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Multi-references shape constraint for snakes

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ABSTRACT

In this research, we intend to present a new method of snakes with an invariant shape prior. We consider the general case where different templates are available and we have to choose the most suitable ones to define the shape constraint. A new external force is then proposed which is able to take into account several references at the same time with proportional weighting factors. Both a Fourier based shape alignment method and a complete and stable set of shape descriptors are used to ensure invariance and robustness of the prior knowledge to Euclidean transformations. To illustrate the efficiency of our approach, a set of experiments are applied on synthetic and real data. Promising results are obtained and commented.

Keywords

Snakes, shape constraint, complete and stable invariant descriptors, shape alignment.

1 INTRODUCTION

Image segmentation is a fundamental step in image processing. There have been tremendous researches for this problem. In many issues, segmentation implies a crucial role like in medical diagnosis, tracking and pattern recognition. Snakes have been widely used for object detection by a closed contour. The principle consists in moving a curve iteratively by minimizing an energy functional. The minimum is reached at object boundaries. Active contour methods can be classified into two families: parametric and level-set based active contours. The first family, called also snakes [Kass88, Cohen91, Xu98], uses an explicit representation of the contours to detect objects. The second one [Malladi95, Caselles97, Chan01] uses an implicit representation of the contours by level set approach to handle topological changes of the evolving front. Given that active contours in both families depend only on image gradient, there is still no way to characterize the global shape of an object. Especially in presence of occlusions and clutter, all the previous models converge to the wrong contours

For this purpose, many works introduced prior knowledge on the target object to be detected that can be geometric or statistic constraint on shape and/or texture.

Leventon & al. [Leventon00] associated a statistical shape model to the geodesic active contours [Caselles97]. Chen & al.[Chen01] defined an energy functional based on the quadratic distance between the evolving curve and the averge shapes of the target object after alignment. Bresson & al. [Bresson03] extended [Chen01] approach by integrating the statistical model of shape in the energy functional proposed by [Caselles97]. Fang & al. [Fang07] introduced a statistical shape prior into geodesic active contour to detect partially occluded object. PCA is computed on level set functions used as training data and the set of points in subspace is approximated by a Gaussian function to construct the shape prior model. To speed up the algorithm, an explicit alignment of shape prior model and the current evolving curve is done to calculate pose parameters. Mezghich & al. [Mezghich13] defined a new stopping function for the [Malladi95] model which is based on a reference shape after registration by phase correlation. For all the presented previous works, the authors use an edge-based level set active contour. Region-based approach is based on minimizing an energy functional to segment objects in the image. Experiments show that these models can detect objects with smooth boundaries and noise since the whole region is explored.

Foulonneau & al., [Foulonneau04] introduced a geometric shape prior into a region-based active contours [Chan01] based on the distance between the region inside the target and the reference shape. This distance is computed using the Legendre moments, which ensures invariance to translation and scaling. An extension of this work to the case of affine transformations is presented in [Foulonneau06]. Cremers &

al. [Cremers03] constructed a variational approach that incorporates a shape difference term into the same segmentation model. A labeling function is defined to indicate the regions in which shape priors should be enforced. Mezghich & al., [Mezghich12] defined also a new geometric shape prior based on curves alignment by Fourier transform. The model is able to detect partially occluded object under rigid transformations.
Like the level-set based models, many works introduced prior knowledge for snakes given that these models are well adapted for detection in real time (we have to manage only a reduced set of points). Staib & al., [Staib92] proposed to model shape by a Gaussian probability distribution. Optimization is performed using the maximum a posteriori based on Bayesian rule to define shape constraint. Diffusion Snakes [Cremers02] introduce a statistical prior knowledge on the evolving front to the Mumford-Shah model. Charmi & al. [Charmi08] use a complete and stable set of Fourier-based shape descriptors to define a new geometric constraint to the snake model which is invariant to Euclidean transformations and in [Charmi09], a shape alignment method is used as alternative to solve the problem of the starting point of the parametrized cure that represent the contour in the computation of descriptors.
In all the cited approaches, the template shape to be used is known in advance. In our knowledge, there have been a limited number of researches that treat the general case where we have a training data composed of several references and the model have to take into account the total information provided. In [Fang06] a statistical shape prior model is presented to give more robustness to object detection. This shape prior is able to manage different states of the same object, thus a Gaussian Mixture Model (GMM) and a Bayesian classifier framework are used. Using the level set functions for representing shape, this model suffer from the curse of dimensionality. Hence PCA was used to perform dimensionality reduction. In [Foulonneau09], a multi-references shape prior is presented for a region-based active contours. Prior knowledge is defined as a distance between shape descriptors based on the Legendre moments of the characteristic function of many available shapes.
Motivated by the two last presented works, we try in this research to propose a multi-references shape constraint for Snake. We construct a new statistical prior-driven term that is defined based on a given cluster of similar shapes according to the object to be detected. A complete and stable set of invariants descriptors is used to make the prior force parametrized with a studied weighting factors that give a significant sense. An alignment curves method is also used to guarantee invariance and robust point's curves matching. The improved model can retain all the advantages of snakes and have the additional ability of being able to handle the case of many references in presence of partial occlusions and noise.
The remainder of this paper is organized as follows : In Section 2, we will briefly recall the principle of the snake model. Then, we will devote Section 3 to present the used shape features for invariant shape description. In Section 4, the adopted shape alignment method based on Fourier transform is presented. Then, the multi-references shape constraint will be defined and explained in Section 5. A set of experimental results will be the focus of section 6. Finally, we conclude the work and highlight some possible perspectives in Section 7.

