Robust Object Segmentation using Active Contours and Shape Prior

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Keywords: Active Contours, Shape Prior, Phase Correlation, Rigid Transformation.

Abstract: In this paper, we intend to present new method to incorporate geometric shape prior into region-based active contours in order to improve its robustness to noise and occlusions. The proposed shape prior is defined after the registration of binary images associated with level set functions of the active contour and a reference shape. The used registration method is based on phase correlation. This representation makes it possible to manage several objects simultaneously. Experimental results show the ability of the proposed geometric shape prior to constrain an evolving curve towards a target shape. We highlight, on synthetic and real images, the benefit of the method on segmentation results in presence of partial occlusions, low contrast and noise.

1 INTRODUCTION

Active contour models have been introduced in 1988 (Kass et al., 1988). The principle of these methods is to move a curve iteratively minimizing energy's functional. The minimum is reached at object boundaries. Active contour methods can be classified into two families : parametric and geometric active contours. The first family, called also Snakes, uses an explicit representation of the contours and depends only on image gradient to detect objects (Kass et al., 1988; Cohen, 1991). Theses models are able to segment only one object in the image. To overcome this problem, an implicit representation of the active contours via level set approach (i.e. geometric active contours) has been used (Osher and Sethian, 1988) to handle topological changes of the front. A number of active contour models based on level set theory has been then proposed which can be divided into two categories : The boundary-based approach which depends on an edge stopping function to detect objects (Malladi et al., 1995; Caselles et al., 1997) and the region-based approach which is based on minimizing an energy's functional to segment objects in the image (Chan and Vese, 2001). Experiments show that region-based models can detect objects with smooth boundaries and noise since the whole region is explored. However, 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. To solve the above mentioned problems, different attempts include shape prior into the active contour model. Many works have been proposed which can be classified into statistical or geometrical shape priors. A statistical shape model (Leventon et al., 2000) was associated to the geodesic active contours (Caselles et al., 1997). A set of training shapes is used to define a Gaussian distribution over shapes. At each step of the surface evolution, the maximum a posteriori (MAP) position and shape are estimated and used to move globally the surface while local evolution is based on image gradient and curvature. A new energy's functional based on the quadratic distance between the evolving curve and the average shape of the target object after alignment was defined by (Chen et al., 2001). This term is then incorporated into the geodesic active contours. In 2007, (Fang and Chan, 2007) introduced a statistical shape prior into the 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. An additional geometric shape prior into region-based active contours was introduced by (Foulonneau et al., 2004). Prior knowledge is defined as a distance between shape descriptors based on the Legendre moments of the characteristic function. A new geometric shape prior for a region-based active contours (Chan and Vese, 2001) was defined by (Charmi et al., 2010) after alignment of the evolving contour and the reference shape. The model has been successful in case of single object in

Amine Mezghich M., Sellami M., M'hiri S. and Ghorbel F. (2013).
Robust Object Segmentation using Active Contours and Shape Prior.
In *Proceedings of the 2nd International Conference on Pattern Recognition Applications and Methods*, pages 547-553
DOI: 10.5220/0004263005470553
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the image. It is well known that the level set approach solves the problem of topology changing of the parametric Snake. However, the introduction of shape prior by the aforementioned models does to segment a single object in the image. In this paper we focus on adding shape prior to Chan and Vese's model (Chan and Vese, 2001) based on registration by phase correlation of binary images associated with level set functions of the evolving contour and the shape of reference. The improved model can retain all the advantages of (Chan and Vese, 2001) and have the additional ability of being able to handle images with multiple objects in presence of noise and partial occlusions. The remainder of this paper is organized as follows : In Section 2, we recall the principle of Chan and Vese's model. The proposed shape prior and the used registration method will be presented in Section 3. Experimental results are presented and commented in Section 4. Finally, we conclude the work and highlight some possible perspectives in Section 5.

