SHAPE PRIOR FOR AN EDGE-BASED ACTIVE CONTOURS USING PHASE CORRELATION

Mohamed Amine Mezghich, Malek Sellami, Slim M'Hiri and Faouzi Ghorbel

GRIFT Research Group, CRISTAL Laboratory
École Nationale des Sciences de l'Informatique, ENSI
Campus Universitaire de la Manouba, 2010 Manouba, Tunisia
ma.mezghich@cristal.rnu.tn, {malek.sellami,slim.mhiri,faouzi.ghorbel}@ensi.rnu.tn

ABSTRACT

In this paper, we intend to present a new method to incorporate geometric shape prior into an edge-based active contours in order to improve its robustness to partial occlusions, low contrast and noise. The proposed shape prior is defined after the registration, based on phase correlation, of binary images associated with level set functions of the active contour and a reference shape making the model invariant with respect to Euclidean transformations. Experimental results on synthetic and real images show the ability of the proposed approach to constrain an evolving curve towards a target shapes that may be occluded and cluttered under rigid transformations.

Index Terms— Active contours, shape prior, phase correlation, rigid transformations

1. INTRODUCTION

Segmentation is a crucial step in image processing. Its role is to partition the image into homogeneous regions. Active contours [1, 2, 3, 4, 5] have been widely used in this field. One can classify them into two families : The boundary-based approach which depends on an edge stopping function to detect objects and the region-based approach which is based on minimizing an energy's functionnal to segment objects in the image. Region-based models are more robust than boundary-based methods since the information of the whole region is explored. However, they need more computations and the region is restricted to be uniform and occlusion free. Given that classical active contours are intensity-based models, there is still no way to caracterize the global shape of an object. Especially in presence of occlusions and clutter, all the previous models converge to the wrong contours. To solve the above mentioned problems, different attempts incorporate shape prior into the active contour models. Leventon et al., [6] associated a statistical shape model to the geodesic active contours [3]. At each step of the surface evolution, the maximum a posteriori position and shape are estimated and used to move globally the surface while local evolution is based on image gradient and curvature. Chen et al., [7] defined an energy's functional based on the quadratic distance between the evolving curve and the average shapes of the target object after alignment. This energy is then incorporated into the geodesic active contours. Bresson et al., [8] extended [7] approach by integrating the statistical model of shape proposed by [6] in the energy functional. Fang and Chan [9] introduced a statistical shape prior into the geodesic active contour to detect partially occluded object. To speed up the algorithm, an explicit alignment of the shape prior model and the current evolving curve is done to calculate pose parameters. Foulonneau et al., [10] introduced a geometric shape prior into a region-based active contours [5] based on the Legendre moments of the characteristic function and in [11], Charmi et al., defined a geometric shape prior for the region-based active contours after alignment of the evolving contour and the reference shape. It's well known that shape priors based on contour alignment methods force these approaches to segment only single object in the image and go without the contribution of level set, i.e. its ability to segment multiple objects at once (see [8]). Besides, contour alignment methods are not adapted to estimate the rigid transformation parameters in the case of objects with holes (which often occurs in medical imagery like MRI brain's white matter). This justifies the use of the registration methods instead of those based on contours alignment. In this work, we focus on adding a new geometric shape prior to an edge-based active contours [4] that use the relative motion parameters between objects of the same shape and have different pose, size and orientation, estimated by phase correlation. We assume that the shape of reference is known in advance (like the work of [10]). The improved model can retain all the advantages of the level set approach and have the additional ability of being able to handle the case of images with multiple objects in presence of noise, partial occlusions and low contrast. The remainder of this paper is organized as follows : In Section 2, we will recall the used shape registration method based on phase correlation. Then, the proposed shape prior will be presented in Section 3. Experiments will be presented and commented in order to study the robustness of the model in Section 4. Finally, we conclude the work and highlight some perspectives in Section 5.

