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TRACKING VIDEO OBJECTS USING ACTIVE CONTOURS AND GEOMETRIC PRIORS

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RÉSUMÉ :

Ce rapport traite du suivi d'un objet tout au long d'une séquence. Les techniques de tracking s'appuient en général soit sur des modèles déformables, tels que les modèles de contours actifs ou de maillage, soit sur des modèles caractérisant les régions. Nous proposons un nouveau critère de tracking reposant sur un a priori géométrique, et sa version améliorée prenant en compte, de plus, les caractéristiques des régions de l'image. Notre algorithme de tracking se situe dans un cadre théorique d'optimisation par contours actifs. L'a priori géométrique consiste à minimiser la distance pondérée entre le contour actif et un contour de référence. Cet a priori prend la forme d'une fonctionnelle dépendante du contour actif. Afin d'exploiter les informations propres à chaque région, telles que leur homogénéité, le critère de tracking est enrichi de termes statistiques les caractérisant. L'utilisation conjointe d'un a priori géométrique et des caractéristiques des régions permet d'améliorer l'algorithme. Dans un premier temps, chaque terme du critère est dérivé séparement afin d'en déduire l'équation d'évolution du contour actif. Ensuite l'algorithme ne comprenant que le terme géométrique est utilisé pour faire évoluer une courbe d'un visage à un autre. Enfin les descripteurs géométriques et statistiques sont couplés pour améliorer le suivi d'un visage dans une séquence.

MOTS CLÉS :

Segmentation d'image, suivi d'objet video, A priori geometrique, Descripteur statistique, Méthode des ensembles de niveaux

ABSTRACT:

KEY WORDS :

Image Segmentation, Video object tracking, Geometric prior, Statistical descriptor, Levet Set

Tracking Video Objects Using Active Contours and Geometric Priors

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Abstract. This paper deals with objects tracking over time in video sequences. Tracking techniques are usually based on deformable templates, such as active contour models, or active meshes, or are region-based models, using object features. We propose a new tracking criterion based on geometric priors and its improvment using additional region-based features. Our tracking algorithms are embedded on optimization theory framework using active contours. The geometric prior consists in minimizing the weighted distance between the evolving contour and a reference one. We formulate this prior as a functional depending on the evolving active contour. We add to the tracking criterion some statistical region-based terms to exploit information intrinsic to the object and background regions, for instance homogeneity. Thus we improve the algorithm efficiency using jointly geometric prior and region-based features. First we provide the differentiation of each criterion and then we deduce the related evolution equation driving the active contour. Finally we apply the geometric tracking to make a curve evolve from one face towards another one, and merge geometric and statistical descriptors for imroving face tracking.

Introduction

Video segmentation consists in extracting arbitrarily shaped image regions corresponding to specific semantic objects. Tracking processes analyze the shape deformations of objects as they evolve over time in a video sequence. Although the tasks of segmentation and tracking can be viewed as a two-stage analysis paradigm they are often processed as an integrated task in a one-stage analysis paradigm [20].

Active contours are powerful tools for image segmentation. They can be embedded in a minimization framework including region and boundary functionals.

Boundary functionals were first proposed by Kass et al. [15] and geodesic active contours by Caselles et al. [4, 5] for active contour segmentation. Region based active contours were first introduced by Ronfard and al. [22] and Cohen et al. [9]. Then Zhu and al. [27], Chan et al. [7], Leventon and al. [16], Paragios et al. [19] introduced statistical descriptors. Finally, Jehan et al. [12–14] addressed the active contour segmentation problem where region features are embedded in region functionals.

Tracking techniques are usually based on deformable templates, such as active contour models [17] or active meshes [25], or are region-based, using object features [20, 3, 23].

In this paper, we present new tracking algorithms in the framework of optimization theory using active contours. The first contribution of the paper is to define a general criterion for tracking video objects through several frames. The first criterion is based on geometric prior and minimizes the weighted distance between the evolving contour and a reference one. Then, the algorithm efficiency is improved by combining region-based features to geometric descriptor.

The second contribution is to differentiate each component of the criterion in order to compute the velocity F, which makes the contour Γ_n of the n^{th} frame of the video track the object boundaries. The evolution equation is written as:

$$\begin{cases} \frac{\partial \Gamma_n(\tau)}{\partial \tau} & = F\mathbf{N} \\ \Gamma_n(0) & = \Gamma_{n,0} \end{cases}$$

where $\Gamma_{n,0}$ is any initial curve and $\mathbf{N}$ the unit normal of Γ_n.

In section 1, we present the tracking algorithm in a general framework and the differentiation of each component of the criterion. Sections 2 and 3 are focusing on the applications of the criterions. In section 2, we apply this algorithm using only the geometric descriptor to make a curve evolve from one face towards another one. In section 3, we add statistical region-based descriptors to the criterion for face tracking purpose on a real sequence, and finally we conclude.

