MULTIMODAL SEGMENTATION COMBINING ACTIVE CONTOURS AND WATERSHEDS

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ABSTRACT

This paper presents a segmentation method combining an active contour approach with a watershed pre-segmentation. Segmentation is performed on two modalities: one being the color of the regions, the other one being the change due to motion. On the one hand, watershed methods are very efficient to provide an oversegmentation of homogeneous color regions. On the other hand, active contours methods are efficient to obtain a smooth segmentation. We apply in this paper an active contour method to segment the change detection mask. The incertitude on the motion induces artifacts on the resulting contours. Our original contribution consists in using the intra-image watershed segmentation to correct the contours. To reach such a goal, we construct a distance map from the oversegmentation of the homogeneous color region. The active contour is then corrected to better fit to the real object by introducing a specific term based on this distance map in the evolving equation of the active contour.

1. INTRODUCTION

1.1 Segmentation using different modalities

Nowadays, multimodality is often used in image and signal processing. For instance, in medical imagery, the CT-Scan, the Pet-Scan and the MR imagery bring different and complementary gray-level information. Segmentation algorithms in such an application area can take benefit from these complementary information [1]. Still color images can also be considered as being multimodal as each color brings a different signal information. In video sequences, it is possible to extract the motion field and to consider it as being a fourth modality. Segmentation in video sequences often combines the four modalities. In this paper, we propose to first focus our segmentation algorithm on the motion field modality. Unfortunately, due to occlusion considerations, there exists always a certain incertitude on the edges of the moving objects. For that reason we use in a second step the color information to limit the discrepancies on the objects boundaries.

1.2 Segmentation combining active contours and watersheds

Segmentation algorithms can be divided in two main groups: the morphology based segmentation, such as the watersheds [2], and the energy based segmentation, such as active contours [3] or deformable partitions [4]. Watershed methods have the particularity to provide oversegmented images and the resulting segmentation suffers from the lack of smoothness. On the contrary, active contours methods lead to smooth results and are powerful tools for tracking moving objects. Nevertheless, the main problem of this method is the limited accuracy of the boundary detection due to the occlusion problem.

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In this paper, we present a novel approach to combine watersheds and active contours. Some methods already combined the snakes and watershed approach [5, 6, 7]. In [5], the snakes energy criterion is used to fuse over-segmented regions returned by watershed while in [6], the watershed segmentation is represented as an energy minimization. In [7], the result of the watershed segmentation is used to initialize the active contour. In this paper, the idea is to use the watershed result as a distance criterion in the active contour algorithm. We formulate a new energy criterion based on the Euclidian distance to the watershed lines. This allows an attraction towards the watershed region boundaries, providing smooth results. Our algorithm proceeds in two steps. First, we track moving objects with region-based motion active contours. Then, we refine the segmentation using our new watershed criterion. This sequential evolution allows to drive the curve without being slowed down or stopped by the watershed lines not corresponding to the desired object boundaries.

This paper starts with an overview of the active contours segmentation algorithms in section 2. Section 3 describes our original method combining active contours and watershed segmentationj. Finally, section 4 presents promising experimental results.

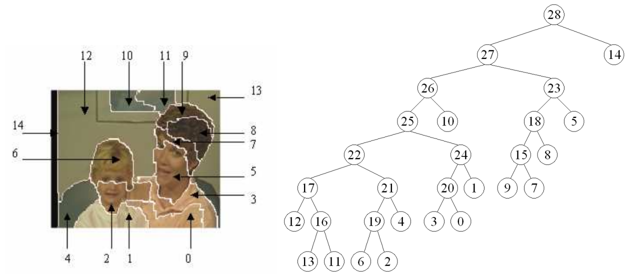
2. PREVIOUS WORK ON ACTIVE CONTOURS

Active contours are powerful tools for image and video segmentation or tracking. They can be formulated in the framework of variational methods. The basic principle is to construct a PDE (Partial Differential Equation) from the minimization of an energy criterion. The PDE deforms the contour iteratively in order to decrease the energy criterion and to converge towards a (local) minimum of the criterion hopefully corresponding to the objects to be segmented. The curve, noted Γ, evolves in its normal direction, under a velocity field deduced from the minimization of an energy criterion. Originally, snakes [3] or geodesic active contours [8] are driven towards the edges of an image through the minimization of a boundary integral of features depending on edges. Active contours driven by the minimization of region functionals in addition to boundary functionals appeared later. They have been developed in [9, 10, 11, 12, 13]. The energy of such active contours can be written as :