2. SHAPES REGISTRATION

We adopt the well know method of phase correlation in Fourier space that is appropriate to estimate the translation vector (see [12]) and for estimating the rotation angle and the scaling factor, we use the proposed method of phase correlation in Fourier-Mellin space. We brefiely recall this method which is based on the Analytical Fourier-Mellin Transform (AFMT), see [13] for a detailed description. A comparative study with other global registration methods is presented in [14]. Let $f(r, \theta)$ be a polar representation of the image with the radius r according to the center of gravity of the image to offset translation and θ the angle according to the horizontal. It was pointed out in [15] that the crucial numerical difficulties in computing the Fourier-Mellin transform of an image might be solved by using the Analytical Fourier-Mellin Transform (AFMT) given by

$$M_{f_\sigma}(k, v) = \frac{1}{2\pi} \int_0^{+\infty} \int_0^{2\pi} f(r, \theta) r^{\sigma - iv} e^{-ik\theta} \, \frac{dr}{r} d\theta, \tag{1}$$

where $\sigma > 0$ is a fixed and strictly positive real number. Since no discrete transform exists, three approximations of the AFMT have been designed : the direct, the cartesian and the fast algorithm (see [16]). Let $f_{\phi_{ref}}$ and f_ϕ be two binary images associated respectively with level set functions ϕ_{ref} and ϕ. Denote by $M_{f_{\sigma,\phi_{ref}}}$ and $M_{f_{\sigma,\phi}}$ the AFMT of respectively $f_{\phi_{ref}}$ and f_ϕ with the same value of σ. $f_{\phi_{ref}}$ and f_ϕ have the same shape if and only if there is a similarity $(\alpha_0, \beta_0) \in G = (R_+^*, S^1)$ such that

$$\forall (r, \theta) \in G, f_\phi(r, \theta) = f_{\phi_{ref}}(\frac{r}{\alpha_0}, \theta - \beta_0), \tag{2}$$

The action of planar similarities in Fourier-Mellin space leads to

$$M_{f_{\sigma,\phi}}(k, v) = \alpha_0^{\sigma - iv} e^{-ik\beta_0} M_{f_{\sigma,\phi_{ref}}}(k, v), \tag{3}$$

By calculating the normalized cross-spectrum, only information on phase difference will be preserved

$$\Phi(k, v) = \frac{M^*_{f_{\sigma,\phi_{ref}}}(k, v) M_{f_{\sigma,\phi}}(k, v)}{|M^*_{f_{\sigma,\phi_{ref}}}(k, v)||M_{f_{\sigma,\phi}}(k, v)|} = \alpha_0^{-iv} e^{-ik\beta_0}, \tag{4}$$

Phase correlation of two images represented respectively by $f_{\phi_{ref}}$ and f_ϕ is defined as

$$C_{Tfm}(\alpha, \beta) = \int_0^{+\infty} \sum_Z \Phi(k, v) \alpha^{iv} e^{ik\beta} dv, \tag{5}$$

We can deduce the images transformation's parameters (α, β) by estimating (α_0, β_0) that maximize the correlation function C_{Tfm}. Having the parameters of rigid transformation between the two binary images. We perform the registration of the image $f_{\phi_{ref}}$ according to the following formula [17]

$$f^{reg}_{\phi_{ref}}(x, y) = \alpha f_{\phi_{ref}}(\frac{(x-a)\cos\theta + (y-b)\sin\theta}{\alpha}, \frac{-(x-a)\sin\theta + (y-b)\cos\theta}{\alpha}), \tag{6}$$

where (a, b) represents the translation vector, θ the rotation angle and α is the scaling factor. On the resulting image (Fig.1), the pixels in black (resp. white) correspond to positive areas (resp. negative) of the signed distance map which is associated to level set function. The image on the right of Fig.1 shows the product function given by

$$f_{prod}(x, y) = f^{reg}_{\phi_{ref}}(x, y) \cdot f_\phi(x, y), \tag{7}$$

By construction, the function f_{prod} is negative in the areas of

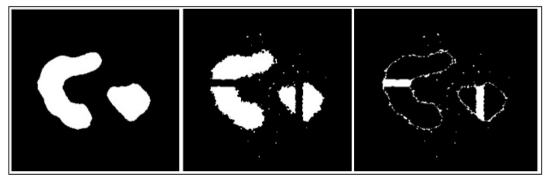

Fig. 1. $Left : f^{reg}_{\phi_{ref}}, Middle : f_\phi, Right : f_{prod}$.

variability between the two binary images (occlusion, clutter, missing parts etc.) whereas in positive regions, the objects are similar. Thus, in what follows, we propose to update the level set function ϕ only in regions of variability between shapes to make the evolving contours overpass the spurious edges and recover the desired shapes of objects. This property recalls the Narrow Band technique used to accelerate the evolution of the level set functions [4].

