ENSEMBLE OF ACTIVE CONTOUR BASED IMAGE SEGMENTATION

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ABSTRACT

Most image segmentation methods based on active contour model are sensitive to the contour initialization. For the images of complex contents, it is difficult to initialize the contour properly and the biased initialization may lead to low-quality segmentation results. Aiming to tackle this problem, we propose an ensemble strategy to improve the contour-based segmentation. The optimal segmentation ensemble is obtained through maximizing the weighted mutual information between the probability distributions of multiple segmentation results. Experimental results validate that the ensemble of contour-based segmentation is robust to the biased initialization and produces stable and precise results for the images of complex contents.

Index Terms— Active contour, segmentation ensemble

1. INTRODUCTION

Active Contour models have been widely used in the areas of image analysis and computer vision [1-5]. For the contour-based image segmentation, the contours are driven to reach the object boundary through minimizing the fitting energy [6-9]. There are two kinds of active contours: Parametric Active Contours and Geometric Active Contours [10-12]. Parametric active contours are formulated in terms of curve function and depend much on the curve parameters [13-14]. Geometric active contours do not entail the curve parameterization and can handle the topological change of contours in a natural and efficient way [15-18].

However, the segmentation based on geometric active contours is sensitive to the contour initialization [19, 20]. For the images of complex contents, it is generally difficult to initialize the contour curves completely and precisely. The biased initial contour on foreground may misguide the contour evolution and produce inaccurate segmentation. To tackle this problem, we expect to integrate multiple segmentation results induced by biased contour initialization to achieve the high-quality segmentation. This ensemble strategy is motivated by Ensemble Learning [21, 22], in which a group of low-quality classifiers or clustering are combined to improve the learning performance. To the best of our knowledge, the research on the ensemble of contour-based segmentation is still limited.

The ensemble process of contour-based segmentation is summarized as follows. First, we construct the probabilistic representation of the contour-based segmentation based on the dictionary of discriminative image patches. Second, we evaluate the quality of each segmentation result as the weight for ensemble. Finally, we maximize the weighted mutual information between the probability distributions of multiple segmentation results to obtain the optimal probabilistic representation of the segmentation ensemble.

The remainder of this paper is organized as follows. Section 2 introduces the ensemble strategy of the contour-based segmentation. In Section 3, experimental results validate the effectiveness of the proposed ensemble method. The work conclusion is given in Section 4.

2. IMAGE SEGMENTATION ENSEMBLE BASD ON ACTIVE CONTOURS

2.1. Probabilistic representation with dictionary

To integrate the contour-based segmentations in probability, it is required to compute the probabilities of image pixels belonging to foreground and background. The probabilistic representation of pixels is formulated through constructing a dictionary of discriminative image patches [23, 24]. The patch of a pixel is defined as its $m \times m$ neighborhood template ($m = 3$), the patches of all the pixels are grouped into k clusters with K-means algorithm and the cluster centers are utilized to form k elements of image dictionary.

Suppose Ω is the universal set of image pixels, the label map $\mathrm{L}_{in} : \Omega \rightarrow \{0, 1\}$ indicates whether a pixel locates inside the contour (foreground) or not. Based on the image dictionary, we can transform the binary labels into the probabilities of foreground and background with respect to the active contours. First we compute the probabilities of dictionary elements belonging to the foreground, i.e. the region inside contour. Because the dictionary is constructed through clustering patches, each element in the dictionary has a number of patches assigned to it. For a dictionary element, its probability belonging to the foreground is the pixel-wise average of the label values of all the patches corresponding to it. The pixel-wise frequency of dictionary elements belonging to the contour-inside region can be computed as

$$d_{in} = diag(B \cdot l_1)^{-1} \cdot B \cdot l_{in} \tag{1}$$

in which B is a binary matrix which has $k \cdot m^2$ rows and $|\Omega|$ columns to indicate the correspondence between the dictionary pixels and image pixels, l_1 is the column of ones and l_{in} is the label vector of L_{in}.

To handle the imbalanced distribution of pixels in the foreground Ω_{in} and background Ω_{out}, the frequency vector d_{in} is normalized component-wise to the probability.

$$p_{in}^{dic} = \frac{d_{in} / |\Omega_{in}|}{d_{in} / |\Omega_{in}| + d_{out} / |\Omega_{out}|} \tag{2}$$

Based on the probabilities of dictionary elements, we can compute the probabilities of image pixels belonging to the foreground and background. For each pixel in the image, there are m^2 overlapped patches covered it. The foreground probability of an image pixel is computed as the average probabilities of the dictionary elements that correspond to the patches covered the pixel. The foreground probabilities of all the image pixels are computed as follows.

$$p_{in}^{img} = diag(B^T \cdot l_1)^{-1} \cdot B^T \cdot p_{in}^{dic} \tag{3}$$

The background probabilities of pixels can be also computed as $p_{out}^{img} = 1 - p_{in}^{img}$. Different from the binary labels in traditional contour-based methods, the probabilities of pixels provide a quantitative map $\Omega \to [0,1]$ and thereby form a probabilistic representation of the image content respect to contour curves. Figure 1 illustrates the foreground probabilities of image pixels.

