A New Information Fusion Approach for Image Segmentation

Wentao Xu[† ‡], Ratchadaporn Kanawong[†], Ye Duan[† *], Guixu Zhang[‡]

[†] Computer Science Department, University of Missouri-Columbia, MO, 65211USA
[‡] Computer Science Department, East China Normal University, Shanghai, 200062 China
*Corresponding author: duanye@missouri.edu

Abstract—**In this paper we propose a new hybrid image segmentation algorithm that integrate the region-based method with the boundary-based method. More specifically we take an information fusion approach based on the Tensor Voting framework that seamlessly fuse the information from the region-based Mean Shift method with the boundary-based Canny Edge Detection algorithm. We have tested our algorithm on several images from the Caltech 101 database [18]. Experiments results show the new algorithm is very efficient and can achieve very good segmentation results.**

Index Terms—**Hybrid image segmentation, Information fusion.**

I. Introduction

Image segmentation is a fundamental problem in image processing and computer vision. In general, image segmentation approaches can be divided into two main categories: region-based (region growing, region merging) [1] and boundary-based (snake and balloon) techniques [2-4].

Region-based methods provide quick segmentation results by assigning membership to voxels according to homogeneity statistics, however since there is no easier way to distinguish boundaries and interior pixels/voxels of the object, this method can lead to noisy boundaries and holes in the interior.

Boundary-based methods attempt to align an initial deformable boundary with the object boundary by minimizing an energy functional which quantifies the gradient features near the boundary. The main drawback of these methods is their sensitivity to the initial conditions. To avoid being trapped in local minima, most of these algorithms require the model to be initialized near the solution or supervised by high-level guidance, thus for boundary based methods, defining the initial geometry prior to deformation (i.e. the seed) is also a critical issue that has yet to be resolved. Without a proper method for seed contour initialization, the seed will deform to local rather than global minima in most circumstances due to image noise.

Recently several hybrid methods are proposed that combine region-based and boundary-based approaches in order to overcome the disadvantages of each approach alone. Ronfard used region-based information to drive the explicit deformable models in their techniques [5], while Chakraborty and Duncan [6], Jones and Metaxas [7-9], Chen and Metaxas [10] have addressed these issues by interlacing region-based and boundary-based methods into a united, iterative segmentation process. The efficacy of these types of algorithms exceeds that of region-based or boundary-based methods independently, but the most notable disadvantages of these methods are that they have relatively low efficiency compared with other segmentation algorithms.

This paper presents a new hybrid image segmentation method that combines the region-based method with the boundary-based method. More specifically, we takes an information fusion approach to integrate information extracted from the region-based Mean Shift algorithm [11] with the information extracted from the boundary-based Canny Edge algorithm [12] into one unified framework based on the Tensor Voting algorithm [16]. It differs from previous hybrid methods in that it implements region-based and boundary-based approaches in two separate phases, which allows more efficient segmentation and effectively avoids local minimum. Our new algorithm fully exploits the robustness of the Mean Shift algorithm and the efficiency of the Canny Edge Detection algorithm, as well as the outlier removal capability of the Tensor Voting algorithm. Experiments results show the new algorithm can achieve very good segmentation results.

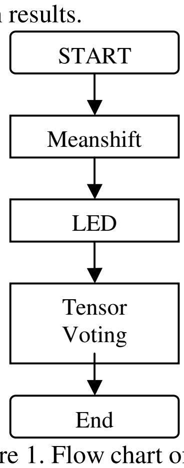


Figure 1. Flow chart of the algorithm.

II. Algorithm

Our information fusion based image segmentation framework consists of the following three main steps:

1) Initial segmentation by Mean Shift;
2) Localized edge detection (LED):
3) Refined segmentation by Tensor Voting.

Starting with an input image, we will employ the Mean Shift algorithm to obtain an initial boundary contour of the object. Next, the Canny Edge Detection algorithm will be applied to the local neighborhood regions of the initial boundary contour to extract salient edges. Finally we will apply the Tensor Voting algorithm to integrate the initial boundary contour with the detected edges to obtain a refined segmentation of the input image. Step 1 to 3 can iterates several times until a satisfied result is obtained. We will describe each of the main steps in more details in the following sections. Fig. 1. shows the flow chart of the algorithm.