2 REGION-BASED ACTIVE CONTOURS

The region-based active contours model (Chan and Vese, 2001) tries to stop the curve evolution with an energy minimization approach rather than using an edge-stopping function. Based on level set technique (Osher and Sethian, 1988), the propagating front corresponds always to the zeros level set of an evolving surface ϕ. The proposed energy is

$$\begin{aligned} E_{CV}(\phi,c_1,c_2) = \mu \textstyle\int_\Omega \delta(\phi)|\nabla\phi(x,y)|dxdy \\ +\nu \textstyle\int_\Omega H(-\phi(x,y))dxdy \\ +\lambda_1 \textstyle\int_\Omega |f(x,y)-c_1|^2 H(-\phi(x,y))dxdy \\ +\lambda_2 \textstyle\int_\Omega |f(x,y)-c_2|^2 H(\phi(x,y))dxdy, \end{aligned} \quad (1)$$

where Ω is the image domain, f is the image intensity, $\mu, \nu \geq 0$ and λ_1, $\lambda_2 > 0$ are fixed parameters. H is the Heaviside function and δ is the Dirac measure. If we consider z as a level set of ϕ we can write

$$H(z) = \begin{cases} 1, if z \geq 0 \\ 0, if z < 0 \end{cases}, \quad \delta(z) = \frac{dH(z)}{dz}, \quad (2)$$

Parameters c_1 and c_2 are respectively the averages of gray-level intensities inside and outside the evolving curve (Chan and Vese, 2001).

3 SHAPE PRIOR FORMULATION

Our goal is to define new geometric shape prior to impose a constraint on the evolving contour to converge to the target shape. If one takes a template shape which is not defined in the image reference, it is necessary to apply a transformation to align it with the shape to segment (rotation, translation, scaling factor). To estimate the parameters of this transformation, many approaches in literature (section 1) use alignment methods of the evolving contour and that of the reference shape. Contour alignment methods force these approaches to segment only single object in the image and go without the contribution of the level set approach, i.e. its ability to segment multiple objects at once. To segment images with multiple objects, we propose in this work a shape prior that uses the relative motion parameters, between objects of the same shape and have different size and orientation, estimated by phase correlation. Initially we use the method of phase correlation in Fourier space that is appropriate to estimate the translation vector. Second, and as discussed in the next section, we use phase correlation in Fourier-Mellin space for estimating the rotation and the scaling factor.

3.1 Translation Estimation by Phase Correlation

Given two images f and g and their Fourier transforms respectively F and G. Suppose that $f(i,j) = g(i-a, j-b)$. Translation vector (a,b) can be estimated by computing the Fourier transform of the cross-power spectrum given by

$$\psi(u,v) = \frac{F(u,v)}{G(u,v)} = e^{-2i\pi(u\,a+v\,b)}, \quad (3)$$

In Fig.1, we estimate the translation between two binary images which differ by translation vector equals to (a,b)=$(25,15)$. Fig.2 presents the prominent peak

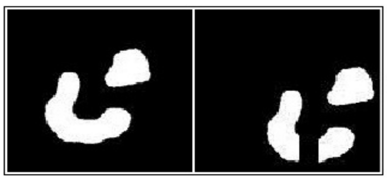

Figure 1: Two binary images which differ by a translation.

which corresponds to the translation vector. We note that this method of translation estimation by phase correlation is robust under occlusions and noise, which often occur in real applications, compared to translation estimation by centroid which may lead to wrong values.

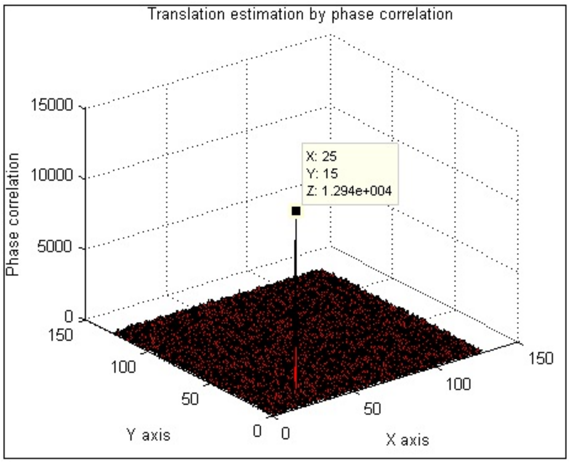

Figure 2: Fourier transform of the cross-power spectrum.