3. THE PROPOSED SHAPE PRIOR

Geometric active contours are iterative segmentation methods which use the Level Set approach [2] to determine the evolving front at each iteration. Working with level set approach makes it possible to manage topology changing of the contour like splitting and merging, and consequently the segmentation of an arbitrary number of objects in the image. In [4], the level set approach is used to model the shape of objects with an evolving front. The evolution's equation of the level set function ϕ, which is the embedding function associated to the active contour, is

$$\phi_t + F|\nabla \phi| = 0, \tag{8}$$

F is a speed function of the form $F = F_0 + F_1(K)$ where F_0 is a constant advection term equals to (± 1) depending of the object inside or outside the initial contour. The second term is of the form $-\epsilon K$ where K is the curvature at any point and $\epsilon > 0$, is a constant real. To detect objects in the image, the authors proposed the following function which stops the level set function's evolution at the object boundaries

$$g(x,y) = \frac{1}{1+|\nabla G_\sigma * f(x,y)|}, \tag{9}$$

where f is the image and G_σ is a Gaussian convolution filter of standard deviation σ. This stopping function has values that are closer to zero in regions of high image gradient and values that are closer to unity in regions with relatively constant intensity. Hence, the discrete evolution equation is

$$\frac{\phi^{n+1}(i,j)-\phi^n(i,j)}{\Delta t} = -g(i,j)\ F(i,j)\ |\nabla \phi^n(i,j)|, \tag{10}$$

It's obvious that the evolution is based on the stopping function g which depends on the image gradient. That's why this model leads to unsatisfactory results in presence of occlusions, low contrast and even noise. To make the level set function evolves in the regions of variability between the shape of reference and the target shape, we propose the new stopping function as follows

$$g_{shape}(x,y) = \begin{cases} 0,\ if\ \psi(x,y) >= 0, \\ sign(\phi_{ref}(x,y)), else, \end{cases} \tag{11}$$

where $\psi(x,y) = \phi(x,y) \cdot \phi_{ref}(x,y)$, ϕ is the level set function associated to the evolving contour, while ϕ_{ref} is the level set function associated to the shape of reference after registration. As it can be seen, the new proposed stopping function only allows for updating the level set function in the regions of variability between shapes. In these regions g_{shape} is either 1 or -1 because in the case of partial occlusions, the function is equals to 1 in order to push the edge inward (deflate) and in case of missing parts, this function is equals to -1 to push the contour towards the outside (inflate). This property recalls the Balloon snake's model proposed by Cohen in [18] in which the direction of evolution (inflate or deflate) should be precised from the beginning. In our work, the direction of evolution is hundled automatically based on the sign of ϕ_{ref}. The total discrete evolution's equation that we propose is

$$\frac{\phi^{n+1}(i,j)-\phi^n(i,j)}{\Delta t} = -(w\, g(i,j) + (1-w)\, g_{shape}(i,j))\ \ F(i,j)|\nabla \phi^n(i,j)|, \tag{12}$$

where w is a weighting factor between the image-based force and knowledge-driven force.

4. EXPERIMENTAL RESULTS

We will start by presenting the robustness of the proposed shape prior to constrain the evolution of an active contour towards a given shape, then the proposed model will be applied to the segmentation problem.

4.1. Robustness of the proposed shape prior

To illustrate the ability of the proposed shape prior to constrain geometrically an active contour, we experiment first the evolution of the contour under the influence of the proposed shape prior term only (i.e. $w = 0$). We present in Fig.2 an example of successive evolutions between several shapes of different topologies. We have chosen for initial curve a green square. The first shape of reference is a tree leaf. An intermediate step in this evolution is shown by the first row and the final curve (when convergence is reached) is presented by the last column. This last configuration of the contour is used as an initial curve for the next experiment by taking the image of the left and right ventricles of the heart as a reference and then finally in the same way by taking the shape of a pen and a ring as shapes of reference. This simulation shows that the proposed shape prior can well constrain an active contour to take a given shape (known as reference) and handling non trivial geometric shapes with holes and complex topologies.