Initial Segmentation by Mean Shift

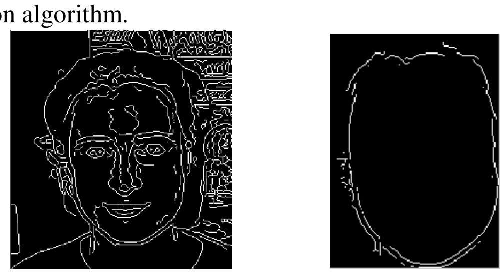
The initial segmentation is done based on the Mean Shift algorithm [11]. Mean Shift is a powerful general purpose technique for clustering scattered data. Instead of assuming a fixed number of clusters as is common with other clustering methods (e.g. *K*-means), Mean Shift extracts the modes of the density function. More specifically, Mean Shift segmentation based on color domain is an iterative approach to cluster image by searching a number of density. Firstly, an initial mean x is estimated. Secondly, the kernel density function K(x) is computed. Thirdly, x is replaced by m(x):

$$m(x) = \frac{\sum_{x_i \in N(x)} K(x_i - x)x_i}{\sum_{x_i \in N(x)} K(x_i - x)} \tag{1}$$

where $N(x)$ is the neighborhood of x. These three steps will iterate until it converges. Fig. 5(a) and Fig. 5(b) show an example of the Mean Shift based initial segmentation. For a complete description of Mean Shift, please refer to the original paper [11].

Localized Edge Detection

Since Mean Shift algorithm is a region-based clustering algorithm, it might not be very sensitive to the discontinuity of the image gradient and thus can miss important image edges. To overcome this issue, after an initial boundary contour is extracted from the Mean Shift algorithm, we will apply a Localized version of the Canny Edge Detection algorithm [12] next to provide complement information which will be fused in the following Tensor Voting step. The Localized Edge Detection (LED) will apply only to the local neighborhood around the region of interest, which is obtained by applying the mathematical morphology dilation operation with a disc element onto the boundary contour extracted from the above initial segmentation step. Fig. 2. shows an illustration of the Localized Edge Detection algorithm.



(a) (b)

Figure 2. Localized Edge Detection: (a) Canny edge detection result, (b) Localized edge detection result.

Refined Segmentation by Tensor Voting

Tensor voting [13-16] is a method of information propagation where tokens convey their orientation preferences to their neighbors in the form of votes. Each vote is an estimate of orientation or termination of a perceptual structure consisting of just two tokens: the voter and the receiver. Smooth perceptual structures are fitted between the two locations to generate the orientation estimates at the receiver. The strength of the votes attenuates both with distance and with increased curvature of the hypothesized structure, making straight continuations preferable to curved ones following the principles of smooth continuation and simplicity.

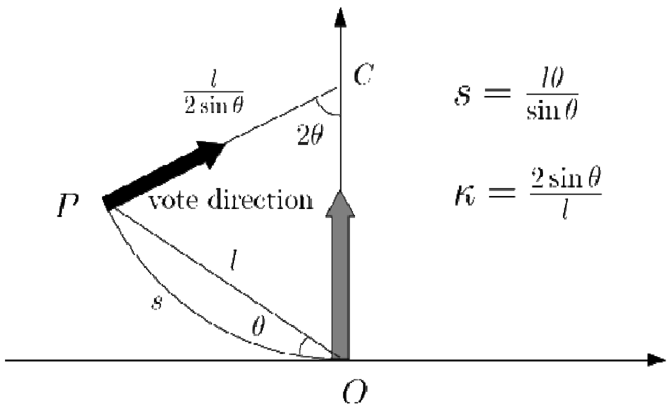


Figure 3. Tensor Voting between two points.