2 THE SNAKE MODEL

Active contours or Snakes [Kass88] consists of a parametrized curve $v(l) = (x(l), y(l))$ which moves under the influence of a functional energy until it reaches the edges of the object of interest. The functional energy is essentially composed of three terms:
- E_{int} : The internal energy which allows the smoothing of the contour and avoids the appearance of the corners,
- E_{image} : The external energy which pushes the curve towards the strong gradient of the image.
- E_{cont} : An external constraint forces that push the evolving curve to be similar to a given reference shape for example.
Hence, snake enery is as follows :

$$E^*_{snake} = \int_0^1 E_{int}(v(l)) + E_{image}(v(l)) + E_{cont}(v(l))dl, \tag{1}$$

Where E_{int} and E_{image} are defined as follows:

$$E_{int}(v(l)) = w_1|v^{'}(l)|^2 + w_2|v^{''}(l,t)|^2, \tag{2}$$

$$E_{image}(v(l)) = -w_3|\nabla(G_\sigma * I)|^2, \tag{3}$$

With w_1, w_2 and w_3 are a weighting factors of the different Snake's energy terms. I is the given image and G_σ is a Gaussian filter with a deviation equals to σ. The Snake equation was first solved by Kass & al. (See [Kass88], Appendix section, for a detailed description) using an Euler framework, which gives after discretization the following equation:

$$(I_N + t\,A)v(t) = v(t-1) + t\,F_{ext}(v(t-1)), \tag{4}$$

where A is a symmetric pentadiagonal matrix computed from the coefficients w_1 and w_2 of size N, representing all internal elasticity relations of the snake, t is the time step, N represents the number of points of the snake, I_N is the identity matrix and F_{ext} are the forces derived from the external energy:

$$F_{ext} = -\nabla|\nabla(G_\sigma * I)|^2, \tag{5}$$

3 SHAPE DESCRIPTION USING INVARIANT SET OF FOURIER DESCRIPTORS

Given that we will consider a cluster of closed curves which are similar to the evolving one, we adopt Fourier invariant description by a set of complete and stable features. The completeness property means that two objects have the same shape if and only if they have the same set of invariants. It allows also the reconstruction of shapes from their invariants up to an Euclidean transformation. Whereas the stability property means that a slight shape distortion does not induce a noticeable divergence of invariants. The used set of invariants Fourier descriptors (see [Ghorbel98] for more details) is as follows :

$$\begin{cases} I_{k_0}(\gamma) = |C_{k_0}(\gamma)|, \quad C_{k_0}(\gamma) \neq 0 \\ I_{k_1}(\gamma) = |C_{k_1}(\gamma)|, \quad C_{k_1}(\gamma) \neq 0, \quad k_1 \neq k_0 \\ I_k(\gamma) = \frac{C_k(\gamma)^{k_0-k_1} C_{k_0}(\gamma)^{k-k_1} C_{k_1}(\gamma)^{k_0-k}}{I_{k_0}^{k-k_1-p}(\gamma) I_{k_1}^{k_0-k-q}(\gamma)}, \\ k \neq k_0, k_1 \ \ and \ \ p,q > 0, \end{cases} \tag{6}$$