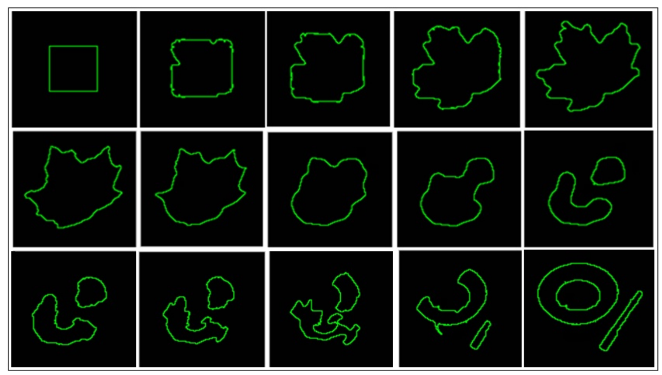

Fig. 2. Curve evolution under the proposed shape prior only.

4.2. Application to the segmentation problem

In this section, the proposed model with shape prior will be applied to the segmentation problem. Consequently the model will evolves under both data and prior terms. In order to reduce the computational complexity and to have a good estimation of the parameters of the rigid transformation as in [9, 10], we first evolve the active contour without shape prior until convergence (i.e. $w = 1$). This first result provides an initialization for the model with prior knowledge. To promote the convergence to the target shape, we give more weight to prior knowledge (generally $w <= 0.5$). In the next experiment, we compare our model to that proposed by Fang and Chan in [9]. The shape of reference is provided by image (a). Images (b) and (c) represent repectivelly the results obtained by our model and the model of Fang and Chan. It is visually clear that in region of variability (occlusion), the proposed approach gives a better result. By the second row, we handle a situation where the object to be detected is no longer connected (due to missing parts or hole). In such situations, methods based on contours alignment does not allow to estimate the parameters of the rigid transformation (rotation and scale). Thanks to registration by phase correlation, our

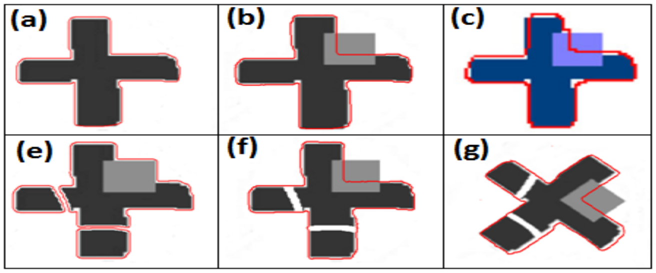

Fig. 3. (a) : The reference, (b) : Result obtained by our model, (c) : Result obtained by Fang and Chan model, (e) : Segmentation without shape prior, (f) and (g) : Segmentation with the proposed model.

model can handle this case and consequently the detection of the target object. In Fig.4, the case of real image with several objects under partial occlusion and different types of noise (Gaussian, Salt and Pepper and Speckle) is considered. Segmentation without shape prior fails to detect the familiar objects (second image of first row). However, using the shape prior, the proposed model succeeds in segmenting the desired objects (third image of first row). For the second row, a rotation of $-90°$ with differents kind of noise are applied. Results seems to be satisfactory. In what follows, our model

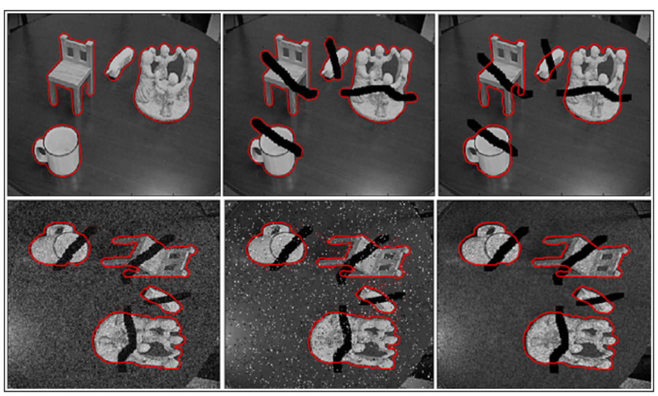

Fig. 4. Segmentation of real image with several objects under partial occlusion and noise.