$$J(\Gamma) = \iint_{\Omega_{obj}} k^{obj} d\mathbf{x} d\mathbf{y} + \iint_{\Omega_{back}} k^{back} d\mathbf{x} d\mathbf{y} + \int_{\Gamma} k^{\Gamma} ds \qquad (1)$$

where Ω_{obj} and Ω_{back} are the object and background regions. k^{obj}, k^{back}, k^{Γ} are respectively the object, the background and the contour descriptors. If the region descriptors k^{obj} and k^{back} do not depend on the regions, the derivative of the criterion (1) gives the following evolving equation [10]:

$$\frac{\partial \Gamma}{\partial \tau} = \left(k^{obj} - k^{back} + k^{\Gamma} \kappa - \nabla k^{\Gamma} . \mathbf{N} \right) \mathbf{N} \qquad (2)$$



(a) Regions in the image (b) Regions in the binary tree

Figure 1: Watershed Fusion Process

where κ is the curvature of Γ and τ the evolution parameter.

One main drawback of motion segmentation method is that boundary detection is not accurate due to the incertitude on the motion and on the background estimation.

3. ACTIVE CONTOUR USING WATERSHED PRE-SEGMENTATION

3.1 Criterion on watershed region boundaries

3.1.1 Watershed presegmentation

Any gray level image can be considered as a topographical surface. The watershed algorithms aim to divide this topographical surface in different catchment basins separated by the watershed lines. Immersion-based watershed algorithm introduced by [2] are often used to provide an initial partition of the image into homogeneous color regions. Because of the noise, the watershed segmentation results in an oversegmentation. Salembier suggested in [14] to organize the oversegmented regions in a binary partition tree to reduce the number of regions. We follow the fusion process presented in [15]. The two adjacent regions in the image that are the most similar according to a spatio-temporal criterion will be first merged. The resulting new region is then considered as a whole region and the fusion process can continue. This merging yields to the creation of a binary partition tree which allows to easily choose the final number of regions. Figure 1 shows an example of an initial partition of 15 regions and the corresponding fusion tree. Notice that the watershed line introduced in our algorithm corresponds to the unsmoothed boundaries of the region partition. Those regions are the result of a merging process based on a spatio-temporal criterion. Therefore, the watershed lines do not truly corresponds to the highest color gradient of the image. Thanks to this property, it is possible to attract the active contour on edges that have a low gradient.

3.1.2 Attraction of the curve by the watershed lines

Our goal is to attract the active contours towards the watershed lines. Gastaud et al. introduced in [16] an attraction criterion to a single curve being the reference contour:

$$J_C(\Gamma) = \int_{\Gamma} \varphi(u(\Gamma, \Gamma^{ref}))ds \tag{3}$$

where φ is a differentiable function of the geometric signed distance u:

$$u(X, \Gamma^{ref}) = \begin{cases} -min_{Y \in \Gamma^{ref}} |X - Y| & \text{if } X \text{ is outside } \Gamma^{ref} \\ min_{Y \in \Gamma^{ref}} |X - Y| & \text{if } X \text{ is inside } \Gamma^{ref} \end{cases} \tag{4}$$

X is the vector of the coordinates of a point of the contour Γ and Y the coordinates of a point of the reference contour Γ^{ref}. Let ∇u be:

$$\nabla u = \begin{cases} -\frac{X-Y}{|X-Y|} & \text{if } X \text{ is outside } \Gamma^{ref} \\ \frac{X-Y}{|X-Y|} & \text{if } X \text{ is inside } \Gamma^{ref} \end{cases} \tag{5}$$

The evolution equation corresponding to this curve is given by [16]:

$$\frac{\partial \Gamma_C}{\partial \tau} = \left[- < \nabla u, \mathbf{N} > \varphi'(u) + \kappa \varphi(u) \right] \mathbf{N}. \tag{6}$$

where κ is the curvature of the curve and $\mathbf{N}$ the inward unit normal of the curve Γ.