1 Setting a general tracking framework

Our new tracking algorithm is based on the active contour method. The active contour is driven towards the boundary of the object, following an evolution equation defined by the minimization of an energy criterion. The current frame I_n is divided into two regions: Ω_n^{out} the background and Ω_n^{in} the object. The common boundary of Ω_n^{in} and Ω_n^{out} is denoted Γ_n. The energy criterion is defined from features characterizing regions and contours. Let us denote the criterion by $J_n(\Omega_n^{out}, \Omega_n^{in}, \Gamma_n)$.

We search for the partition $(\Omega_n^{out}, \Omega_n^{in}, \Gamma_n)$ which minimizes the criterion. Thus, we introduce a dynamical auxiliary variable in the criterion by making the regions continuously dependent on an evolution parameter τ.
Then the evolution equation is deduced from the differentiation of the criterion $J_n(\Omega_n^{out}(\tau), \Omega_n^{in}(\tau), \Gamma_n(\tau))$.

First we state assumptions required in a tracking framework. Then we present the criterion and the evolution equation derived from the criterion.

1.1 Assumptions

In order to set a general framework for tracking video object through several frames, we will assume:

- The invariance of the motion compensated shape i.e. we can predict the current frame shape from the previous one by estimating object global motion. [24].

- The invariance of the object content based: statistical features such as mean or variance, or object histograms are constant through video frames.

1.2 General tracking criterion

Let Γ_{n-1} be the boundary of the object region Ω_{n-1}^{in} of the frame I_{n-1}. Let us define Γ_n^{ref} as a reference contour for the frame I_n. Γ_n^{ref} is predicted from Γ_{n-1} by estimating the global motion of Γ_{n-1} between I_{n-1} and I_n. Let us denote by Γ_n the contour encompassing Ω_n^{in}.

Let us define the tracking criterion by:

$$\begin{aligned} J_n(\Omega_n^{out}, \Omega_n^{in}, \Gamma_n) = & \int_{\Gamma_n} \varphi(d(\Gamma_n, \Gamma_n^{ref}))ds \\ & + \lambda \int_{\Omega_n^{in}} \psi^{in}(K_{ref}^{in}, K_n^{in}(\Omega_n^{in}))\ dxdy \\ & + \lambda \int_{\Omega_n^{out}} \psi^{out}(K_{ref}^{out}, K_n^{out}(\Omega_n^{out}))\ dxdy \\ & + \epsilon \int_{\Gamma_n} ds \end{aligned} \tag{1}$$

where:

- $d(\Gamma_n, \Gamma_n^{ref})$ is the geometric distance between the contours Γ_n and Γ_n^{ref} i.e. for each $x \in \Gamma_n$, $d(x, \Gamma_n^{ref}) = \min_{y_{ref} \in \Gamma_n^{ref}}(|x - y_{ref}|) = |x - y(x)|$ (see fig. 1). This distance is weighted by a differentiable function φ.

- I_{ref} is a reference frame, generally the first frame of the video sequence, K_{ref}^{in} and K_{ref}^{out} are respectively the region and background descriptors of the reference frame I_{ref}, $K_n^{in}(\Omega_n^{in})$ is the descriptor of the current frame I_n for pixels belonging to the object, $K_n^{out}(\Omega_n^{out})$ is the descriptor of the current frame I_n for pixels belonging to the background, and ψ^{in} and ψ^{out} differentiable functions [6].

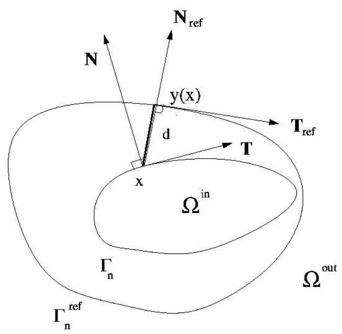


Fig. 1. Distance definition

The first term of the criterion (1) is a geometric one, minimizing the weighted distance between the contour and the estimated reference contour.

The second and third terms of the criterion (1) minimize the difference between features of the reference domains and the evolving domains. The features could be statistical descriptors such as mean, variance, determinant of covariance matrix or region histogram.

The last term is a regularization one, minimizing the length of the contour.

Now we introduce a dynamical auxiliary variable directly in the criterion such as in [14]. Each region becomes dependent on an evolution parameter τ. $\Gamma_n(\tau)$ is an active contour evolving towards the object boundary.
Let us denote $J_n(\Omega_n^{out}(\tau), \Omega_n^{in}(\tau), \Gamma_n(\tau))$ as:

$$\begin{aligned} J_n(\tau) = &\int_{\Gamma_n(\tau)} \varphi(d(\Gamma_n(\tau), \Gamma_n^{ref}))ds \\ &+ \lambda \int_{\Omega_n^{in}(\tau)} \psi^{in}(K_{ref}^{in}, K_n^{in}(\Omega_n^{in}(\tau)))dxdy \\ &+ \lambda \int_{\Omega_n^{out}(\tau)} \psi^{out}(K_{ref}^{out}, K_n^{out}(\Omega_n^{out}(\tau)))dxdy \\ &+ \epsilon \int_{\Gamma_n(\tau)} ds \end{aligned} \tag{2}$$

The contour evolution equation is obtained by differentiating the criterion in an Eulerian framework. The second and third terms of the criterion (2) are differentiated in details in [14] and [1]. The differentiation of the regularization term is achieved in [2].