is applied to medical images obtained from Brain Web Simulated Data Base[1]. We focus on the segmentation of white matter that may contain holes depending on the slice. The reference images are provided by the first row (slices 56, 58 and 62). We have chosen to initialize the model for different slices with a simple rectangle (green curve). The obtained results without the constraint of shape included in the model are presented in the third row. Starting with these results and after the registration step, final segmentation based on shape prior knowledge and image-based information is presented by the last row. The table below shows the value of RMSE (Root

[1]http://mouldy.bic.mni.mcgill.ca/brainweb/

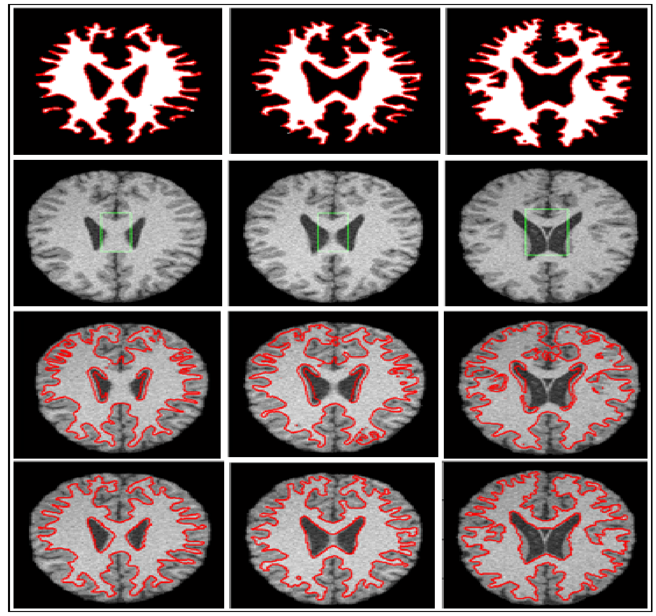

Fig. 5. Segmentation of brain white matter.

Mean Square Error), execution time until convergence and the time for parameters estimation (in seconds) of the rigid transformation for different values of w and this for slice 56. The images size is 256 x 256. We set the total number of iterations equals to 500. The prior knowledge is introduced at the iteration 400 for different values of w. Fig.6 presents

w	RMSE	Execution time	Motion estimation time
1	0.549	24.563	-
0.8	0.237	26.264	0.430
0.4	0.230	27.009	0.470
0.1	0.222	24.798	0.375
0	0.216	27.161	0.526

Table 1. Variation of the RMSE and the execution time depending on the weighting factor w.

the variation of the RMSE depending on the weighting factor w for slices 56, 58 and 62. We note that with a low weight of the shape constraint, the proposed model arrives to constrain the contour evolution towards the reference shape. Given these encouraging results, we plan in future work to apply our model in a medical context for the extraction of target structures based on medical atlas.

5. CONCLUSION

To summarize, new method of geometric active contours with shape prior is presented in this research. The proposed model is able to constrain the evolving curve to be similar to a given

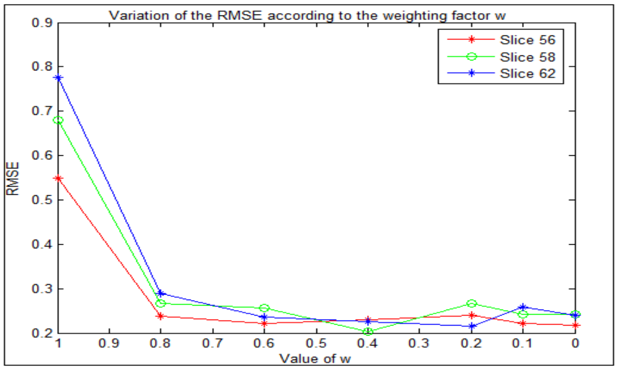

Fig. 6. Variation of the RMSE depending on the weighting factor w for slices 56, 58 and 62.

template. This approach uses the registration of binary images associated to level set functions of respectively the evolving contour and a reference shape by phase correlation. Experiments have shown the ability of the newly added term to improve the robustness of the detection process in presence of textured background, missing parts and partial occlusions of the target objects. The addition of shape prior has not increased significantly the execution time given that the proposed approach does the registration only once and it is done by the Fast Fourier Transform unlike [10] where at each iteration shape descriptors are calculated for a given order. As future perspectives, we are working on applying our model in the context of medical application where the shape of reference is given by medical atlas in order to aid in the diagnosis. Also, we plan to extend this approach to more general transformations such as affine transformations.

