Automated Parameterization of Active Contours:
A Brief Survey

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Abstract—Active contours yield segmentation results which depend on an initial empirical parameterization stage. The latter is a tedious and time-consuming process that requires technical skills from the end user. Automated adjustment of active contour parameters is still a challenging issue. This survey reviews state-of-the-art active contours which attempt to cope with the issue of empirical parameterization, so as to secure the objectivity and robustness of the segmentation results. Numerous attempts utilize information associated with contour evolution and shape priors, whereas others are hybrid, driven by both empirical and automatically obtained parameter settings. Most recent models are spatially varying and versatile regarding the application and the energy functional to be minimized.

Keywords—Active Contours, Automated Parameter Adjustment, Segmentation.

I. INTRODUCTION

Empirical parameterization of active contours [1]-[8] is a laborious process which requires considerable time to be performed as well as technical skills from the end user. Moreover, the obtained segmentation results are highly subjective and reproducibility is complicated. Even though in most cases the segmentation quality is acceptable, it is controversial since it relies on the technical skills of the end user.

Although a generally applicable framework for automated parameter adjustment that eliminates heuristic considerations is yet to be developed in active contour research, several approaches address this issue. Such approaches are of crucial importance since they are potentially capable of relieving users from the trial and error process as well as to endow segmentation results with objectivity and robustness.

Region-based active contours are widely applied on image segmentation due to their inherent noise-filtering mechanism and their topological adaptability. Furthermore, they are robust to weak edges and intensity inhomogeneity [9]-[13]. They are guided by the minimization of an energy functional E_{total} described as follows:

$$E_{total} = w_{reg} \cdot E_{reg} + w_{df} \cdot E_{df} \qquad (1)$$

where E_{reg} and E_{df} are regularization and data fidelity energy terms, respectively, whereas w_{reg} and w_{df} are the corresponding weighting parameters which are typically adjusted in an empirical manner.

This survey reviews active contour parameter adjustment approaches, which aim to confront the challenging issue of automated parameterization. These approaches are classified according to the information utilized in the computation of parameters. To the best of our knowledge, such a review is missing in active contour literature.

II. AUTOMATIC ACTIVE CONTOUR MODELS

A. Time-Dependent Active Contour Parameterization

Tsai et al. [14] proposed a region-based, shape-driven active contour model for medical image segmentation by applying principal component analysis to a collection of signed distance representations of the training data. According to this model, parameters are calculated by means of the gradient descent algorithm which minimizes an energy functional as follows:

$$w^{t+1} = w^t - a_w \cdot \nabla wE$$
$$p^{t+1} = p^t - a_p \cdot \nabla pE \qquad (2)$$

where $w = \{w_1, w_2, ... w_k\}$ are the shape weights for the k eigenshapes, $p = \{p_1, p_2, ... p_n\}$ pose parameters used to jointly align the n binary images, a_w, a_p positive step-size parameters and E the energy functional. The model is capable of embedding various region-based energy functionals to be minimized via the gradient descent algorithm and shape and pose parameters are updated dynamically within the iterative procedure of active contour evolution. However, cases of erroneous behavior of the

active contour in the early evolution stages have not been encountered. Figure 1 depicts the block diagram of the pipeline of Tsai et al. model [14].
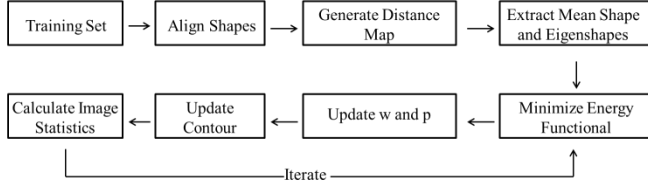

Fig. 1. Block diagram of the pipeline of Tsai et al. model [14].

Pluempitiwiriyawej et al. [15] proposed a stochastic active contour scheme for automated segmentation of cardiac MR images. The energy functional that is minimized combines both region-based and edge-based information by utilizing shape priors of the heart and is defined as follows:

$$E(\varphi) = \lambda_1 \cdot E_1(\varphi) + \lambda_2 \cdot E_2(\varphi) + \lambda_3 \cdot E_3(\varphi) + \lambda_4 \cdot E_4(\varphi) \qquad (3)$$

where the first, second, third and fourth term incorporates region-based, edge-based, shape prior information and smoothness regulation, respectively and are described according to the following:

$$E_1(\varphi) = \int_\Omega -\ln[p_1(I(x,y))] \cdot H(\varphi(x,y))$$
$$-\ln[p_2(I(x,y))] \cdot [1 - H(\varphi(x,y))] dxdy \qquad (4)$$

