# Evaluation of Morphological Reconstruction, Fast Marching and a Novel Hybrid Segmentation Method

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**Abstract.** An evaluation of two traditional segmentation algorithms of Morphological Reconstruction and the Fast Marching method along with a novel hybrid segmentation approach is presented. After introducing the Fast Marching and the Morphological Reconstruction segmentation, we propose a novel hybrid segmentation approach in multi-stage, which is derived from both an improved Fast Marching method and the Morphological Reconstruction. To demonstrate the effectiveness and accuracy of the three methods, we employ an MRI brain image in our experiments, in which "gold standard" is known. The evaluation is measured accordingly in accuracy and speed when running a 2.0 GHz based windows XP PC. The accuracy results of average 0.9738, 0.6302 and 0.9734 measured in similarity indexes of the Morphological Reconstruction, the Fast Marching and the hybrid approach are achieved, respectively. The computing performance required 188.6, 22.3 and 43.4 in seconds accordingly.

## 1 Introduction

Medical image segmentation is a fundamental technique for computer assisted surgery and therapy. There are many medical image segmentation methods described in the literature. They may be basically divided into two groups: Model-based and Region -based methods. The Snake [1], introduced by Kass et al, provides a general model-based solution to the segmentation problem. Level Set [2] is another classical model-based segmentation method. By introducing an additional dimension, the complicated problems of contour breaking and merging could be effectively handled. However, it brings more computational costs in. Many efforts have been addressed to reduce its complexity. Narrow Band level set [4] and Fast Marching [3] methods improved the situation from different respects. However, the model-based methods are usually fast but sometimes not accurate enough.

In contrast to the model-based methods, the segmentation algorithms, which are operated in region base, can achieve more accurate results. Watershed and Morphological Reconstruction [5] are two main representatives and both derived from mathematical morphology. The second algorithm is also known as a morphological region growing approach with powerful reconstruction ability. Although the region-based algorithms improved the accuracy, they are usually more computationally expensive.

In this paper, we present a hybrid algorithm that integrates the Fast Marching method and the morphological reconstruction to take the advantage of both rapid from model-based method and accurate from region-based approach. Meanwhile, an evaluation of three algorithms using a standard MRI brain image is performed to demonstrate their features.

The rest of this paper is organized as follows: in section 2, we review the Level Set, Fast Marching and Morphological Reconstruction algorithms. In section 3, we introduce the novel hybrid segmentation strategy. In the experiment of section 4, we evaluate the three segmentation approaches based on a standard criterion.

## 2 Fast Marching and Morphological Reconstruction

### 2.1 Level set and Fast Marching

The Level Set method is essentially a moving interface problem. It embeds the interface as the level set of a higher dimensional function, so called level set function.

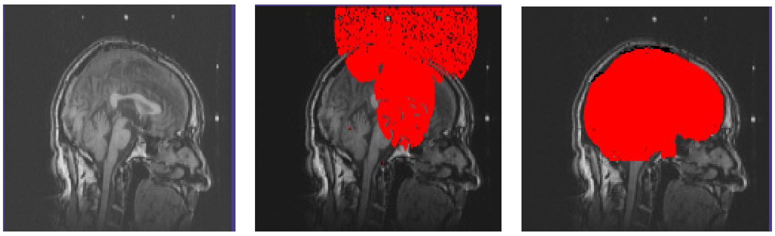
We may locate the front by finding the zero level set of the level set function as:

$$\Gamma(\mathrm{t}) = \{ \Phi(x, t) = 0 \} \tag{1}$$

and differentiate with respect to t, we can get

$$\frac{\partial \Phi}{\partial t} + v \left| \nabla \Phi(x, t) \right| = 0 \tag{2}$$

where the speed function v is related to image features and front characteristic.



(a) (b) (c)

**Fig. 1.** Examples of the Fast Matching results. (a) Source Image; (b) Traditional Fast Matching; (c) Improved Fast Matching.

Fast Marching is a special case of the Level Set, where the sign of the speed Function is always unchanged (positive or negative). Therefore the front is always moving forward or backward. This restriction makes the fast marching approach much more rapid than the more general level set method.

### 2.2 Improvement of the Fast Marching

The traditional Fast Matching method has a major drawback that it is very hard to control the front during the propagation. In the case of the existing of connection between the object and its neighboring regions, the front can easily lead to an overflow. An example is shown in Fig.1(b).