6. REFERENCES

[1] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes : active contour models," *Int. J. of Comp.Vis.*, vol. 1, pp. 321–331, 1988.

[2] S. Osher and J.A. Sethian, "Fronts propagating with curvature-dependent speed: algotithms based on hamilton-jacobi formulation," *J.of Computational Physics*, vol. 79, pp. 12–49, 1988.

[3] V. Caselles, R. Kimmel, and G. Sapiro, "Geodesic active contours," *Int. J. of Comp. Vis.*, vol. 22, pp. 61–79, 1997.

[4] R. Malladi, J. Sethian, and B. Vemuri, "Shape modeling with front propagation : A level set approach," *PAMI*, vol. 17, pp. 158–175, 1995.

[5] T. Chan and L. Vese, "Active contours without edges," *IEEE Trans. Imag. Proc.*, vol. 10, pp. 266–277, 2001.

[6] M. Leventon, E. Grimson, and O. Faugeras, "Statistical shape influence in geodesic active contours," in *Proc. of IEEE Conference on Computer Vision and Pattern Recognition*, 2000, pp. 316–323.

[7] Y. Chen, S. Thiruvenkadam, H.D. Tagare, F. Huang, D. Wilson, and E.A. Geiser, "On the incorporation of shape priors into geometric active contours," in *Proc. of IEEE Workshop on Variational and Level Set Methods in Computer Vision,*, 2001, pp. 145–152.

[8] P. Vandergheynst X. Bresson and J.P. Thiran, "A priori information in image segmentation : energy functional based on shape statistical model and image information," in *ICIP*, 2003, pp. 425–428.

[9] W. Fang and K.L. Chan, "Incorporating shape prior into geodesic active contours for detecting partially occluded object," *Pattern Recognition*, vol. 40, pp. 2163–2172, 2007.

[10] A. Foulonneau, P. Charbonnier, and F. Heitz, "Contraintes geometriques de formes pour les contours actifs orientes region : une approche basee sur les moments de legendre," *Traitement du signal*, vol. 21, pp. 109–127, 2004.

[11] M.A.Charmi, M.A.Mezghich, S.M'Hiri, S.Derrode, and F.Ghorbel, "Geometric shape prior to region-based active contours using fourier-based shape alignment," in *IST*, 2010, pp. 478–481.

[12] B. Marcel, M. Briot, and R. Murietta, "Calcul de translation et rotation par la transformation de fourier," *Traitement du signal*, vol. 14, pp. 135–149, 1997.

[13] Slim M'Hiri, Mohamed Amine Mezghich, and Malek Sellemi, "Contours actifs avec a priori de forme base sur la transformee de fourier-mellin analytique," *Traitement du Signal*, vol. 29, pp. 123–142, 2012.

[14] M. Sellami and F. Ghorbel, "An invariant similarity registration algorithm based on the analytical fourier mellin transform," in *EUSIPCO*, 2012, pp. 390–394.

[15] F. Ghorbel, "A complete invariant description for grey-level images by the harmonic analysis approach," *Traitement du signal*, vol. 53, pp. 1043–1051, 1994.

[16] S. Derrode and F. Ghorbel, "Robust and efficient fourier-mellin transform approximations for gray level image reconstruction and complete invariant description," *Computer Vision and Image Understanding*, vol. 83, pp. 57–78, 2001.

[17] T. Chan and W. Zhu, "Level set based shape prior segmentation," in *CVPR*, 2005, pp. 1164–1170.

[18] L. Cohen, "On active contour models and balloons," *Graphical Models Image Process*, vol. 53, pp. 211–218, 1991.