3.2 Rotation and Scaling Factor Estimation by the Analytical Fourier-Mellin Transform

In order to introduce phase correlation in Fourier-Mellin space, recall that the Fourier-Mellin Transform (FMT) is the Fourier transform on the group of planar similarities $G = (R^*_+, S^1)$ where S^1 is the unit circle. Let $f(r,\theta)$ be a polar representation of the image with the radius r according to the center of the image to offset translation and θ the angle according to the horizontal. It was pointed out in (Ghorbel, 1994) 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

$$M_{f^\sigma}(k,v) = \frac{1}{2\pi}\int_0^{+\infty}\int_0^{2\pi} f(r,\theta) r^{\sigma - iv} e^{-ik\theta}\,\frac{dr}{r} d\theta, \quad (4)$$

for all $k \in Z$, $v \in R$, and $\sigma \succ 0$. The AFMT of an object f can be seen as the usual FMT of the distorted object $f^\sigma(r,\theta) = r^\sigma f(r,\theta)$. The AFMT gives a complete description of gray-level objects since f can be retrieved by its inverse transform given by

$$f(r,\theta) = \int_0^{+\infty}\sum_Z M_{f^\sigma}(k,v) r^{-\sigma+iv} e^{ik\theta} dv, \quad (5)$$

Since no discrete transform exists, three approximations of the AFMT have been designed : the direct, the cartesian and the fast algorithm (Derrode and Ghorbel, 2001). In the remainder of this work, we used the fast algorithm as follows : with a variable change on the integral ($q = ln(r)$ instead of r), equation (4) can be rewritten into Fourier transform as follows

$$M_{f^\sigma}(k,v) = \frac{1}{2\pi}\int_{-\infty}^{+\infty}\int_0^{2\pi} e^{q\sigma} f(e^q,\theta) e^{-i(k\theta+qv)}\,dq d\theta, \quad (6)$$

The fast algorithm is obtained by computing a two dimensional Fast Fourier Transform (FFT) on the log-polar distorted object $e^{\sigma q} f(e^q,\theta)$. In what follows, we illustrate the steps of our approach to estimate the rotation angle and the scaling factor with an example of a reference image f_{ref} which is rotated 300°, partially occluded and submitted Gaussian noise with deviation equals to 75 (Fig.3). By definition, a level

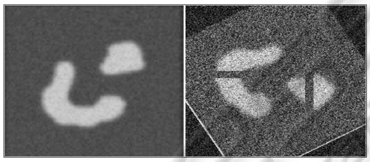

Figure 3: Left: Template image, Right: Test image.

set function assigns negative sign for points inside the evolving contour and positive sign for those outside it. Thus, we associate with a distance map of a level set function ϕ, a binary image f_ϕ. Let $f_{\phi_{ref}}$ and f_ϕ be two binary images associated respectively with level set functions ϕ_{ref} and ϕ (Fig.4) obtained by Chan and Vese's model.

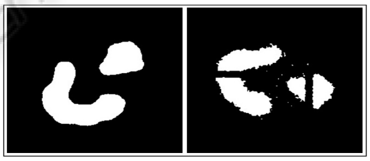

Figure 4: Left: The reference image ($f_{\phi_{ref}}$), Right: The transformed image (f_ϕ).

Let $M_{f^\sigma_{\phi_{ref}}}$ and $M_{f^\sigma_\phi}$ the AFMT of the two functions $f_{\phi_{ref}}$ and f_ϕ. $f_{\phi_{ref}}$ and f_ϕ have the same shape if and only if there is a similarity $(\alpha_0, \beta_0) \in G$ such that

$$\forall (r,\theta) \in G, f_\phi(r,\theta) = f_{\phi_{ref}}(\frac{r}{\alpha_0}, \theta - \beta_0), \quad (7)$$

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

$$M_{f^\sigma_\phi}(k,v) = \alpha_0^{\sigma - iv} e^{-ik\beta_0} M_{f^\sigma_{\phi_{ref}}}(k,v), \quad (8)$$

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

$$\Phi(k,v) = \frac{M^*_{f^\sigma_{\phi_{ref}}}(k,v) M_{f^\sigma_\phi}(k,v)}{|M^*_{f^\sigma_{\phi_{ref}}}(k,v)||M_{f^\sigma_\phi}(k,v)|} = \alpha_0^{-iv} e^{-ik\beta_0}, \quad (9)$$