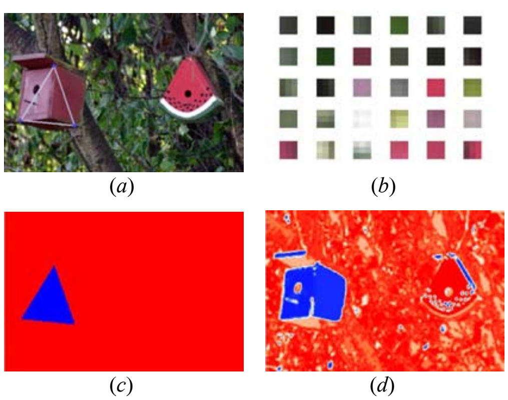


Fig. 1. Probabilistic representation of image with dictionary. (*a*) original image with contour initialization, (*b*) dictionary based on patch clustering, (*c*) binary label map of the initialized contour, in which blue color represents the foreground and red color denotes the background, (*d*) the probabilities of pixels belonging to the foreground and background respect to the contour curve.

2.2. Ensemble of contour-based segmentations

In the segmentation based on active contours, the edges of foreground are represented by continuous closed curves *C*. Let ϕ denotes the Level set function, *C* is regarded as the zero level set [15, 16]. It partitions image pixels into inside and outside regions to form the segmentation. The Heaviside function $H(\phi)$ is used to partition the regions, i.e. $H(\phi) = 0$ for $\phi < 0$ (inside) and $H(\phi) = 1$ for $\phi > 0$ (outside). The optimal contour for segmentation can be achieved through minimizing the energy of curve fitting. Adding the factor of curve length to control the contour smoothness, the general form of fitting energy is defined as

$$\begin{aligned} & F(c_1, c_2, C) = u \cdot Length(C) + \\ & \lambda_1 \int_{inside(C)} |\mu_0 - c_1|^2 \, dxdy + \lambda_2 \int_{outside(C)} |\mu_0 - c_2|^2 \, dxdy \\ & = u \int_\Omega |\nabla H(\phi)| \, dx + \\ & \lambda_1 \int_\Omega |\mu_0 - c_1|^2 H(\phi) dxdy + \lambda_2 \int_\Omega |\mu_0 - c_2|^2 (1 - H(\phi)) dxdy \end{aligned} \tag{4}$$

μ_0 represents the pixel intensity and c_1, c_2 denote the average intensities inside and outside the contour curve. $\delta(\phi)$ is the derivative of function $H(\phi)$, the update of curve evolution is given by the following equation,

$$\begin{aligned} \frac{\partial \phi}{\partial t} &= -\frac{\partial F(c_1, c_2, C)}{\partial \phi} \\ &= \delta(\phi)[u \cdot div(\frac{\nabla \phi}{|\nabla \phi|}) - \lambda_1 (\mu_0 - c_1)^2 + \lambda_2 (\mu_0 - c_2)^2] \end{aligned} \tag{5}$$

For the active contour model based on the probabilistic representation of image, the evolving curve should expand when meeting the pixels of high foreground probability p_{in}, and in the meantime shrink when meeting the pixels of low p_{in}. The energy of curve fitting will reach the minimum when $p_{out} = p_{in}$. Thus the curve evolution function can be reformulated as follows.

$$\frac{\partial \phi}{\partial t} = \frac{1}{2} - P_{in} + \delta(\phi)[u \nabla \cdot (\frac{\nabla \phi}{|\nabla \phi|})] \tag{6}$$

The curve evolution process is summarized in Algorithm 1.

Algorithm 1 : Contour evolution based on probabilities

Initialize the level set function with ϕ^0

for $t = 0$ *to* max *do*

$\frac{\partial \phi}{\partial t} = \frac{1}{2} - P_{in} + \delta(\phi)[u \cdot div(\frac{\nabla \phi}{|\nabla \phi|})]$

$\phi^{t+1} = \phi^t + \Delta t \frac{\partial \phi}{\partial t}$

end for

Similar to the traditional active contour models, the contour-based segmentation with the pixel probabilities is still sensitive to the contour initialization. For the images of simple and significant foreground, it is convenient to initialize the contour curves and the contour evolution can generate precise segmentation results. However, for the images containing complex contents, such as the multiple objects of diverse textures, shapes and colors, it is difficult to initialize the contour properly and the contour curve may not converge to the boundary of foreground. To tackle this problem, we integrate multiple segmentations induced by biased contours to achieve a precise result.

