ENTROPY-BASED SPATIALLY-VARYING ADJUSTMENT OF ACTIVE CONTOUR PARAMETERS

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ABSTRACT

Parameter adjustment is a crucial, open issue in active contour methodology. Most state-of-the-art active contours are empirically adjusted on a trial and error basis. Such an empirical approach lacks scientific foundation, leads to suboptimal segmentation results and requires technical skills from the end-user. This work introduces a method for automatic adjustment of active contour parameters, which is based on image entropy. In addition, instead of being uniform, the parameter values calculated are spatially-varying, so as to reflect textural variations over the image. Experimental evaluation of the proposed method is conducted on thyroid US images, liver MRI images, as well as on real-world photographs. The results indicate that the proposed method is capable of identifying plausible object boundaries, obtaining a segmentation quality which is comparable to the one obtained with empirical parameter adjustment. Moreover, the applicability of the proposed method is not confined on a single active contour variation.

***Index Terms*—**Active Contours, Automatic Parameter Adjustment, Segmentation.

1. INTRODUCTION

Despite the numerous active contour variations introduced in image analysis literature in the last two decades [1], [2], [3], the challenging issue of automated adjustment of active contour parameters remains open. Most often, a parameter set suited for a specific dataset performs significantly worse on others [4]. This encouraged empirical approaches to parameter adjustment, which very often involve manual interaction, as in the case of the active contours recently proposed in [5] and [6]. Although widely adopted by the image analysis community, such approaches are not principled, lead to suboptimal segmentation results and require technical skills from the end-user.

Image analysis literature features only a limited number of attempts to cope with automated parameter adjustment. Recently, Keuper et al. [7] proposed a method for dynamic adjustment of active contour parameters, applicable on the segmentation of cell nuclei from 3D microscopic data. However, the assumption of spherical objects of interest confines the applicability of this method. Allili et al. [8] proposed an approach for estimating hyper-parameters based on probability maximization. Hyper-parameters are used for balancing boundary and region-based terms in the active contour energy functional. Iakovidis et al. [9] presented a framework for the genetic optimization of active contour parameters, within the context of thyroid ultrasound image segmentation. Although this framework liberates the radiologist from manual parameter adjustment, genetic algorithms are time-consuming, non-intuitive and sometimes result in suboptimal parameter vectors. Batur et al. [10] proposed a framework for modeling images of deformable objects based on the active appearance model (AAM). The fixed gradient matrix is replaced with a linearly adaptive which is updated according to the composition of the target texture.

This work introduces a method for automatic adjustment of active contour parameters, which is based on image entropy. From an information-theoretic point of view, entropy is a highly intuitive texture descriptor, supported by several studies [11], [17]-[19]. In addition, instead of being uniform, the parameter values calculated are spatially-varying, so as to reflect textural variations over the image.

The outline of this paper is organized as follows: Section 2 provides a brief background in active contour energy functionals. Section 3 introduces the proposed method whereas Section 4 presents the experimental results. Finally, Section 5 summarizes the conclusions of this study.

2. ACTIVE CONTOUR ENERGY FUNCTIONALS

Active contours are guided by minimizing an appropriately defined energy functional. The segmentation of an image $u_0 : \Omega \rightarrow \Re$, where Ω is a bounded open subset of R^2 with $\partial\Omega$ its boundary, is formulated by seeking for the infimum of the energy functional F:

$$F = \mu \cdot Smoothness + k \cdot Boundary + \sum_i \lambda_i \cdot \mathrm{Re}\,gion_i \tag{1}$$

where μ, k and λ_i are weighting parameters for smoothness, boundary and region-based terms, respectively and i indexes image regions. Boundary-based active contours, such as the original snake introduced by the pioneering work of Kass et al. [12], set λ_i=0, whereas region-based active contours, such as the Chan-Vese model [13], set k=0.

State-of-the-art active contour research includes the Chan-Vese variation proposed by Bresson et al. [5], which is less sensitive to initialization and another variation proposed by Wang et al. [6], which incorporates both regional intensity and regional variance terms. Both variations outperformed the Chan-Vese model in segmentation quality within specific contexts; however the parameters involved in the energy functionals are arbitrary selected, which suggests that with different parameter settings, the outcome of these comparisons might have been different.

3. ENTROPY-BASED SPATIALLY-VARYING PARAMETER ADJUSTMENT

Each term in the energy functional of Eq. (1) is associated with a "force" guiding contour evolution. Accordingly, in the standard active contour approach these forces are weighted uniformly over the entire image by arbitrarily adjusted parameter values. Facing this, the proposed method introduces two ideas: a) adjust parameter values in a principled manner, considering textural information and b) instead of calculating constant parameter values which are uniform over the entire image, calculate spatially-varying parameter values, so as to reflect textural variations.