$$E_2(\varphi) = \int_\Omega -|\nabla G_\sigma * I(x,y)| \cdot |\nabla H(\varphi(x,y)) dxdy \qquad (5)$$

$$E_3(\varphi) = \int_\Omega D^2(x,y) \cdot \delta(\varphi(x,y)) \cdot |\nabla \varphi(x,y)| \, dxdy \qquad (6)$$

$$E_4(\varphi) = \int_\Omega \delta(\varphi(x,y)) \cdot |\nabla \varphi(x,y)| \, dxdy \qquad (7)$$

where p_1, p_2 are the assumed pdfs inside and outside the contour, G_σ the two-dimensional Gaussian kernel with variance σ^2, D^2 the ellipse distance function and δ the Dirac function. Parameters $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ control the strength of each of the terms E_1, E_2, E_3, E_4, respectively. Aiming at automated parameter adjustment, the authors present an annealing algorithm through which parameters adapt their values as the segmentation evolves. The selected annealing schedules are defined as follows:

$$\lambda_1(n) = \lambda_1(1) - \frac{n[\lambda_1(1) - \lambda_1(N)]}{N} \qquad (8)$$

$$\lambda_2(n) = \frac{1}{2}[\lambda_2(1) - \lambda_2(N)] \cdot \left[1 + \cos\left(\frac{n\pi}{N}\right)\right] + \lambda_2(N) \qquad (9)$$

$$\lambda_3(n) = \frac{\lambda_3(N) - \lambda_3(1)}{\cosh[10(\frac{n\pi}{N} - 1)]} + \lambda_3(1) \qquad (10)$$

where n is the iteration number, N the total number of iterations and $\lambda_i(1), \lambda_i(N)$ the initial and final values of λ_i, respectively. It should be noted that λ_4 is selected to constant. Similar to the model of Tsai et al. [14], parameters are updated during contour evolution. Hence, errors in the early stages of evolution will propagate to the later stages of contour convergence.

B. Active Contour Parameterization using Shape Priors

Keuper et al. [16] proposed a probability-based method for dynamic adjustment of active surface parameters for the segmentation of cell nuclei. The method utilizes the total energy of an active surface defined as:

$$E(X) = a \cdot E_{int}(X) + b \cdot E_{ext}(X) \qquad (11)$$

where X is the function of the active surface, E_{int}, E_{ext} the internal and external energies, respectively and a,b weighting parameters. The method is based on 2-sphere-like objects of gray value profiles $r_{x_i} \in R^l$ of surface vertices v_i in radial direction, where l is the number of sampling points on the profile. The weighting parameters which are assigned to vertices v_i are calculated as follows:

$$a_i = 1 - p(B \mid r_{x_i^{ext}}), \quad b_i = p(B \mid r_{x_i^{ext}}) \qquad (12)$$

$$p(B \mid r_{x_i^{ext}}) = \frac{p(r_{x_i^{ext}} \mid B) \cdot P(B)}{P(r_{x_i^{ext}})} \qquad (13)$$

where $P(B)$ is the only high level parameter. The method is beneficial compared to standard active surfaces with constant weighting parameters, yet it is primarily dependent on the shape of the target region.

Liu et al. [17] proposed a localized active contour model for lip contour extraction in which proper parameters are automatically selected. The proposed approach utilizes a minimum-bounding ellipse in order to initialize the evolving curve. The final energy functional to be minimized is given as follows:

$$E(\varphi) = \int_{\Omega_v} \delta(\varphi(u)) \cdot \int_{\Omega_v} B(u,v) \cdot F(I(v), \varphi(v)) dv du \qquad (14)$$
$$+ \lambda \cdot \int_{\Omega_v} \delta(\varphi(u)) \cdot \| \nabla(u) \| du$$

where $B(u,v)$ is a characteristic function, F is a localized region-based force formed by substituting local means for global ones described as:

$$F = -(\mu_{in}(u) - \mu_{out}(u))^2 \qquad (15)$$

and λ a weighting parameter. The level set is initialized as a minimum-bounding ellipse defined as:

$$\frac{X^2}{r_a^2} + \frac{Y^2}{r_b^2} = 1 \qquad (16)$$

$$X = (x - x_c) \cdot \cos\theta + (y - y_c) \cdot \sin\theta \qquad (17)$$

$$Y = (y - y_c) \cdot \cos\theta - (x - x_c) \cdot \sin\theta \qquad (18)$$

$$r_a = \frac{1}{2}((Lb_x - La_x)^2 + (Lb_y - La_y)^2)^{\frac{1}{2}} \qquad (19)$$

$$r_b = \frac{1}{2}((Vb_x - Va_x)^2 + (Vb_y - Va_y)^2)^{\frac{1}{2}} \qquad (20)$$

where (x_c, y_c) is the origin center of the minimum-bounding ellipse, θ the inclined angle defined to be positive in the counter-clockwise direction and L_a, L_b, V_a, V_b the left, right, upper, lower corner, respectively. The parameters of the ellipse are selected automatically; however λ is still empirically determined. Additionally, the proposed approach hinges on the shape of the target region.