Where C_k is the well known Fourier descriptor. To compare shapes, we use the following distance between descriptors:

$$d(\gamma_1,\gamma_2) = \sum_k (|I_k(\gamma_1) - I_k(\gamma_2)|^{\frac{1}{2}})^2 \tag{7}$$

4 SHAPES ALIGNMENT USING FOURIER DESCRIPTORS

Curves alignment and matching are important steps for variability studies between shapes and the construction of prior knowledge. We use the method presented by Persoon & Fu [Persoon86] which is based on Fourier transform that makes it fast. We will recall the outline of this method. For a given planar object represented by it's parametric closed curve we have :

$$\begin{aligned} \gamma : [0,2\pi] &\rightarrow C \\ t &\mapsto x(t) + i\,y(t), \end{aligned} \tag{8}$$

Let γ_1 and γ_2 be centred (according to the center of mass) and normalized arclength parameterizations of two closed planar curves having shapes F_1 and F_2. Suppose that γ_1 and γ_2 have a similar shape under rigid transformation. In shape space this is equivalent to have

$$\gamma_1(t) = \alpha e^{i\theta} \gamma_2(t+t_0), \tag{9}$$

where α is the scaling factor, θ the rotation angle, t_0 is the difference between the two starting points of γ_1 and γ_2. Rigid motion estimation is obtained by minimizing the following quantity:

$$E_{rr}(\gamma_1,\gamma_2) = min_{(\alpha,\theta,t_0)} ||\gamma_1(t) - \alpha e^{i\theta}\gamma_2(t+t_0)||_{L^2}, \tag{10}$$

Using Fourier descriptors $C_k(\gamma_1)$ and $C_k(\gamma_2)$, minimizing E_{rr} becomes equivalent to minimize $f(\theta,t_0)$ in Fourier domain

$$f(\theta,t_0) = \sum_{k\in Z} |C_k(\gamma_1) - \alpha e^{i(kt_0+\theta)} C_k(\gamma_2)|^2, \tag{11}$$

In [Persoon86], the authors proposed an analytical solution to compute t_0 and θ. t_0 is one of the zeros of the following function

$$\begin{aligned} g(t) = &\sum_k \rho_k \sin(\psi_k + kt) \sum_k k\rho_k \cos(\psi_k + kt) - \\ &\sum_k k\rho_k \sin(\psi_k + kt) \sum_k \rho_k \cos(\psi_k + kt), \end{aligned} \tag{12}$$

where $\rho_k\ e^{i\psi_k}$=$C_k^*(\gamma_1)C_k(\gamma_2)$, θ is chosen to satisfy Eq. (11) and minimize $f(\theta$,$t_0)$ where t_0 is one of the roots of g.

$$tan\theta = -\frac{\sum_k \rho_k \sin(\psi_k + kt_0)}{\sum_k \rho_k \cos(\psi_k + kt_0)}, \tag{13}$$

Having the value of θ and t_0 that minimize $f(\theta$,$t_0)$, the scaling factor is given by

$$\alpha = \frac{\sum_k \rho_k \cos(\psi_k + kt_0 + \theta)}{\sum_k C_k^*(\gamma_2) C_k(\gamma_2)}, \tag{14}$$

Based on Nyquist-Shannon theorem and B-spline approximation of the $g(t)$'s curve, the first implementation of this method and its application in rigid motion estimation for video compression was provided in [Ghorbel98]. In figure 1, we show an example of two parametrized curves of the same shape but under different rotation and scale factor. The right image shows

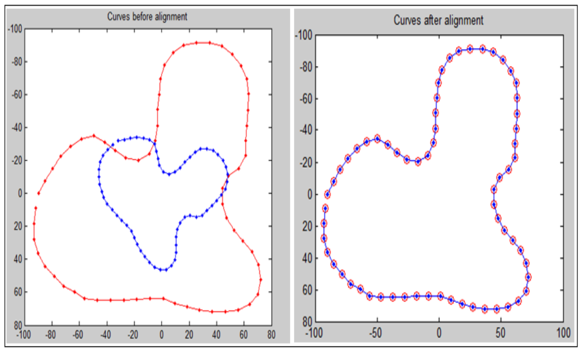

Figure 1: Two curves before and after alignment using the presented method.

results after alignment. Figure 2 represents the associated g function. The roots are draw with green circle.

This method will be used to align the training references to the active contour to define prior knowledge after the evolving curve being stable.

