set image segmentation. The two key ideas are user label propagation via a generalized distance transform and random field level sets. The generalized distance transform propagates user labels by taking into account image intensity information. This generalizes previous approaches which propagate user labels in a purely geometric fashion. Random field level sets restrict the range of the level set function to the probability interval $[0, 1]$. This uses both the sign and the value of the level function.

The ideas above are combined by incorporating average belief and prior segmentation terms into region-based level set

None	Points	Scribble	Both
48.22s	24.51s	17.70s	38.49s

Table 2. Total segmentation time (user labeling and algorithm computation) for different labeling scenarios.

cost functional. We tested the method on a liver segmentation task, and showed improved performance over previous approaches. Nevertheless, better ways of comparing algorithms are needed when user information is exploited, as some algorithms may prefer particular types of user labels, e.g., key points vs. dense scribbling. Future work involves using our framework with learned shape priors, improving the probabilistic formulation of level sets and the associated optimization algorithms, and minimizing the number and empirical tuning of parameters.

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