Phase correlation of two images represented respectively by $f_{\phi_{ref}}$ and f_{ϕ} is defined as (Sellami and Ghorbel, 2012)

$$C_{Tfm}(\alpha,\beta) = \int_0^{+\infty} \sum_Z \Phi(k,v)\alpha^{iv} e^{ik\beta} dv, \quad (10)$$

Fig.5 shows the surface of phase correlation using

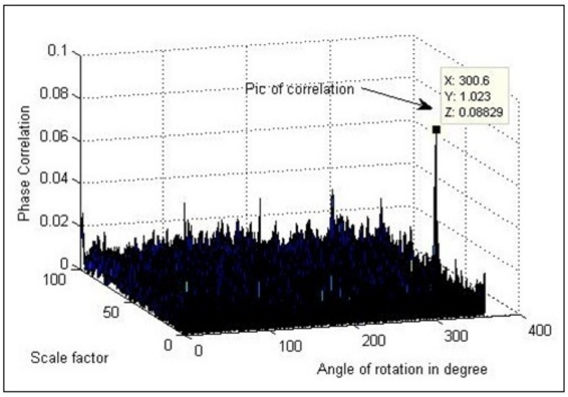

Figure 5: Surface of phase correlation.

the log-polar representation of binary images $f_{\phi_{ref}}$ and f_{ϕ}. The obtained prominent peak corresponds to ($\theta = 300°$, $\alpha = 1$).

3.3 The Proposed Geometric Shape Prior

After estimating the parameters of rigid transformation between binary images (Fig.4). We perform the registration of the image $f_{\phi_{ref}}$ according to the following formula (Chan and Zhu, 2005)

$$f^{reg}_{\phi_{ref}}(x,y) = \alpha f_{\phi_{ref}}\left(\frac{(x-a)\cos\theta+(y-b)\sin\theta}{\alpha}, \frac{-(x-a)\sin\theta+(y-b)\cos\theta}{\alpha}\right), \quad (11)$$

On the resulting left image of Fig.6, the pixels in black (resp. white) correspond to positive (resp. negative) areas of the distance map. The image on the right shows the product function given by

$$f_{prod}(x,y) = f^{reg}_{\phi_{ref}}(x,y) \cdot f_{\phi}(x,y), \quad (12)$$

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

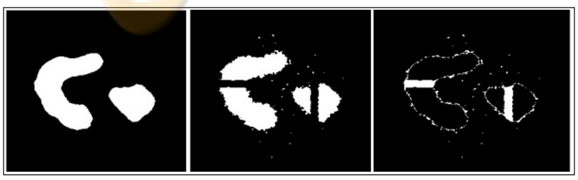

Figure 6: Left: $f^{reg}_{\phi_{ref}}$, $Middle: f_{\phi}$, $Right: f_{prod}$.

variability between the two binary images (occlusion, clutter, missing parts etc.). Thus we propose to minimize the following energy

$$E_{shape} = \int_{\Omega} H(g(x,y))dxdy, \quad (13)$$

where $g(x,y)$=-$\phi(x,y) \cdot sign(\phi_{ref}(x,y))$. As we can see, this energy corresponds to the area of variability between shapes and it is minimum only if the evolving contours correspond to the true contours of the objects to be detected. The new energy's functional to be minimized is

$$E(\phi, c_1, c_2) = w E_{CV} + (1-w) E_{Shape} \quad (14)$$

where w is a weighting factor. Using the gradient descent method for the level set function ϕ, $\frac{\partial E}{\partial \phi} = -\frac{\partial \phi}{\partial t}$, the total discrete evolution equation is

$$\frac{\phi^{n+1}_{ij} - \phi^n_{ij}}{\Delta t} = w\,\delta_\varepsilon(\phi^n_{ij})[-\mu K_{i,j} + \nu + \lambda_1 (f_{i,j} - c_1)^2 - \lambda_2 (f_{i,j} - c_2)^2] + (1-w)\, sign(\phi_{ref_{i,j}})\, \delta_\varepsilon(g^n_{ij}), \quad (15)$$

where $K_{i,j} = div(\frac{\nabla\phi_{i,j}}{|\nabla\phi_{i,j}|})$ and δ_ε is a regular form of δ as in (Cremers et al., 2003). Since we are interested in updating the level set function in the regions of variability between objects of respectively the reference and the target images, we take $\delta_\varepsilon(g^n_{ij}) = 0$ for all points which are outside these regions. This property recalls the technique of narrow-band used to accelerate the evolution of the level set functions (Malladi et al., 1995).