The tensor field generated by a voting procedure allows effective and robust communications among the data to extract both coherent geometry (through the tensor structure) and likelihood information (through the saliency field). Fig. 3. gives a brief review of the basic idea behind the tensor voting method in 2D. Suppose that there exists a smooth curve connecting the origin *O* and a point *P* and the normal to the curve at *O* is known. Then what is the most likely normal direction at *P*? It is argued in [16] that the osculating circle connecting *O* and *P* is the most likely connection since it keeps the curvature constant along the hypothesized circular arc. So the most likely normal is given by the normal to the circular arc at *P* (thick black arrow in Fig. 3.). This normal at *P* is oriented such that its inner product with the normal at *O* is nonnegative. The length of this normal, which represents the voting strength, is inversely proportional to the arc length *s* and curvature *k*. So the decay function of vote strength is defined as (2):

$$DF(s,\kappa,\sigma) = e^{-\left(\frac{s^2 + c\kappa^2}{\sigma^2}\right)} \tag{2}$$

where σ controls smoothness, which determines the effective neighborhood size [15], and constant c controls the decay with high curvature.

Votes are cast from token to token and accumulated from their neighboring points. After votes are collected at every location, stick and ball saliency maps are built, local structures such as curves, junctions, region boundaries can be detected based on their high region saliency and high polarity.

In our case, we will combine the boundary contour extracted by the Mean Shift algorithm (Fig. 4(a)) with the edges extracted by the Localized Canny edge detection algorithm (Fig. 4(b)) into one binary image (Fig. 4(c)). We will then compute the gradient vector and the tensor matrix at the edge and contour pixels of the binary image, which will then be casting votes on all the pixels of the image to generate a global tensor field. Fig. 4(d) shows the stick saliency map constructed from the global tensor field. Finally, we will extract the refined object contour based on the stick saliency map (Fig. 4(e)).

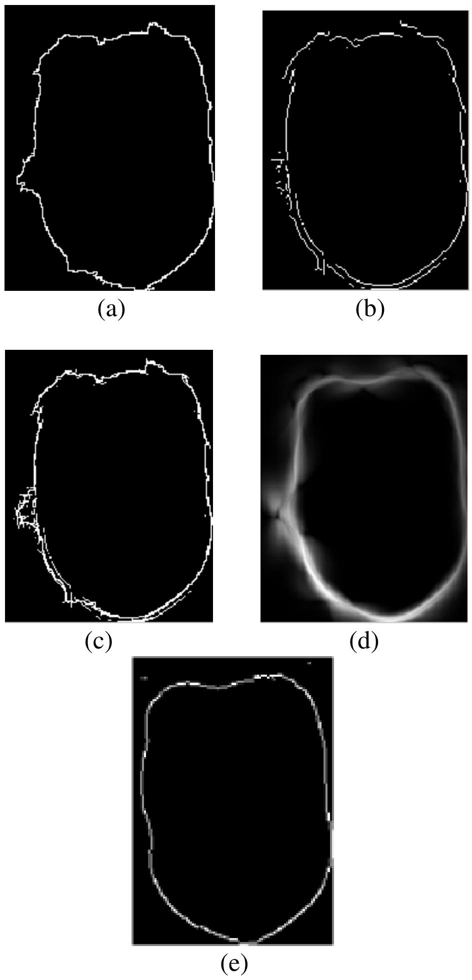


Figure 4. Information fusion by Tensor Voting. (a) Object boundary contour extracted by Mean Shift algorithm; (b) Edges extracted by Localized Canny Edge detection; (c) Boundary contour extracted from (a) is overlaid with edges extracted from (b); (d) Stick saliency map generated by the Tensor Voting; (e) Refined object boundary contour extracted from the stick saliency map of (d).

III. EXPERIMENT AND ANALYSIS

In order to demonstrate the robustness and the efficacy of the proposed algorithm, we had conducted some experiments to compare our algorithm with other popular image segmentation algorithms such as Mean Shift, JSEG [17], as well as Canny edge detection on some face images from the Caltech 101 image database [18]. The preliminary testing results (Fig.5 & Fig.6) show that our algorithm clearly outperforms the above three algorithms. Since Tensor voting is a function of the position of the receiver, the tensor at the voter and the scale of the saliency decay function, in practice, all the tensor votes around each point can be pre-computed to form tensor voting fields at the desired resolution. As a result, computing the votes cast by any second order tensor is reduced to a few look-up operations and linear interpolation [16] which results in very efficiency computation.