1.3 Differentiation of the geometric term

In this paper, we focus on the geometric term differentiation. From now on, we denote $J_n^1(\tau)$ the first term of the criterion (2):

$$J_n^1(\tau) = \int_{\Gamma_n(\tau)} \varphi(d(\Gamma_n(\tau), \Gamma_n^{ref}))ds \tag{3}$$

If we suppose that $\Gamma_n(\tau)$ is parametrized by $p \in [0,1]$, the criterion $J_n^1(\tau)$ can be expressed in terms of $x(p,\tau)$ and $y(p,\tau)$:

$$J_n^1(\tau) = \int_0^1 \varphi(|x(p,\tau) - y(p,\tau)|) \left|\frac{\partial x}{\partial p}(p,\tau)\right| dp \tag{4}$$

By differentiating (4) with respect to τ, we obtain:

$$J_n^{1\prime}(\tau) = \int_0^1 \left(\frac{\partial x}{\partial \tau} - \frac{\partial y}{\partial \tau}\right) \frac{x-y}{|x-y|} \varphi'(d) \left|\frac{\partial x}{\partial p}\right| dp + \int_0^1 \varphi(d) \frac{\partial}{\partial \tau} \left(\left|\frac{\partial x}{\partial p}\right|\right) dp \tag{5}$$

Let $\mathbf{N}$ and $\mathbf{T}$ be the outward normal and tangent of $\Gamma_n(\tau)$. After integration by part of the second term of (5), $J_n^{1\prime}(\tau)$ is of the form:

$$\begin{aligned} J_n^{1\prime}(\tau) = &-\int_0^1 < \left(\mathbf{T}, \frac{x-y}{|x-y|}\right) \varphi'(d)\mathbf{T} - \varphi(d)\kappa\mathbf{N} + \left(\frac{\frac{\partial y}{\partial p}}{\left|\frac{\partial x}{\partial p}\right|}, \frac{x-y}{|x-y|}\right) \varphi'(d)\mathbf{T}, \frac{\partial x}{\partial \tau} > \left|\frac{\partial x}{\partial p}\right| dp \\ &+ \int_0^1 \left(\left(\frac{\partial x}{\partial \tau}, \frac{x-y}{|x-y|}\right) - \left(\frac{\partial y}{\partial \tau}, \frac{x-y}{|x-y|}\right)\right) \varphi'(d) \left|\frac{\partial x}{\partial p}\right| dp \end{aligned} \tag{6}$$

where κ is the mean curvature of $\Gamma_n(\tau)$.

Let us denote by $\mathbf{N}_{ref} = \nabla d = \frac{x-y}{|x-y|}$ and $\mathbf{T}_{ref}$ the outward normal and tangent of Γ_n^{ref}.
As $y(p,\tau) \in \Gamma_n^{ref}$, we deduce that:

$$d(y(p,\tau), \Gamma_n^{ref}) = 0$$

By differentiating this expression with respect to τ and to p, we get:

$$\frac{\partial y}{\partial \tau}.\nabla d = 0 \qquad \text{and} \qquad \frac{\partial y}{\partial p}.\nabla d = 0 \tag{7}$$

i.e. $\frac{\partial y}{\partial \tau}$ and $\frac{\partial y}{\partial p}$ are collinear with $\mathbf{T}_{ref}$.

Therefore, we conclude that:

$$\left(\frac{\partial y}{\partial p}, \frac{x-y}{|x-y|}\right) = 0 \text{ and } \left(\frac{\partial y}{\partial \tau}, \frac{x-y}{|x-y|}\right) = 0 \tag{8}$$

Thus it follows:

$$J_n^{1\prime}(\tau) = \int_0^1 < \frac{\partial x}{\partial \tau}, \frac{x-y}{|x-y|}\varphi'(d) - \left(\mathbf{T}, \frac{x-y}{|x-y|}\right)\varphi'(d)\mathbf{T} - \varphi(d)\kappa\mathbf{N} > \left|\frac{\partial x}{\partial p}\right| dp \qquad (9)$$

Then, writing $\frac{x-y}{|x-y|}$ as a combination of $\mathbf{N}$ and $\mathbf{T}$, $J_n^{1\prime}(\tau)$ is given by:

$$J_n^{1\prime}(\tau) = \int_0^1 < \frac{\partial x}{\partial \tau}, ((-\mathbf{N}_{ref}, \mathbf{N})\varphi'(d) - \varphi(d)\kappa)\mathbf{N} > \left|\frac{\partial x}{\partial p}\right| dp \qquad (10)$$