4 EXPERIMENTAL RESULTS

We will start by illustrating the ability of the proposed geometric shape prior to constrain the evolving contour to be similar to a reference shape (by canceling the Chan and Vese's energy. i.e. $w = 0$). Then we will treat the segmentation problem. In order to reduce the computational complexity and to have a good estimation of the parameters of the rigid transformation, we first evolve the active contour without shape prior until convergence as in (Fang and Chan, 2007) and (Foulonneau et al., 2004). This first result provides an initialization for the model with prior knowledge. Then, the model will evolve under data and prior terms with an important weight assigned to the proposed prior term ($w = 0.4$) to promote the convergence of the evolving contours to the target objects.

4.1 Robustness of the Proposed Shape Prior

To illustrate the ability of the proposed shape prior to constrain geometrically an active contour, we experience at first the evolution of the contour under the influence of the proposed energy term E_{Shape}. Fig.7, first row, shows the evolution of the initial curve which is a green rectangle until its convergence toward the contours of two objects. Starting with the

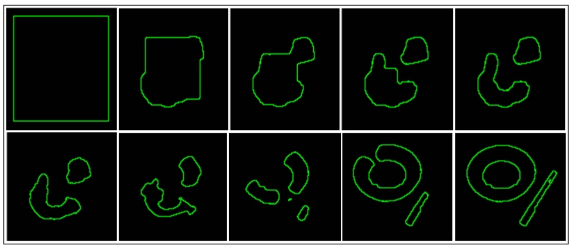

Figure 7: Curve evolution under shape prior only.

final contours, shape prior term will constrain these curves to be similar to the contours of a pen and a disc with a hole (Fig.7, second row). As it can be seen, the shape prior allows forcing the evolving contour to find the target shapes of an arbitrary number of objects.

4.2 Application to the Segmentation

We will evaluate the Chan and Vese's model including the proposed shape prior in the context of image segmentation. We suppose that the image of reference and its associated level set function are given.

4.2.1 Case of Single Object

In this part of experiments we will start by comparing our model to that proposed by (Foulonneau et al., 2004) on a synthetic image in which the object is partially covered by a disk (Fig.8). We recall that Foulon-

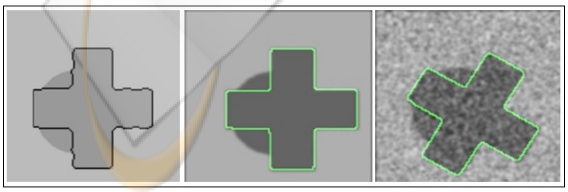

Figure 8: Left: result obtained by Foulonneau et al.'s model, Middle and Right: results obtained by our model.

neau et al.'s model presents invariance with respect to translation and scale factor. As this model is based on the quadratic distance between Legendre descriptors of the target object and the template, then a small order does not provide a satisfactory result and a high order may lead to errors and a huge excution time as it was mentioned by the authors. It is obvious that the result obtained by our model is better. The image on the right shows the robustness with respect to rotation and noise. Table 1 shows the running time until convergence without shape prior, whereas table 2 presents the running time until convergence with shape prior. We recall that for rigid motion estima-

Table 1: Computation time for the experiment of Fig.8 (the middle image) without shape prior.

	Execution time
Foulonneau et al.'s model	1 minute
Our model	10.51 seconds

Table 2: Computation time for the experiment of Fig.8 (the middle image) with shape prior.

	Execution time
Foulonneau et al's model	14 minutes
Our model	26.03 seconds

tion between binary images associated with the level set functions, we used the AFMT of the log-polar sampling of the image based on Fast Fourier Transform (FFT 2D). Thus, time for parameter estimation is 0.412 seconds. We deduce from table 2 that our model is much faster.