Entropy can be defined by the following equation:

$$H = -\sum_i \sum_j C(i,j)\log_2 C(i,j) \qquad (2)$$

where C is the standard gray-level co-occurrence matrix [14]. Entropy values, as determined by this equation, are in the range [0,1], with zero values corresponding to homogeneous image regions. Matrix C is calculated for couples of neighboring pixels (i, j), located so as to form a certain direction. This direction must reflect the dominant directionality in the image; otherwise several texture patterns may not be represented [15].

The proposed method encodes the dominant directionality in the image by means of the orientation of connected components. The latter are identified as regions of q-neighbors, resulting from image binarization with the use of Otsu thresholding [16]. An ellipse embedding each connected component is identified, as illustrated in Fig. 1. The orientation of each connected component is determined by the angle that is formulated between the x-axis and the major axis of the embedding ellipse. Figure 2 illustrates: (a) the orientation of the connected component of Fig. 1, and (b) considered directions of the position operator. Four different directions were considered in our experiments.

In the case that the number of connected components exceeds one, the area of each connected component is calculated. The final orientation is considered equal to the orientation of the connected component of the maximum area. Assuming that there is a low variance between the areas of the connected components, the final orientation is considered equal to the mean value of the orientations of the connected components.

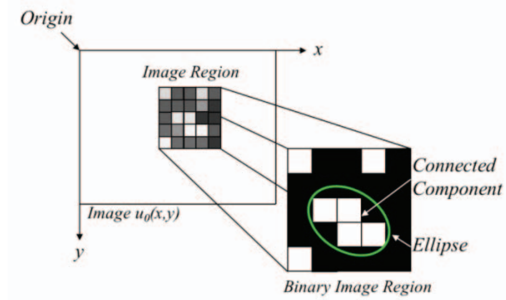
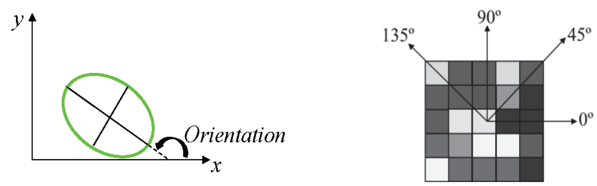


Fig. 1: Binary image region consisting of the ellipse which embeds the connected component.



(a) (b)

Fig. 2: (a) Orientation of the connected component of Fig. 1, (b) Considered directions of the position operator on an image region.

The region-based parameters λ_i and the smoothness-based parameter μ are calculated according to the following equations:

$$\lambda_i = H, \quad \mu = (1/4H)\times 255^2 \qquad (3)$$

This results in a relative amplification of the region-based forces over the smoothness-based forces, in areas of high entropy. Intuitively, when contour lies in "fuzzy" areas of high entropy, boundary information is much less reliable and region-based forces should be amplified [17]-[19]. The experimental results show that contour convergence is actually reached for our automatically adjusted energy functionals. It should be stressed that Eq. (3) were utilized on various types of images with consistent segmentation quality. It is also tempting to recall, that the proposed parameter adjustment process reflects the second law of thermodynamics.

4. RESULTS

Experiments were conducted on three types of images: a) real thyroid ultrasound (US) images containing nodules, b) liver MRI images and c) real-world photographs, in order to demonstrate the capability of the proposed method to: a) automatically adjust active contour parameters and obtain plausible segmentation results, and b) obtain results of comparable segmentation quality than the ones obtained by manually adjusting the active contour parameters. The experiments employ the well-known Chan-Vese model, as well as two state-of-the-art active contours proposed by

Bresson et al. [5] and Wang et al. [6]. The proposed method and these three active contours have been implemented in Matlab R2009b and executed on a 3.2 GHz Intel Pentium workstation. Additionally, q is set to 8, i.e. all neighbors of each pixel are considered for the identification of connected components.

Figure 3 illustrates: (a), (b) examples of thyroid US images, (c), (d) maps of the region-based parameters as calculated by the proposed method, where the parameter values are normalized and quantized in the range [0,255] and (e), (f) delineations of nodules obtained by the Chan-Vese model, where the region-based parameters λ_1, λ_2 and smoothness-based parameter μ (Eq. 1), were automatically adjusted by the proposed method. It can be observed that the proposed method is capable of identifying nodules over the inhomogeneous background and obtaining plausible nodule boundaries.

Figure 4 illustrates: (a) the original liver MRI image utilized by Bresson et al. [5], (b) the map of the region-based parameters calculated by the proposed method in a similar fashion with the case of Fig. 3, (c) the segmentation results obtained by the model of Bresson et al., where region-based and smoothness-based parameter values are set to 0.5, respectively, as suggested by the authors, and (d) the segmentation results obtained by the application of the proposed method. It can be observed that the proposed method is capable to segment the important part of the liver despite the low contrast changes. It should also be stressed that in the case of the proposed method there was no time-consuming manual adjustment of the active contour parameters.