The derivative of $J_n^1(\tau)$ could also be achieved using the general derivation theorem of [11].
According to the Cauchy-Schwarz inequality, we deduce the PDE making the contour evolve:

$$\frac{\partial \Gamma_n(\tau)}{\partial \tau} = [(\mathbf{N}_{ref}, \mathbf{N})\varphi'(d) + \varphi(d)\ \kappa)]\mathbf{N} \qquad (11)$$

Remark 1: This equation is formalized as a combination of two terms: an hyperbolic term $(\mathbf{N}_{ref}, \mathbf{N})\varphi'(d)\mathbf{N}$, and a parabolic one $\varphi(d)\ \kappa\ \mathbf{N}$. To ensure the stability of the numerical scheme discretizing the hyperbolic term, the Courant-Friedrich-Lewy (CFL) condition has to be satisfied ([10]) i.e.:

$$|(\mathbf{N}_{ref}, \mathbf{N})\varphi'(d)\mathbf{N}|\frac{\Delta t}{\Delta x} \leq 1$$

A sufficient condition for stability is to choose φ such as its derivative is bounded.

1.4 Differentiation of the region based terms

We differentiate the object region-based term of the criterion following the method detailed in [14]:

$$J_n^{in}(\tau) = \int_{\Omega_n^{in}(\tau)} \psi^{in}(K_{ref}^{in}, K_n^{in}(\Omega_n^{in}(\tau)))dxdy$$

Let us denote by $\psi^{in}(\tau)$ the function $\psi^{in}(K_{ref}^{in}, K_n^{in}(\Omega_n^{in}(\tau)))$. The descriptor $K_n^{in}(\Omega_n^{in}(\tau))$ is modeled as a combination of m^{in} features $G_j^{in}(\tau)$ attached to the evolving object:

$$K_n^{in}(\Omega_n^{in}(\tau)) = g^{in}(G_1^{in}(\tau), \ldots, G_{m^{in}}^{in}(\tau)) \qquad (12)$$

where $G_j^{in}(\tau)$ can be expressed as:

$$G_j^{in}(\tau) = \int_{\Omega_n^{in}(\tau)} f_j^{in}(x, y, \tau)dxdy \qquad \text{for} \quad j = 1, \ldots, m^{in} \qquad (13)$$

The derivative of J_n^{in} with respect to τ is given by:

$$J_n^{in'}(\tau) = \int_{\Omega_n^{in}(\tau)} \frac{\partial \psi^{in}(\tau)}{\partial \tau} dxdy - \int_{\Gamma_n(\tau)} \psi^{in}(\tau)(\mathbf{v}.\mathbf{N})ds \tag{14}$$

The partial derivative of $\psi^{in}(\tau)$ with respect to τ is computed as:

$$\frac{\partial \psi^{in}(\tau)}{\partial \tau} = \sum_{j=1}^{m^{in}} \frac{\partial \psi^{in}(\tau)}{\partial K_n^{in}(\tau)} \frac{\partial g^{in}(\tau)}{\partial G_j^{in}(\tau)} \frac{\partial G_j^{in}(\tau)}{\partial \tau} \tag{15}$$

where

$$\frac{\partial G_j^{in}(\tau)}{\partial \tau} = \int_{\Omega_n^{in}(\tau)} \frac{\partial f_j^{in}(\tau)}{\partial \tau} dxdy - \int_{\Gamma_n(\tau)} f_j^{in}(\tau)(\mathbf{v}.\mathbf{N})ds \tag{16}$$

and $\mathbf{v}$ is the velocity vector of the active contour.

Thus we deduce from (15) and (16):

$$\begin{aligned}\int_{\Omega_n^{in}(\tau)} \frac{\partial \psi^{in}(\tau)}{\partial \tau} dxdy &= \sum_{j=1}^{m^{in}} A_j^{in}(\tau) \int_{\Omega_n^{in}(\tau)} \frac{\partial f_j^{in}(\tau)}{\partial \tau} dxdy \\ &- \sum_{j=1}^{m^{in}} A_j^{in}(\tau) \int_{\Gamma_n(\tau)} f_j^{in}(\tau)(\mathbf{v}.\mathbf{N})ds \end{aligned} \tag{17}$$

where

$$A_j^{in}(\tau) = \int_{\Omega_n^{in}(\tau)} \frac{\partial \psi^{in}(\tau)}{\partial K_n^{in}(\tau)} \frac{\partial g^{in}(\tau)}{\partial G_j^{in}(\tau)} dxdy$$