IV. CONCLUSION

Region-based image segmentation and boundary-based image segmentation approaches are complementary methods. In this paper, we proposed an information fusion based hybrid image segmentation algorithm that seamlessly integrate the region-based image segmentation with the boundary-based image segmentation. Test results show that our new algorithm is robust and efficient and outperforms some of the state-of-art region-based and boundary based image segmentation algorithms. In the future research, we would like to extend our algorithm to 3D image segmentation for images such as MRI and CT, etc.

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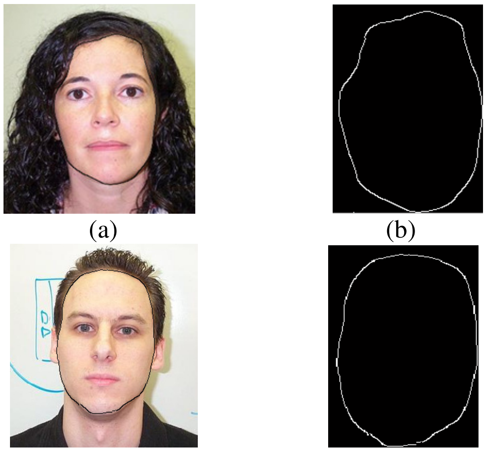
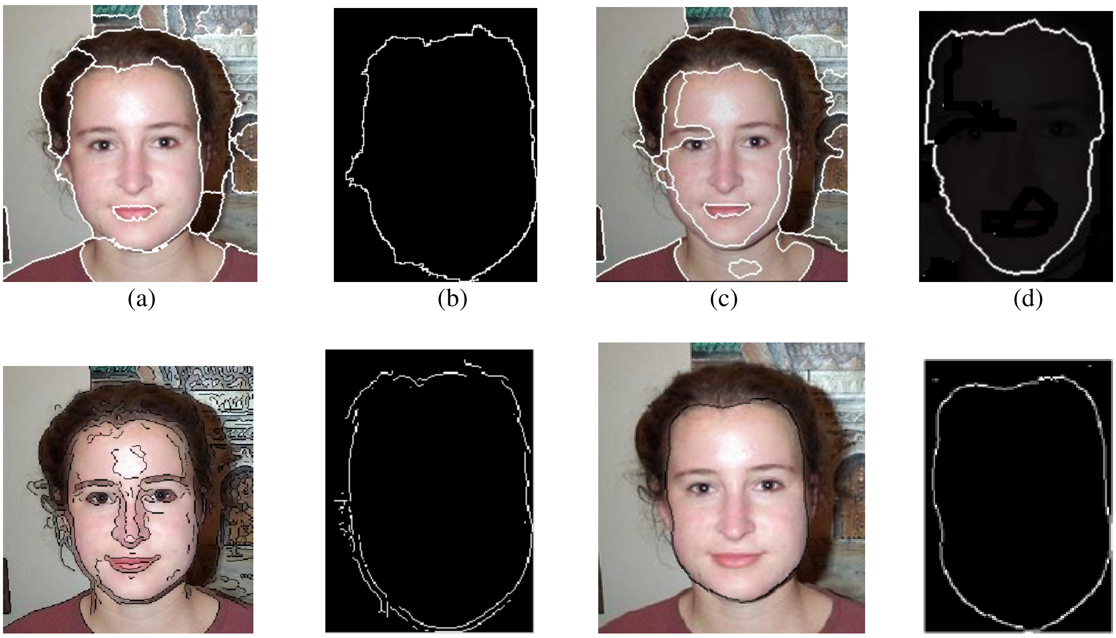


(c) (d)

Figure 6. More results of our algorithm.



(e) (f) (g) (h)

Figure 5. Comparison of our algorithm with other image segmentation algorithms such as Mean Shift, JSEG and Canny edge detection on a face image. (a) Segmentation result of the Mean Shift algorithm; (b) extracted boundary contour of (a); (c) Segmentation result of the JSEG algorithm; (d) extracted boundary contour of (c); (e) Canny Edge Detection result; (f) Edges extracted around the face contour (Figure 2 (b)); (g) Segmentation result of the proposed approach; (h) extracted boundary contour of (g). (The face image is courtesy of the Caltech 101 image database [18]).