C. Hybrid Active Contour Parameterization using both Empirical and Automatically obtained Parameter Settings

Hsu et al. [18] proposed an active contour model called Poisson Gradient Vector Flow (*PGVF*) which employs a genetic algorithm for automated segmentation of liver PET images. The original liver PET image is imported and its edge map is generated by Canny edge detection. The parameters of the latter are calculated by the design of the fitness function, which is defined as follows:

$$F = a \cdot \frac{\max(L)}{\min(N)} \qquad (21)$$

where L,N are the length and total pixel number of the contour line obtained by the binary edge map, which is detected by Canny edge detection, and a a weighting number.

Yushkevish et al. [19] developed an open source active contour-based application, called ITK-SNAP, for automated segmentation of medical images by clinical users, who are unfamiliar with the intrinsic mechanisms of active contour algorithms. ITK-SNAP implements the three-dimensional geodesic active contour model written as:

$$C_t(t,u) = (a \cdot g_I + b \cdot k \cdot g_I + \gamma \cdot \nabla g_I \cdot N) \cdot N \qquad (22)$$

where $C_t(t,u)$ is the contour at time t parameterized by u, k the mean curvature of the contour, N the contour normal, g_I a function that decreases monotonically with the gradient magnitude of image I and a, b, γ modulating weights. To assist the user in setting these parameters, ITK-SNAP employs a structured wizard segmentation workflow and feedback mechanisms. Although performed in a more intuitive manner, parameter settings are still empirically determined.

D. Machine Learning and Spatially Varying Models

Iakovidis et al. [20] proposed a framework for thyroid ultrasound image segmentation which encompasses an automatic parameter tuning mechanism based on genetic algorithms. The proposed framework implements the Variable Background Active Contour (*VBAC*) model [21], which extends the energy functional of the Chan-Vese model [9] by defining the difference $D(\varphi(x,y))$ as follows:

$$D(\varphi(x,y)) = H(\varphi(x,y) + a) - H(\varphi(x,y)) \qquad (23)$$

where a is a positive constant. Parameters w_{reg}, w_{df} and a are automatically adjusted through a genetic optimization problem. Parameters are encoded into a single bit-string, called chromosome. Their values are constrained within discrete, worst-case ranges. The minimum and maximum values of these ranges as well as the sampling rate considered are experimentally determined. This heuristic approach converges slowly in locally optimal solutions.

Allili et al. [22] proposed an automatic estimation of the weighting parameters for segmentation combining boundary and region-based information. Boundary information is formulated using a multi-band edge detector, whereas region-based information is formulated using a mixture of Gaussians. Let $U = (u_1, u_2, ... u_n)$ be a multi-valued image defined on Ω and $\Omega_k, \partial\Omega_k$ are the region and its boundaries, respectively. The energy functional that is minimized is

described as follows:

$$E(\bigcup_{k=1}^{M} \partial \Omega_k(s), \Theta) = a \cdot E_b + b \cdot E_r \tag{24}$$

$$E_b = \sum_{k=1}^{M} \oint_{\partial \Omega_k} g(\nabla I(\partial \Omega_k(s))) ds \tag{25}$$

$$E_r = \sum_{k=1}^{M} \iint_{\Omega_k} -\log[t_k(x)] dx dy \tag{26}$$

where M is the number of regions, Θ the mixture of parameters θ_k of each pdf, $t_k = p(\theta_k | U(x))$ and a,b weighting parameters. According to this method, the latter establish adaptive values as follows:

$$a \propto [\widetilde{E}_b(x)]^{-1}, \quad b \propto [\widetilde{E}_r(x)]^{-1} \tag{27}$$

$$\widetilde{E}_b(x) = \frac{1}{N} \sum_{(u)\in W(x)} E_b(u), \quad \widetilde{E}_r(x) = \frac{1}{N} \sum_{(u)\in W(x)} E_r(u) \tag{28}$$

where $W(x)$ is a square window which surrounds pixel x. This method provides better convergence and robustness to oversegmentation compared to the one utilizing fixed parameters.