Using (14) and (17) the derivative of $J_n^{in}(\tau)$ according to τ can be written as:

$$\begin{aligned} J_n^{in'}(\tau) = &\int_{\Gamma_n(\tau)} -\psi^{in}(\tau)(\mathbf{v}.\mathbf{N})ds - \sum_{j=1}^{m^{in}} A_j^{in}(\tau) \int_{\Gamma_n(\tau)} f_j^{in}(\tau)(\mathbf{v}.\mathbf{N})ds \\ &+ \sum_{j=1}^{m^{in}} A_j^{in}(\tau) \int_{\Omega_n^{in}(\tau)} \frac{\partial f_j^{in}(\tau)}{\partial \tau} dxdy \end{aligned} \tag{18}$$

We will only consider descriptors, such as mean or variance, for which the last integral is null.
The evolution equation is then given by:

$$\frac{\partial \Gamma_n^{in}(\tau)}{\partial \tau} = [\psi^{in}(\tau) + \sum_{j=1}^{m^{in}} A_j^{in} f_j^{in}(\tau)] \ \mathbf{N} \tag{19}$$

The contribution of the background region-based term is computed using the same approach.

1.5 General evolution equation

The general evolution equation is deduced by taking into account terms coming from the differentiation of the regularization, the geometric and the region-based terms of the criterion. To ensure the fastness decrease of the general criterion, according to the Cauchy-Schwarz inequality, the general evolution equation is written as:

$$\frac{\partial \Gamma_n(\tau)}{\partial \tau} = [(\mathbf{N}_{ref}, \mathbf{N})\varphi'(d) + (\varphi(d) + \epsilon)\ \kappa \\ + \psi^{in}(\tau) - \psi^{out}(\tau) + \sum_{j=1}^{m^{in}} A_j^{in} f_j^{in}(\tau) - \sum_{j=1}^{m^{out}} A_j^{out} f_j^{out}(\tau)]\ \mathbf{N} \quad (20)$$

The evolution equation can be implemented using level-set method ([18]) or parametric tools such as B-Splines ([21]).

1.6 Algorithm

The first reference contour Γ_{ref} is obtained using a segmentation algorithm. Then, for each frame we process:

- *Estimation of the reference contour*:
  The reference contour Γ_n^{ref} of the current frame I_n is deduced from the final contour Γ_{n-1} of the previous frame I_{n-1}. For each pixel of the previous final contour Γ_{n-1}, we compute the matching pixel in the current frame. We robustly estimate the affine parametric model best representing the dominant motion of the contour between the previous and the current frame. The reference contour Γ_n^{ref} is initialized as the previous final contour Γ_{n-1} compensated in motion, following the global motion model.

- *A distance map*:
  A distance map from the reference contour Γ_n^{ref} is evaluated. The distance map is positive for pixels belonging to the object and negative for pixels in the background.

- *Initialization and propagation of the active contour*:
  The active contour Γ_n is initialized from the reference contour Γ_n^{ref} and propagated following the evolution equation (20) using level-set method.

2 Application using geometric descriptor

First we outline the contribution of the geometric term by making the contour evolve using only the geometric component of the criterion.

2.1 From the criterion to the evolution equation

Using only the geometric descriptor, the general criterion is defined by:

$$J_n^1(\tau) = \int_{\Gamma_n(\tau)} \varphi(d(\Gamma_n(\tau), \Gamma_n^{ref}))ds$$

The associated evolution equation is:

$$\frac{\partial \Gamma_n^1(\tau)}{\partial \tau} = [(\mathbf{N}_{ref}, \mathbf{N})\varphi' + \varphi\ \kappa]\mathbf{N} \tag{21}$$

Remark 2: The weighting function $\varphi(d)$ has to be differentiable, even, and increasing on $\Re^+$. Moreover, the velocity vector of the active contour should be zero when $d = 0$. Thus φ has to satisfy $\varphi(0) = 0$ and $\varphi'(0) = 0$.
We choose $\varphi(d) = \sqrt{1 + d^2} - 1$ ([8]).

The criterion becomes:

$$J_n^1(\tau) = \int_{\Gamma_n(\tau)} \sqrt{1 + d^2(\Gamma_n(\tau), \Gamma_n^{ref})} - 1 \quad ds \tag{22}$$

We deduce the evolution equation:

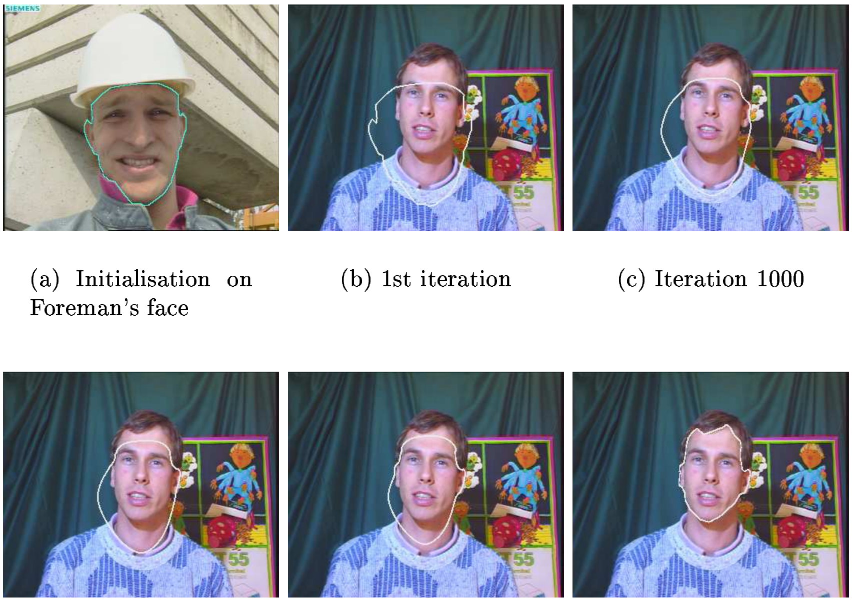
$$\frac{\partial \Gamma_n^1(\tau)}{\partial \tau} = [(\mathbf{N}_{ref}, \mathbf{N})\frac{d}{\sqrt{1 + d^2}} + (\sqrt{1 + d^2} - 1)\ \kappa]\mathbf{N} \tag{23}$$

As $\varphi'(d) = \frac{d}{\sqrt{1+d^2}}$, the contour expands or shrinks whether the contour is in the object ($d < 0$) or outside the object ($d > 0$).

A distance function as descriptor has already been used by Zhao et al. ([26]) for shape reconstruction from unorganized data. They include in their criterion a functional expressing the L^p norm of the distance to the data set. Our approach differs from theirs by choosing φ' bounded by 1, thus we ensure a sufficient condition for stability of the numerical scheme.

2.2 Experimental results

A first application to this general framework consists in making a curve evolve from one shape towards another one.
First we initialize the evolving contour to make it encompass the face of "Foreman" (see figure 2.a). Then we define the reference contour as the curve which encompasses "Erik's" face (see figure 2.f). The active contour evolves from the initial contour towards the reference contour driven by the force related to the geometric component of the criterion (see figure 2.b-e).
The results confirm the efficiency of the geometric descriptor and that the function choice is relevant.



(a) Initialisation on Foreman's face

(b) 1st iteration

(c) Iteration 1000

(d) Iteration 2000

(e) Iteration 3000

(f) Final contour

Fig. 2. From one face (Foreman) to another (Erik)

3 Application using geometric and statistical descriptors

Now we apply the general criterion using geometric and statistical region-based descriptors for tracking purpose.

3.1 From the criterion to the evolution equation

Let us remind the general criterion:

$$\begin{aligned} J_n(\tau) = &\int_{\Gamma_n(\tau)} \varphi(d(\Gamma_n(\tau), \Gamma_n^{ref}))ds \\ &+ \lambda \int_{\Omega_n^{in}(\tau)} \psi^{in}(K_{ref}^{in}, K_n^{in}(\Omega_n^{in}(\tau)))dxdy \\ &+ \lambda \int_{\Omega_n^{out}(\tau)} \psi^{out}(K_{ref}^{out}, K_n^{out}(\Omega_n^{out}(\tau)))dxdy \\ &+ \epsilon \int_{\Gamma_n(\tau)} ds \end{aligned} \quad (24)$$

where the weighting parameters λ and ϵ balance the influence of each term according to the others.

Let us remind the statistical region-based term:

$$
\begin{aligned}
J_n^{in}(\tau) = &\int_{\Omega_n^{in}(\tau)} \psi^{in}(K_{ref}^{in}, K_n^{in}(\Omega_n^{in}(\tau))) \quad dxdy \\
&+ \int_{\Omega_n^{out}(\tau)} \psi^{out}(K_{ref}^{out}, K_n^{out}(\Omega_n^{out}(\tau))) \quad dxdy
\end{aligned}
\tag{25}
$$

We assign to K_{ref}^{in} the variance of the reference object $\sigma^2(\Omega_{ref}^{in})$, to K_{ref}^{out} the variance of the reference background $\sigma^2(\Omega_{ref}^{out})$, to $K^{in}(\Omega_n^{in}(\tau))$ the variance of the evolving object $\sigma^2(\Omega_n^{in})$, and to $K^{out}(\Omega_n^{out}(\tau))$ the variance of the evolving background $\sigma^2(\Omega_n^{out})$.