4.2.2 Case of Multiple Objects

In this second part of experiments, we will present the obtained results for a synthetic image with multiple objects. Then, we will show those associated to the real case. We present through the first image of Fig.9 the template. The second image is the target image in which the objects present missing parts. For the third one, we added a Gaussian noise and for the last image, the objects were rotated by an angle of $-15°$. The obtained segmentation is given by Fig.10.

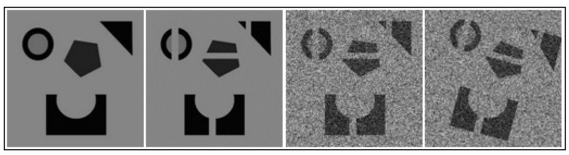

Figure 9: The reference image and three target images.

In the next experiment, segmentation of objects with non trivial topology is considered. In fact objects with holes can't be segmented with an edge-based active contours whereas Chan and Vese's model represents the adapted model for this kind of objects.

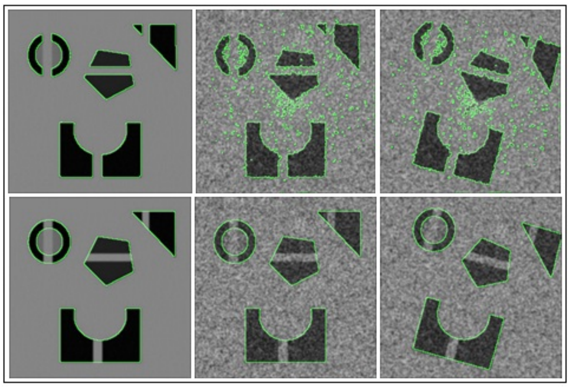

Figure 10: Objects detection without shape prior (first row) and with shape prior (second row).

Fig.11 shows the obtained results for a real image. In the second image of this figure, the objects are partially occluded and rotated $-30°$. For the third image, we added a Gaussian white noise with deviation equals to 75. As it can be seen, the model can detect the real contours. In (Cremers et al., 2003), the authors proposed a geometric shape prior that can handle multiple objects. However, the problem of invariance to geometric transformations was not treated. The registration by phase correlation allowed us to globally align the two binary images to estimate rigid transformation's parameters between them to calculate the proposed shape prior. According to Fig.11, we note that prior knowledge adjusts automatically depending on missing parts or occlusions unlike (Cohen, 1991)'s model where initial position of the curve must be known in advance to know if the curve should inflate or deflate to achieve the desired contours. In Fig.12, we seek to segment the left and right ventricles of the heart on a real images with missing parts, rotation and noise effects. The results seem to be satisfactory.

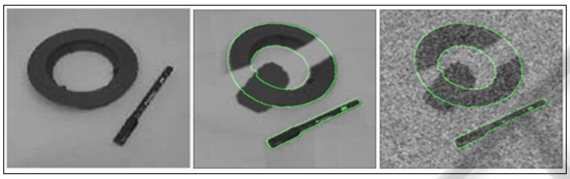

Figure 11: Left: the reference image, Middle: the reference image with missing parts, partial occlusion and rotation, Right: the reference image with missing parts, partial occlusion, rotation and noise.

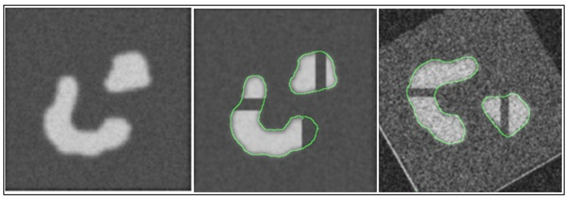

Figure 12: Left: the reference image, Middle: the reference image with missing parts, Right: the reference image with missing parts, rotation ($-60°$) and noise ($\sigma = 75$).

5 CONCLUSIONS

To summarize, new method of region-based active contours with shape prior is presented. The proposed energy constrains the evolving curve to be similar to a given template. This approach uses the registration of level set functions associated with the evolving contour and a reference shape by phase correlation. Experiments have shown the ability of the new added term to improve the robustness of the segmentation 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 of the algorithm given that the proposed approach does the registration only once and it is done by the Fast Fourier Transform unlike (Leventon et al., 2000) and (Foulonneau et al., 2004)'s models where at each iteration parameters estimation is performed. As future perspectives, we are working on extending this approach to more general transformations such as affine transformations.

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