To prevent the front propagation from overflow, we introduce global information of the front into the speed function. Firstly, we define an average energy of the front as:

$$E_{front}(t) = \frac{1}{N_{front}} \sum_{(x,y,z)\in\Gamma(t)} E(x,y,z) \tag{3}$$

where *E(x,y,z)* stands for the image energy at (x,y,z) in the image I(x,y,z),defined as:

$$E(x,y,z) = -\left|\nabla G_{\delta} * I(x,y,z)\right| \tag{4}$$

Where $\boldsymbol{G_{\delta}}$ is a 3D Guassian function with a standard deviation $\boldsymbol{\delta}$. $\nabla$ represents a gradient operation. And $E_{front}(t)$ is associated with the energy of all the points in the front. We introduce it into the speed function F and redefine it as below:

$$F(x,y,z,t) = F(x,y,z)\cdot e^{\beta\cdot E_{front}(t)} = F(x,y,z)\cdot e^{-\beta\frac{1}{N_{front}}\cdot\sum_{(x,y,z\in\Gamma(t))}\left|\nabla G_{\delta} * I(x,y,z)\right|}, \beta > 0 \tag{5}$$

When most points along the front approach to the object edge, $E_{front}(t)$ becomes much smaller than 0, which leads *F(x,y,z,t)* close to 0 to halt the front. By changing the speed function from *F(x,y,z)* to *F(x,y,z,t)*, the front can be efficiently prevented from overflow. An example of the improved fast marching is shown in Fig.1(c).

### 2.3 Morphological Reconstruction

The morphological reconstruction is a typical approach to extract seeded regions, which is defined as:

$$S_{i+1} = (S_i \oplus k) \cap |m| \qquad (i = 0,1,2\cdots) \tag{6}$$

Where, S and k denotes the seed and a small disk shaped structuring element, respectively. $\oplus$ and |m| stand for a dilation operation and the mask accordingly. The mask is achieved via a threshold operation using a histogram analysis.

## 3 Hybrid Segmentation Strategy

The morphological operation during the reconstruction is very computational expensive. To speed up the propagation, we need to define a good seed (marker), which is close enough to the object edge. In that case, the iteration of the morphological reconstruction could be possibly reduced to a reasonable small value.

The Fast Marching method can help us get a good initial marker. We firstly employ the Fast Marching to quickly propagate the front from a user-defined seed. When the front stopped at a position close to the edge, we switch it from the Fast Marching procedure to the Morphological Reconstruction as the marker to refine the front fitting into the edge accurately. As the result, the proposed hybrid approach can achieve a result much quicker than the morphological reconstruction with similar accuracy. The procedure of the hybrid segmentation approach is described in Fig 2.

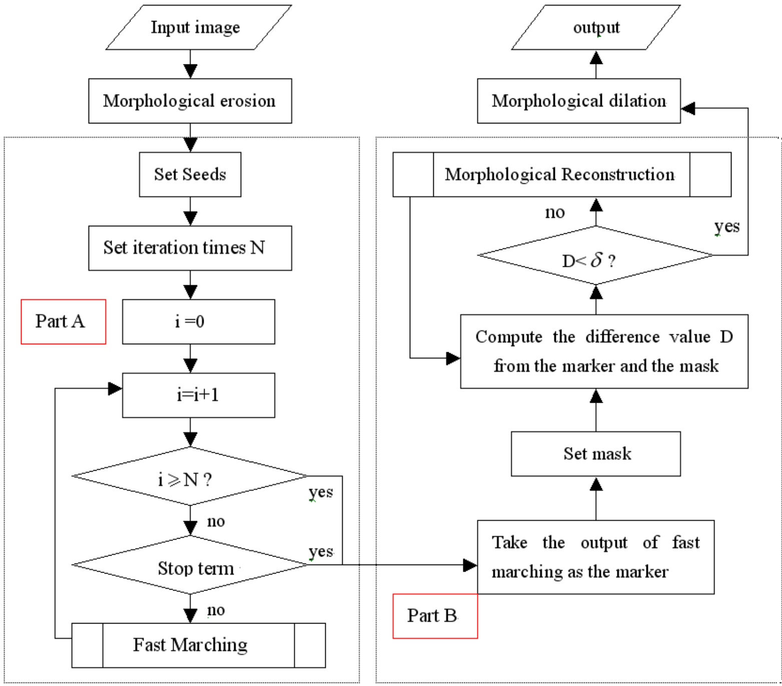



**Fig.2.** Flow chart of the hybrid segmentation approach, where part A and B belong to the Fast Marching and the Morphological Reconstruction, respectively. In Part B, δ represent a user defined error tolerance between the marker and the mask.

## 4 Evaluation Experiment

A "TkSegmentation" software was developed to perform the evaluation, which is based on Visualization Toolkit (VTK), Insight Toolkit (ITK) and Python programming environment, and running on a P-IV 2.0 GHz Windows-XP PC.