The variance is a descriptor used for homogeneous region tracking. Let us define ψ^{in} and ψ^{out} such as $\psi(r) = \psi^{in}(r) = \psi^{out}(r) = log(1 + r^2)$:

$$
\begin{aligned}
J_n^{in}(\tau) = &\int_{\Omega_n^{in}(\tau)} \psi(\sum_{i=1}^{3}(\sigma_i^2(\Omega_{ref}^{in}) - \sigma_i^2(\Omega_n^{in}(\tau)))^2)dxdy \\
&+ \int_{\Omega_n^{out}(\tau)} \psi(\sum_{i=1}^{3}(\sigma_i^2(\Omega_{ref}^{out}) - \sigma_i^2(\Omega_n^{out}(\tau)))^2)dxdy
\end{aligned}
$$

where i denotes the color space (1=Y, 2=U, 3=V), $\sigma_i^2(\Omega)$ the variance of the domain Ω in the i^{th} color space.

Let us denote by $S_{i,n}^{\bullet}$ the value $\sigma_i^2(\Omega_n^{\bullet}) - \sigma_i^2(\Omega_{ref}^{\bullet})$ for $i = 1, 2, 3$ and $\bullet = in$ or out. $r_n^{\bullet}$ denotes $\sum_{i=1}^{3}(S_{i,n}^{\bullet})^2$ where $\bullet = in$ or out.

As the object descriptor is region-dependent, we obtain the following equation:

$$
\begin{aligned}
J_n^{in'} = &\int_{\Gamma_n(\tau)} [2\psi'(r_n^{in}) \sum_{i=1}^{3}(S_{i,n}^{in}((I_{i,n} - \mu_i^{in})^2 - \sigma_i^2(\Omega_n^{in}(\tau)))) \\
&- 2\psi'(r_n^{out}) \sum_{i=1}^{3}(S_{i,n}^{out}((I_{i,n} - \mu_i^{out})^2 - \sigma_i^2(\Omega_n^{out}(\tau)))) \\
&+ \psi(r_n^{in}) - \psi(r_n^{out})] \quad (\mathbf{v}.\mathbf{N})ds
\end{aligned}
\tag{26}
$$

where $I_{i,n}$ represents i^{th} color space of the current frame, and $\mu_i^{\bullet}$ the mean of $\Omega_n^{\bullet}$ on this color space, where $\bullet = in$ or out.

Finally, the global evolution equation is:

$$
\begin{aligned}
\frac{\partial \Gamma_n(\tau)}{\partial \tau} &= [(\mathbf{N}_{ref}, \mathbf{N}) \frac{d}{\sqrt{1+d^2}} + (\sqrt{1+d^2} - 1 + \epsilon)\ \kappa \\
&+ \lambda(2\psi'(r_n^{in}) \sum_{i=1}^{3} (S_{i,n}^{in}((I_{i,n} - \mu_i^{in})^2 - \sigma_i^2(\Omega_n^{in}(\tau)))) \\
&- 2\psi'(r_n^{out}) \sum_{i=1}^{3} (S_{i,n}^{out}((I_{i,n} - \mu_i^{out})^2 - \sigma_i^2(\Omega_n^{out}(\tau)))) \\
&+ \psi(r_n^{in}) - \psi(r_n^{out}))]\mathbf{N} \qquad (27)
\end{aligned}
$$

The evolution equation is implemented using the level set method ([18]).

3.2 Experimental results

In this section, we present experimental results obtained by tracking a face through 50 frames of a sequence called *Erik*. We show results coming from our tracking algorithm using only the geometric term, and our tracking algorithm using in addition the regularization and the statistical region-based terms.

First, the process has been tested using only the geometric descriptor. The tracking algorithm is initialized from the reference contour, which is computed by estimating the global motion of the final previous contour. Thus, a lack of accuracy occurred in a frame is propagated through following frames, and after a few frames the active contour drifts from its right position. Moreover, the contour is irregular. Thus we add region-based and regularization terms to the criterion. We process the algorithm with both geometric, region-based and regularization terms. As expected, the region-based terms balance the influence of the other terms in case of discrepancy and the regularization term smoothes the active contour as well as it shortens the contour. The results are therefore more accurate, as presented in the right images of fig(3).

Conclusion

In this paper we propose a new tracking algorithm based on the active contour theory framework. On one hand, tracking based on motion estimation suffers from drifting. On the other hand, region-based segmentation suffers from non temporal coherency. Therefore we define a criterion combining geometric reference, obtained from the previous frame segmentation and motion estimation, and region-based segmentation. Then we perform the differentiation of this criterion to find out the evolution equation of the active contour. Finally we apply this general framework to statistical region-based and geometric descriptors. Experimental results show the efficiency of the algorithm for face tracking through several frames.

Applications of this approach to image and vision problems such as registration and reconstruction are straightforward. Registration of multi-modal images or 3D reconstruction should be highly improved by combining geometric a priori information of the shape and statistical measures features obtained from the data.