The ensemble of segmentations is performed based on the probabilistic representation of images. In the optimal ensemble result, the foreground/background probabilities of pixels should be close to the distributions of the high-quality segmentations and far from the low-quality ones. The similarity between the probability distributions of different segmentation results is measured by Mutual Information (MI) and the objective of segmentation ensemble is formulated by the weighted sum of mutual information. Suppose there are *n* contour-based segmentation results and their foreground (or background) probabilities are $\{p_1^{img}, p_2^{img}, ..., p_n^{img}\}$, the probabilistic representation of the optimal segmentation ensemble is obtained by

$$p^* = \arg\max_p \sum_{i=1}^{n} w_i \cdot MI(p, p_i^{img}) \tag{7}$$

in which $MI(\cdot)$ is the mutual information function and w_i is the weight to evaluate the quality of the *i*th contour-based segmentation.

The weight of segmentation quality consists of the evaluations from three aspects: quality of segmented regions, region dispersal and the consistency between the segmented regions and the initial contour regions. The weight of the *i*th segmentation result is computed as follows.

$$w_i = \frac{region\ quality_i * consistency_i}{dispersal_i} \tag{8}$$

Suppose there are *h* segmented regions $\{R_1, ..., R_h\}$ in the *i*th segmentation result, the region quality is computed based on the region size $|R|$ and the variance σ of region intensities. The segmentation of large pure regions is of high quality.

$$region\ quality_i = \sum_{l=1}^{h} |R_l| / \sum_{l=1}^{h} \sigma_l \tag{9}$$

Assume the intensity distributions of pixels in both the initial foreground and segmented foreground are Gaussian, the consistency between the segmentation and the initial contour region can be measured by the KL divergence between the intensity distributions, which is transformed into the following formula,

$$consistency_i = \sum_{\substack{p,q \in \{1,2\}, \\ p \neq q}} [\log \frac{\sigma_p}{\sigma_q} + \frac{\sigma_q{}^2 + (\mu_q - \mu_p)^2}{2\sigma_p{}^2} - \frac{1}{2}] \tag{10}$$

in which μ_1, μ_2 and σ_1, σ_2 are the means and variances of the intensities of the initial and segmented foreground respectively.

Region dispersal is used to punish the segmentation containing many trivial segmented regions. For the *i*th segmentation of h_i regions, its region dispersal is computed by the following *S*-shaped function, in which $\bar{h}$ is the median of region numbers of all the segmentation results.

$$dispersal_i = [1 + e^{-(\frac{h_i - \bar{h}}{\bar{h}})}] / e^{-(\frac{h_i - \bar{h}}{\bar{h}})} \tag{11}$$

2.3. Optimization of segmentation ensemble

To obtain the optimal ensemble of the contour-based segmentation, we adopt Particle Swarm Optimization (PSO) strategy to optimize the ensemble objective of formula (7). The optimization process aims to search for the foreground probabilities of pixels to maximize the cumulative mutual information between the probability distributions of multiple segmentation results. A probability vector p^0 and an update vector v^0 of image pixels are initialized as the position and velocity of particles in probability space and the particles will move to the optimal position to maximize the mutual information. In the specific algorithm, we denote the local and global optimal position in probability space as p_{pd} and p_{gd} and the local and global maximum mutual information as $info_{pd}$ and $info_{gd}$. We also set the inertia coefficient ω=1 to adjust the particle speed, the weighting coefficients $z_1, z_2 = 2$ to balance the local and global particles and the constraint factor *r* to restrict the probability updating. Algorithm 2 summarizes the PSO optimization process of segmentation ensemble.

Algorithm 2 : Optimization for segmentation ensemble

Input: probabilities of *n* segmentations $\{p_1, p_2, ..., p_n\}$,
particle number *pcn*, random numbers $\xi, \eta \in [0,1]$,
Output: global optimum probability vector p_{gd}

initialize $p^0 = \sum_{i=1}^{n} w_i p_i / \sum_{i=1}^{n} w_i,\ v^0 = \varepsilon * Rnd(0,1) * 1;$
for $t = 0$ *to* max *do*
  for $d = 1$ *to pcn do*
    $p_d^{t+1} = p_d^t + r \cdot v_d^t;$
    $v_d^{t+1} = \omega v_d^t + z_1 \xi (p_{pd}^t - p_d^t) + z_2 \eta (p_{gd}^t - p_d^t);$
    $info_{pd}^{t+1} = \sum_{i=1}^{n} w_i \cdot MI(p_d^{t+1}, p_i);$
    if $info_{pd}^{t+1} > info_{pd}^t$ {
      update $info_{pd}^{t+1} = info_{pd}^{t+1};$
      update $p_{pd}^{t+1} = p_d^{t+1};$
      if $info_{pd}^{t+1} > info_{gd}^t$ {
        update $info_{gd}^{t+1} = info_{pd}^{t+1};$
        update $p_{gd}^{t+1} = p_d^{t+1};$}}
  end for
end for