The source data employed in our experiments includes CT or MRI datasets of brain, heart and kidney studies. A standard CJH27 image volume derived from an average of 27 T1 weighted images of a normal brain was employed in the evaluation study, which is shown in Fig.3(a). CJH27 is a 181×217×181 voxel volume, with isotropic 1 $mm^3$ voxels. This standard brain was generated from a set of 3D "fuzzy" anatomical models. Each model represents a typical tissue class (white matter, gray matter, CSF, etc.). This model was then used as input for an MR simulator (MNI Brainweb[1]) that produces a realistic MR volume image for which "ground truth" is known with respect to its components.

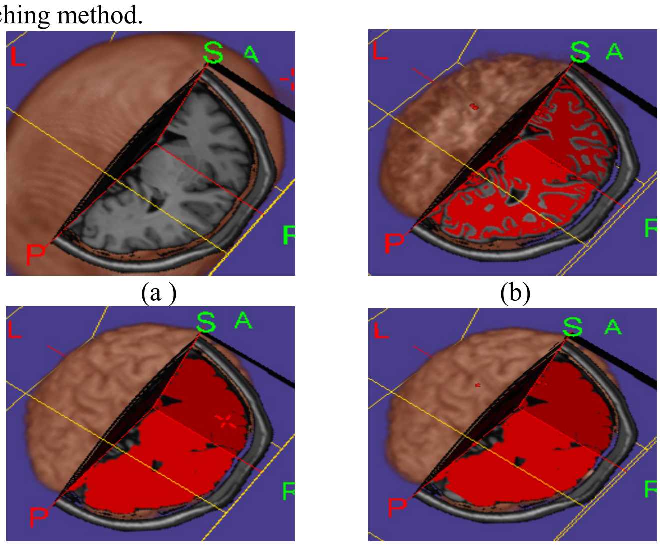
[1] http://www.bic.mni.mcgill.ca/brainweb/

We evaluated the three segmentation methods in two aspects: the accuracy of the segmented result and the efficiency of the segmentation procedure.

### 4.1 Accuracy

We first evaluated the accuracy of the segmented results. The example results are shown in Fig.3.(b)-(d). The normal Fast Marching result shown in (b) indicates that most of the surface could not be accurately reconstructed. The Morphological Reconstruction brings us a more accurate result as shown in (c). The result of the proposed approach shown in (d) is quite similar to the one of the Morphological Reconstruction.

In order to quantify the segmentation accuracy, we employed the idea of "similarity index" in our experiment, which is introduced by Zijdenbos [6]. We evaluated the three methods and concluded into the Table.1. The initial seeds were repeatedly defined at various locations three times. The result of our proposed approach is quite similar to the morphological reconstruction, and much better than the one from the Fast Matching method.




(a ) (b) (c) (d)

**Fig.3.** Segmentation results, where the 2D results are indicated in high-lighted regions. (a) source image; (b) the Fast Matching result; (c) the Morphological Reconstruction result and (d) the proposed hybrid approach

### 4.2 Efficiency

The computing times of the three segmentation algorithms were measured during the experiment. Table 2 describes the results of each method when three initial seeds were repeatedly defined. We can find that even the proposed hybrid method is still more costly than the Fast Matching method, but significantly improved from the Morphological Reconstruction method. It is considered as a near real time algorithm.

The reason why the hybrid approach is much faster than the traditional morphological Reconstruction is that the numbers of the iteration during the reconstruction were significantly reduced. In the example, the total iterations of Morphological reconstruction and Hybrid Approach were 30 and 3 respectively.

**Table.1.** Comparison of Similarity Index value of different approaches

| | 1 | 2 | 3 | average |
|---|---|---|---|---|
| Morph. Reconstruction | 0.9737 | 0.9731 | 0.9747 | 0.9738 |
| Fast Marching | 0.6278 | 0.6298 | 0.6334 | 0.6302 |
| Hybrid Approach | 0.9737 | 0.9734 | 0.9721 | 0.9734 |

**Table.2.** The computing time of the three segmentation method

| | 1 | 2 | 3 | average |
|---|---|---|---|---|
| Morph. Reconstruction | 197.5” | 184.4” | 184.1” | 188.6” |
| Fast Marching | 22.3” | 19.6” | 25.1” | 22.3” |
| Hybrid Approach | 41.7” | 45.8” | 42.6” | 43.4” |

## 5 Conclusion

In this paper, we presented an essential evaluation study using two typical segmentation methods and a novel hybrid segmentation approach based on a standard criterion. The evaluation results in both accuracy and efficiency revealed that the proposed hybrid approach takes the advantage of both accurate from region-based algorithm and rapid from the model-based approach, which achieved a near real time segmentation performance and high accurate results.

As future works, we are scheduling to choose more algorithms from both model-based and region-based algorithms into our evaluation study. We are going to design more sophisticated analysis methods other than the similarity index to inspect experimental results more precious, and the evaluation results will be virtually presented.

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