It is possible to apply the approach of Gastaud et al. to a reference contour being the watershed lines.

Let W be the set of curves corresponding to the watershed lines taken as a reference contour. And let $d(X,W) = \min_{Y \in W} |X - Y|$ be the Euclidian distance of the evolving point X to W. In practice, d can be computed by distance map algorithms [17]. Notice that $d = |u|$. Although we cannot derive a criterion due to discontinuities of the derivative of d on the skeleton, we notice that $< \nabla u, \mathbf{N} > u = < \nabla d, \mathbf{N} > d$ where $\nabla d = \frac{X-Y}{|X-Y|}$.

We propose the following evolution equation, choosing $\varphi(d(X,W))$ $= d^2(X,W)$:

$$\frac{\partial \Gamma_W}{\partial \tau} = \left[- < \nabla d, \mathbf{N} > 2d + \kappa d^2 \right] \mathbf{N} = F_W \mathbf{N}. \tag{7}$$

3.2 Segmentation process

Now we present our algorithm which works in two steps. The first step focuses on the motion modality. It is a moving object segmentation with a common motion detection criterion. The second step refines the result of the motion detection by attracting the curve to the watershed lines. This step uses only the color modalities.

3.2.1 First step: moving object detection

The first step performs the moving object segmentation with the motion detection criterion introduced in [18]:

$$J_M(\Gamma) = \iint_{\Omega_{obj}} \alpha d\mathbf{x} d\mathbf{y} + \iint_{\Omega_{back}} |I_n - B_n| d\mathbf{x} d\mathbf{y} + \int_{\Gamma} \lambda ds \tag{8}$$

where α and λ are positive constants, B_n is the background estimation image and I_n the current frame. This leads to the following evolving equation:

$$\frac{\partial \Gamma_M}{\partial \tau} = [\alpha - |I_n - B_n| + \lambda \kappa] \mathbf{N} \tag{9}$$

This step brings the evolving curve close to the wanted final contour. However, the accuracy can be improved by performing the second step.

3.2.2 Second step: Watershed constraints

From the initial watershed partition, we compute the distance map d. Then, we can perform the second step of the active contour algorithm.

The energy criterion for this step joins the criterion presented in section 3.1.2 and a constant term which constrains the curve length. We get the following evolving equation:

$$\frac{\partial \Gamma_W}{\partial \tau} = \left[-2 < \nabla d, \mathbf{N} > d + \kappa d^2 + \lambda \kappa \right] \mathbf{N}. \tag{10}$$

The first term attracts the evolving curve towards the watershed regions border and the second term smoothes the contours. When a point of the evolving curve lays on a watershed region skeleton or on a watershed line, the rigidity and the curvature of the curve contribute to the point evolution. Notice that the starting curve of the second step is close to the final watershed regions. This considerably reduces the number of skeletons crossed by the evolving curve.

3.3 Implementation

Equations (3.2.1) and (3.2.2) are implemented using the Level Sets method [19]. They can be also implemented using parametric splines [20]. The Level Sets method implicitly manages topological changes as splits and merges. The method consists in embedding the evolving curve as the zero Level Set of an higher dimensional function ϕ. The time-dependent Level Set function ϕ is defined such as:

$$\phi\left(\Gamma(s,\tau),\tau\right) = 0 \tag{11}$$

where τ and s are the evolving and arc length parameters respectively. We assume that ϕ is a signed distance function around the zero level. Evolving equation is expressed in the Level Set function by the derivation of equation (11):

$$\phi_\tau + \frac{\partial \Gamma}{\partial \tau} \nabla \phi = 0. \tag{12}$$

By using the active contours evolution equation, $\frac{\partial \Gamma}{\partial \tau} = F\mathbf{N}$, and the normal unit definition, $\mathbf{N} = -\nabla\Phi/|\nabla\Phi|$, we obtain the following evolution equation:

$$\frac{\partial \Phi}{\partial \tau} = F|\nabla\Phi|. \tag{13}$$

The implementation of equations (3.2.1) and (3.2.2) is provided by replacing the evolving force in equation 13.