3. EXPERIMENTAL RESULTS

The experiments include the tests of ensemble strategy and overall evaluation. In the first test, we validate that the ensemble strategy is effective to improve the contour-based segmentation. In the overall evaluation test, comparing with other contour-based and interactive segmentation methods, we demonstrate that the segmentation ensemble can achieve precise segmentation for the images of complex contents. All the testing images are collected from the Segmentation Evaluation Database [25]. We adopt the criteria of Accuracy, Precision, Recall and F1 score to evaluate the segmentation.

To verify the ensemble strategy based on the weighted mutual information, we compare the segmentation results generated by single active contour with dictionary (ACD), unweighted ensemble of active contours (UACD), in which the ensemble is simply performed through averaging the pixel probabilities, and the weighted ensemble of active contours (WACD). The contour curves for segmentation are casually initialized and some ones are biased on the foreground. Figure 2, 3 illustrate the segmentation results. We can find that the weighted ensemble greatly improves the quality of contour-based segmentation, especially for the segmentation of the details in complex foreground.

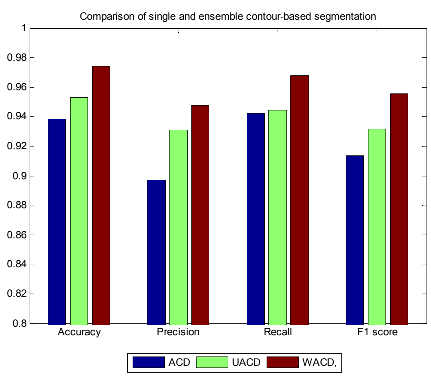
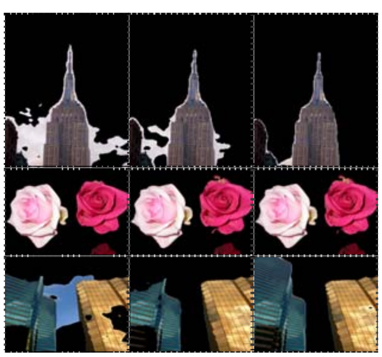


Fig. 2. Segmentation qualities of ACD, UACD and WACD



(*a*) (*b*) (*c*)

Fig. 3. Segmentation results (*a*) ACD (*b*) UACD (*c*) WACD

In the overall evaluation test, we compare the proposed weighted ensemble method (WACD) with the typical contour-based methods including Region-Scalable Fitting (RSF) [17], Distance Regularized Level Set Evolution (DRLSE) [6], Chan-Vese model (CV) [15], Active Contour with Dictionary (ACD) [24] and an interactive method of Graph-based Manifold Ranking (GMR) [26]. The segmentation results are shown in Figure 4 and 5.

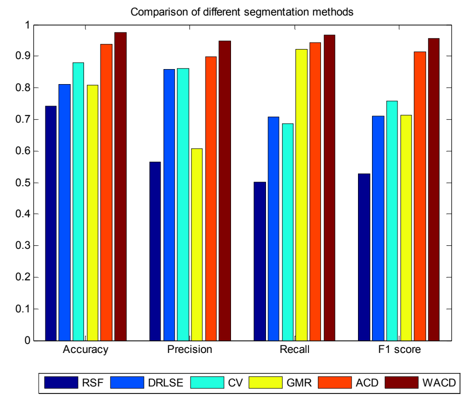


Fig. 4. Segmentation qualities of different methods

(*a*) (*b*) (*c*) (*d*) (*e*) (*f*)

Fig. 5. Segmentation results (*a*) RSF (*b*) DRLSE (*c*) CV model (*d*) GMR (*e*) ACD (*f*) WACD

Because of the space limitation, we just illustrate a few testing images. From the abundant experimental results, we observed that for the images of complex contents, the weighted ensemble segmentation outperforms the single contour-based and interactive segmentation. The ensemble strategy makes the segmentation robust to the biased contour initialization and induces stable and precise results.

4. CONCLUSIONS

This paper proposes an ensemble strategy to improve the robustness of contour-based segmentation to the biased initialization. The ensemble is performed through optimizing of mutual information between the probability distributions of multiple segmentation results. Experiments validate the effectiveness of the proposed ensemble method.

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