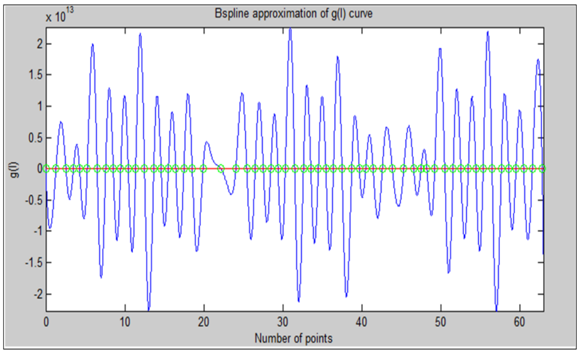

Figure 2: The correspondent g function

5 MUTLI-REFERENCES SHAPE CONSTRAINT FOR SNAKE

Consider a given set of N references having similar shape according to the evolving curve. It may be that among these templates, some of them are very similar to the target contour than the others. So convergence should be guided by this subset of curves. For this purpose, we need to defined a new weighting evolution schema that take into account this consideration. We presented in section 3 a distance $d(\gamma_1, \gamma_2)$, $(eq.7)$, between the invariant set of two curves. This distance will be used as criterion to study similarity between each reference and the target shape. It will provide us a mathematical way to sort the training data.
Let γ be the active contour and γ_{ref}^i be the i^{th} reference, The proposed prior force will be as follows:

$$F_{prior} = \sum_{i=1}^{N} g_i \cdot (\gamma - \gamma_{ref}^i), \tag{15}$$

where $g_i = \frac{1}{1+d_i^p}, p > 1$ and $d_i = d(\gamma, \gamma_{ref}^i)$.
As it can be seen, for a «near» reference γ_{ref}^i, we have $d_i^p \approx 0$, so $g_i \approx 1$, then this reference will be taken into account in the evolution process.
For a «far» reference having $d_i^p \approx \infty$, $g_i \approx 0$. So this reference will not influence the convergence to the desired shape. We can deduce that the proposed function g_i plays an important role to encourages evolution towards similar templates with natural weighting factor. We note that g_i recalls the edge-stopping function on high image gradient for the classic level set based active contours, see [Malladi95].
Hence the total evolution equation that we propose is :

$$\begin{aligned}(I_N + t\,A)v(t) = v(t-1) + t[c_1\,F_{ext}(v(t-1)) \\ +c_2\,F_{prior}(v(t-1))],\end{aligned} \tag{16}$$

where c_1 and c_2 are two weighting factors related respectively to the data and the prior forces.

The proposed algorithm is then composed of two steps :

1- **Step 1 : Off-line step**
- It consists in the computation of invariants descriptors for each reference and its alignment according to a selected one.
2- **Step 2 : On-line step**
- Start the snake with only image driven-force.
- Having the contour being stable, we perform alignment of the N references according to the evolving front.
- We compute the proposed force F_{prior}
- Then, we evolve the model under both forces, the image and the prior ones.

6 EXPERIMENTAL RESULTS

To assess the robustness of the proposed approach, a set of experiments is performed. At first, we will evaluate the behavior of the new added force F_{prior} on simulated images. Then, we will experiment the proposed model on real images with partially occluded objects.

6.1 Results on simulated data

We consider in this first experiment a partially occluded object. Five references are considered to be added as prior knowledge (figure 3).

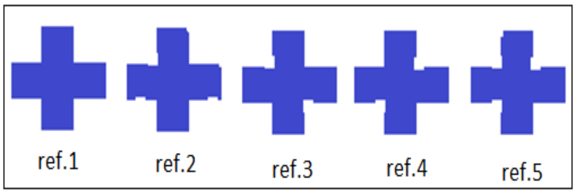

Figure 3: Some used references.

Each curve is sampled to 120 points. Results of segmentation are shown in figure 4. By the (a) image, we show the obtained detection using the classic snake model based on image driven forces.
In the (b) image, we present the segmentation using the snake model with shape prior. We use only one reference which is the closest one (here we get $ref.4$) according to the distance $d = d(\gamma, \gamma_{ref}^4)$. This idea was proposed in [Charmi09].
By the (c) image, we show the obtained result with the proposed multi-references shape prior. Visually, it is clear that the detection using our model seems to be better than in (b). In fact, by our approach all the templates participate in the process of detection.
In (d), we present the aligned curves used as references.

By the table below, we present the obtained distance between each reference and the evolving curve. The weighing factors g_i are presented by the second row $(p = 2)$.