References

1. G. Aubert, M. Barlaud, O. Faugeras and S.Jehan-Besson: Image segmentation using active contours: calculus of variations or shape gradients? Technical Report 2002-18-FR. I3S, CNRS-UNSA and INRIA, Sophia Antipolis (2002)
2. G. Aubert and Kornprobst P.: Mathematical problems in image processing. Partial differential equations and the calculus of variations. Springer Verlag, Applied Mathematical Sciences, 2001.
3. M.J Black.: Combining intensity and motion for incremental segmentation and tracking over long image sequences. In *ECCV*, Santa Margherita, Italy, 1992. 485-493
4. V. Caselles, R. Kimmel and G. Sapiro: Geodesic active contours. *IJCV*, vol 22 (1): 61-79, 1997.
5. V. Caselles, F. Catte, T. Coll and F. Dibos: A geometric model for active contours in image processing. *Numerische Mathematik*, vol 66: 1-31, 1993.
6. A. Chakraborty, L. Staib and J. Duncan: Deformable boundary finding in medical images by integrating gradient and region information. *IEEE Transactions on Medical Imaging*, vol 15: 859-870,1996.
7. T. Chan and L. Vese: An active contour model without edges. In *Scale-Space Theories in Computer Vision*, Corfou, Greece, 1999.
8. P. Charbonnier, L. Blanc-Féraud, G. Aubert and M. Barlaud: Deterministic edge-preserving regularization in computed imaging. In *IEEE Transaction on Image Processing*, vol 6 (2): 298-311,1997.
9. L. Cohen: On active contour models and balloons. In *Computer Vision, Graphics and Image Processing : Image Understanding*, vol 53: 211-218,1991
10. R. Courant, K.O. Friedrichs and H. Lewy: Ueber die partiellen Differenzengleichungen der mathematischen Physik. *Mathematische Annalen* 100 (1928), 32-74. Translated as: On the partial difference equations of mathematical physics. *IBM Journal of Resarch and Development* 11 (1967), 215-234.
11. M. Delfour and J.P. Zolesio: Shapes and geometries: Analysis, Differential Calculus and Optimization. *SIAM series on Advances in Design and Control*, 2001.
12. S. Jehan-Besson,M. Barlaud and G. Aubert: Video Object Segmentation Using Eulerian Region-Based Active Contours. In *ICCV*, Vancouver, Canada, 2001.
13. S. Jehan-Besson, M. Barlaud and G. Aubert: DREAMS: Deformable Regions driven by an Eulerian Accurate Minimization Method for image and video Segmentation. *IJCV*, 2003.
14. S. Jehan-Besson, M. Barlaud and G. Aubert: DREAMS: Deformable Regions driven by an Eulerian Accurate Minimization Method for image and video Segmentation. Application to face detection in color video sequences. In *ECCV*,Copenhagen, Denmark, 2002.
15. M. Kass, A. Witkin and D. Terzopoulos: Snakes: Active contour models. *IJCV*, vol 1: 321-332, 1988.
16. M. Leventon, E. Grimson and O. Faugeras: Statistical shape influence in geodesic active contour. In *CVPR*, Hilton Head Island, South Carolina, 2000.

17. F. Leymarie and D. Levine: Tracking deformable objects in the plane using an active contour model. *PAMI*, vol 15(6):617-634, 1993.
18. S. Osher and J.A. Sethian: Fronts propagating with curvature-dependent speed: Algorithms based on Hamilton-Jacobi Formulation. *JCP*, vol 79: 12-49, 1988.
19. N. Paragios and R. Deriche: Geodesic active regions for motion estimation and tracking. In *ICCV*, Corfu, Greece, 1999.
20. S. Pateux: Tracking of video objects using a backward projection technique. In *VCIP*, Perth, Australia, 2000.
21. F. Precioso and M. Barlaud: B-Spline active contours with handling of topology changes for fast video segmentation. *Eurasip Special issue: Image analysis for multimedia interactive services*, 2002.
22. R. Ronfard: Region-based strategies for active contour models. *IJCV*, vol 13(2): 229-251, 1994.
23. M. Rousson and R. Deriche: A Variational Framework for Active and Adaptative Segmentation of Vector Valued Images. In *WMVC*, Orlando, Florida, 2002.
24. S. Soatto and A.J. Yezzi: DEFORMOTION. Deforming Motion, Shape Average and the Joint Registration and Segmentation of Images. In *ECCV*, pages 32-47, Copenhagen, Denmark, 2002.
25. S. Valette, I. Magnin and R. Prost: Active mesh for video segmentation and objects tracking. In *ICIP*, volume 2, pages 77-80, Thessaloniki, Greece, 2001.
26. H.-K. Zhao, S. Osher, B. Merriman and M. Kang: Implicit and non-parametric shape reconstruction from unorganized data using a variational level set method. *Comp. Vis. and Image Understanding*, vol 80(3): 295-314, 2000.
27. S. Zhu and A. Yuille: Region competition: unifying snakes, region growing, and Bayes/MDL for multiband image segmentation. *PAMI*, vol 18(9): 884-900, 1996.

Fig. 3. On the left: tracking using geometrical term; on the right: tracking using in addition statistical region-based and regularization term.