4. RESULTS: COMPARISONS WITH ACTIVE CONTOURS WITHOUT THIS DISTANCE

The algorithm performance is evaluated on the sequence *Mother* (Fig. 2) for $\alpha = 1.3$, $\lambda = 11$ and the sequence *Akiyo* (Fig. 3) for $\alpha = 0.8$, $\lambda = 8$. The first step algorithm provides the results shown in figures 2(c) and 3(c). They present some disparities between the contour and the object boundaries. There exists some incertitude because of the few motion of the objects. Figures 2(d) and 3(d) present the watershed regions for the two images given in input of the second step algorithm. For the sequence *Mother*, we use the initial watershed partition and for the sequence *Akiyo*, we fuse the initial partition, 3596 regions, in 100 regions. Figures 2(f) and 3(f) show the second step results. In comparison with the results returned by region-based moving information, the use of the watersheds significantly improves the performances. The little discrepancy behind the left ear of the daughter is due to the presence of a watershed line in the oversegmented regions. It is caused by the high number of regions in that area. The regularity term and the application of the constraints on watershed regions refine segmentation, erase incertitude due to the few motion of objects and smooth the results. Moreover, it appears that the results, shown in figures (f), are smoother than the ones returned by the watershed oversegmentation (see figures 2(d) and 3(d)).

5. CONCLUSION

In this paper, we have presented a new method of multimodal segmentation combining active contours and watershed presegmentation. The proposed algorithm is sequentially performed in two steps. The first one exploits a motion modality criterion. Then, the second one attracts the evolving curve towards the borders of watershed homogeneous color regions. The design of watershed based criterion constitutes the contribution of the work. We have obtained very promising results. This approach is applicable for moving object detection in video for static camera. Future works will concentrate on the use of a mutual information-based criterion [1] instead of a motion-based criterion for multimodal medical images for instance.

6. ACKNOWLEDGMENTS

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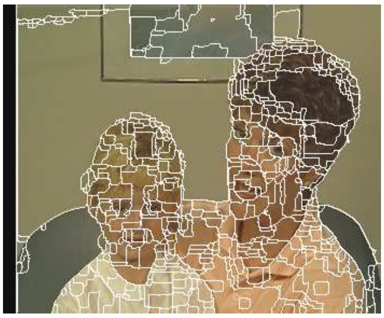
(a) Initial contour

(b) Step 1: Intermediate iteration

(c) Step 1: Final iteration, initial contour of step 2



(d) Step 2: Watershed lines (490 regions)

(e) Step 2: Intermediate iteration

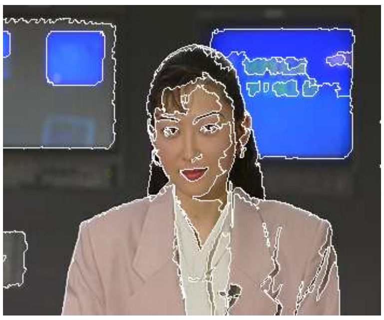
(f) Step 2: Final segmentation

Figure 2: Two step algorithm on sequence Mother with propagation (b) and results (c) of moving object segmentation (step 1), propagation (e) and results (f) of watershed-driven segmentation (step 2).

(a) Initial contour

(b) Step 1: Intermediate iteration

(c) Step 1: Final iteration, initial contour of step 2



(d) Step 2: Watershed lines (100 regions)

(e) Step 2: Intermediate iteration

(f) Step2: final segmentation

Figure 3: Two step algorithm on sequence Akiyo with propagation (b) and results (c) of moving object segmentation (step 1), propagation (e) and results (f) of watershed-driven segmentation (step 2).