At the beginning, only snake forces are considered so we take $c_1 = 1$ and $c_2 = 0$. At a given iteration, when the evolving contour became stable, we introduce the

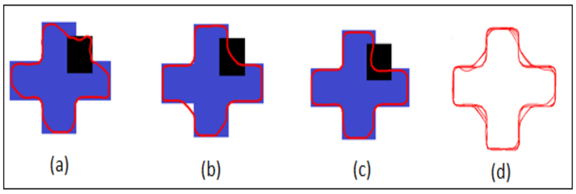

Figure 4: The obtained segmentation result with and without shape prior.

	Ref.1	Ref.2	Ref.3	Ref.4	Ref.5
$d(\gamma,\gamma^i_{ref})$	2.183	1.938	2.382	1.899	2.232
g_i	0.209	0.266	0.176	0.277	0.200

Table 1: The weighing factors used for each reference.

prior force F_{prior} using $c_1 = 0.7$ and $c_2 = 0.3$.
We end this part by testing our proposed model on partially occluded object under noise, missing part and clutterd background. We use the same configuration as for the previous experiment. Results are show by figure 5.

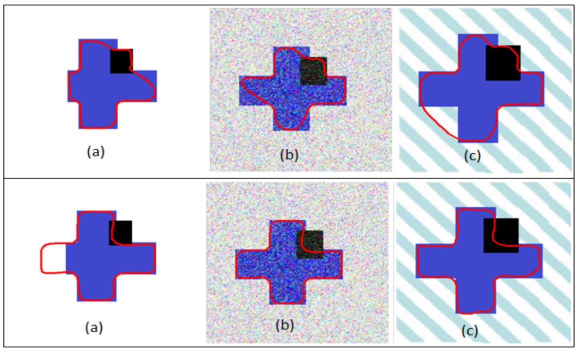

Figure 5: Object detection under missing part (a), noise (b) and clutter (c).

In what follows, the proposed model is applied to real data. Two applications are considered: the first one consists in the tracking of moving object under cluttered background and by the second experiment, we try to detect the left ventricle of the heart in myocardial scintigraphy slices under low contrast.

6.2 Application 1 : Tracking of moving object under clutter background

The object to be detected presents deep concavity which is unresolved problem by the classic snake model. Besides, the background is cluttered. As it ca be seen, our model succeeds in finding the true contours of the target object.
We used for each row 4 references to construct prior shape knowledge. For the first row, the contour is sampled to 200 points, and for the second one, we used 400 points. Finally, for the last one, we take 300 points. Figure 7 shows the used references for each object after sampling and alignment according to the evolving curve.

Figure 6: First column : Initial contour, Second column : Result without prior knowledge, Last column : Result with prior knowledge.

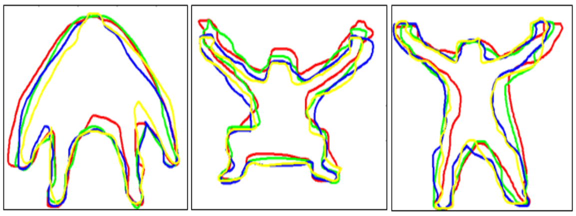

Figure 7: The used references.

6.3 Application 2 : Segmentation of myocardial scintigraphy images

For this type of image, usually object of interest are in low contrast, so snakes fail to detect the target object as it is show in image (b) of figure 8. Using references (provided by the expert) associated to the previous and the next slices according to the current one, result obtained by the proposed model are presented by image (c). As it is shown, results seems to be encourages us-

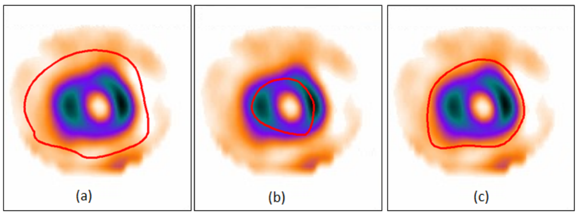

Figure 8: (a):initial contour; (b):segmentation without prior; (c):segmentation with prior knowledge.

ing only 2 references.

7 CONCLUSION

A new shape constraint for the snake model is presented in this paper. The method is able to manage several references with a studied weighting factors under invariance to rigid transformations. Results show robust object detection under partial occlusion, clutter and noise.

Besides, given that the method is based on Fast Fourier Transform (FFT) for shape alignment and descriptors computation, the method can be applied for tracking moving object in real time.The medical context represents also a challenging field in future work.

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