Mylona et al. [23] proposed a framework for self-adjustment of region-based active contours, based on texture cues. The latter are mined by filtering methods characterized by multi-resolution, anisotropy, localization and directionality. This information is encoded by entropy-based image "heatmaps", which are able to weight the regularization and data fidelity terms appearing in the region-based energy functional. Parameters are spatially varying, so as to reflect regional image features, and are calculated as follows:

$$w_{reg} = (1/w_{df}) \times N \times M, \quad w_{df} = \arg_{Ijk} \max(IE_{jk}(I_{jk})) \tag{29}$$

where N, M are the rows and columns of the input image, respectively, I_{jk} the band-pass directional subband obtained by the contourlet transform [24] representing the local feature space and IE_{jk} the information entropy of the kth direction in the jth level of the transform defined by:

$$IE_{jk} = -\sum_{n=1}^{N_{jk}} \sum_{m=1}^{M_{jk}} p_{jk}(m,n) \cdot \log p_{jk}(m,n) \tag{30}$$

$$p_{jk}(m,n) = \frac{|I_{jk}(m,n)|^2}{\sqrt{\sum_{n=1}^{N_{jk}} \sum_{m=1}^{M_{jk}} [I_{jk}(m,n)]^2}} \tag{31}$$

The framework of Mylona et al. can be applied to various image modalities, such as biomedical, textured and real-world images and does not require *a priori* knowledge on the shape of the target region. Moreover, it is versatile i.e. can be embedded in various active contour variations.

III. CONCLUSIONS

This survey reviews current active contour parameterization approaches. Their key objective is to relieve domain users from the cumbersome process of empirical parameterization, as well as from extensive developer support, endowing segmentation results with robustness and reproducibility.

The existing automated parameterization approaches attempt to adjust either weighting parameters navigating contour evolution or other types of parameters, which come with supporting algorithms, such as Canny edge detection or Gaussian mixtures, which are integrated into an active contour model.

Several parameterization approaches, as the model of Tsai et al. [14] and Pluempitiwiriyaweg et al. [15], calculate parameters without encountering possible erroneous behavior of the contour in the early evolution stages. Other approaches, including those of Keuper et al. [16] and Liu et al. [17], focus on specific applications and are highly dependent on *a priori* knowledge, considering the size and the shape of the target region. Alternatives, like the models of Hsu et al. [18] and Yushkevish et al. [19] aim on specific applications, whereas they introduce new fixed parameters.

A number of state-of-the-art parameterization approaches, like those of Ma et al. [25] and McIntosh et al. [26], try to solve the trade-off between energy terms without adjusting each individual parameter separately. Kokkinos et al. [27], Iakovidis et al. [20] and Erdem et al. [28] utilize machine learning algorithms. Nevertheless, these approaches still require technical skills from the end user.

On the other hand, the approaches of Allili et al. [22] and Mylona et al. [23] are spatially varying, reflecting regional image features, and versatile with respect to the application. Additionally, they do not depend on the shape of the target region.

Table 1 summarizes active contour parameter adjustment approaches and compares them with respect to: 1) the level of automation, 2) time-dependency, 3) use of shape priors, 4) spatial variability and 4) use of machine learning. By and large, a 'wish list' of desired features for automated active contour parameterization contains: 1) full automation, 2) time-independency, 3) versatility with respect to the energy

Table 1. Summary of active contour parameter adjustment approaches

Model	Year	Methodology	Automation	Time Dependency	Shape Priors	Spatial Variance	Machine Learning
Tsai et al.	2003	Principal component analysis	Full	Yes	Yes	No	Yes
Pluempitiwiriyaweg et al.	2005	Annealing schedules	Full	Yes	Yes	No	Yes
Keuper et al.	2010	Probability-based	Full	No	Yes	Yes	Yes
Liu et al.	2010	Minimum-bounding ellipse initialization	Semi	No	Yes	No	No
Allili et al.	2008	Multi-band edge detector and mixture of Gaussians	Semi	Yes	No	No	No
Hsu et al.	2008	Genetic algorithm	Semi	No	No	No	No
Yushkevish et al.	2005	Geodesic active contour model	Semi	Yes	No	No	No
Ma et al.	2010	Morphological approach	Semi	No	No	No	No
McIntosh et al.	2007	Balance of trade-off between terms	Semi	No	No	No	No
Kokkinos et al.	2009	Probabilistic modeling	Semi	No	No	No	Yes
Erdem et al.	2009	Approximation of the Mumford-Shah model	Semi	No	No	No	Yes
Iakovidis et al.	2007	Genetic algorithm	Semi	No	No	No	Yes
Mylona et al.	2013	Multi-directional texture cues	Full	No	No	Yes	No

functional, 4) general applicability with respect to the application and the shape of the target region, 5) spatial variability, and 6) user-friendly deprived of developers support.

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