Figure 5 illustrates: (a) the original real-world photograph utilized by Wang et al. [6], (b) the map of the region-based parameters calculated by the proposed method in a similar fashion with the case of Fig. 3, (c) the segmentation results obtained by the model of Wang et al., where region-based and smoothness-based parameter values are set to 0.1 and 0.01×255^2, respectively, as suggested by the authors and (d) the segmentation results obtained by the application of the proposed method. It is evident that the results in the case of the proposed method are more plausible, more so in the upper left and upper right as well as in the lower boundaries of the target object.

It should be noted that the maps of region-based parameters contain pixels marked as white in the case where their neighborhood area is characterized by a high value of entropy. On the contrary, pixels marked as black refer to neighborhood areas characterized by a low value of entropy. Region-based parameters are visualized in a similar fashion with the case of the velocity function illustrated in Fig. 3(d-f) and Fig. 4(d-f) in the work of Jehan-Besson et al. [19].

5. CONCLUSIONS

This work introduces a method for automatic adjustment of active contour parameters, addressing a crucial, open issue in active contour methodology: the arbitrary parameter settings. For this purpose, active contour parameters are adjusted in a principled manner, by means of image entropy. Entropy is calculated from the standard co-occurrence matrix, using the dominant image directionality of connected image components. The latter are identified as regions of q-neighbors, emerging on the binary output of Otsu thresholding. In addition, instead of being uniform, the parameter values calculated are spatially-varying, so as to reflect textural variations over the image.

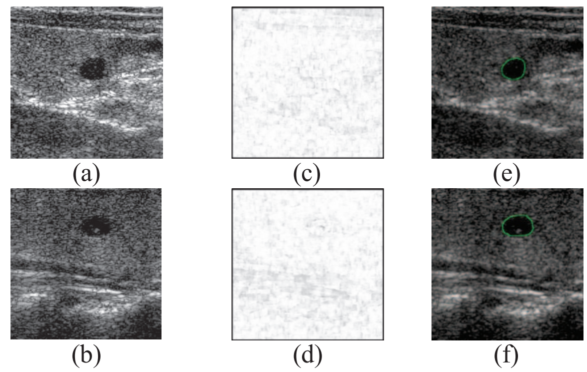


Fig. 3: (a), (b) Thyroid US images containing nodules, (c), (d) maps of the region-based parameters, as calculated by the proposed method, (e), (f) delineations of nodules obtained by the proposed method.

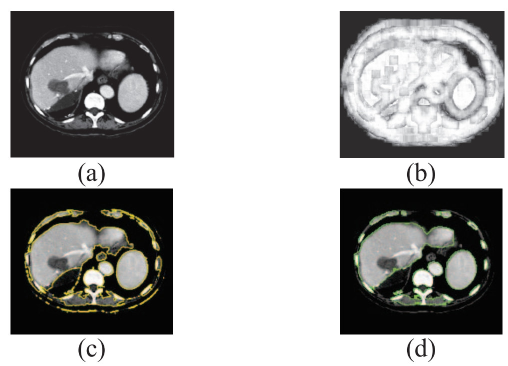
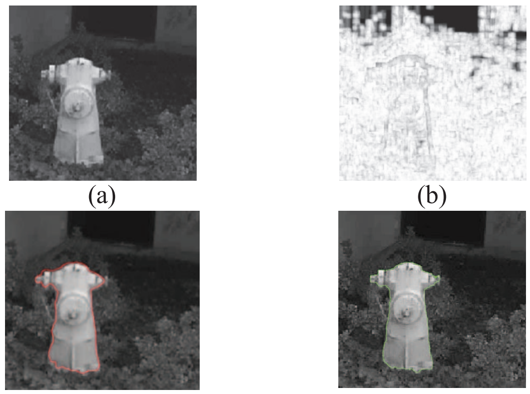


Fig. 4: (a) Original liver MRI image, (b) map of the region-based parameters, as calculated by the proposed method, (c) segmentation results obtained by the model of Bresson et al., (d) segmentation results obtained by the application of the proposed method.

The experimental evaluation of the proposed method has been conducted on thyroid US images, liver MRI images, as well as on real-world photographs. The results indicate that the proposed method is capable of identifying plausible object boundaries, obtaining a segmentation quality which is comparable to the one obtained with empirical parameter adjustment. Further experiments which were conducted on a set of labeled images, lead to similar conclusions. These results are not presented in this paper due to space restrictions. It should be stressed that the applicability of the proposed method is not confined on a single active contour variation. Future perspectives of this work include experimentation on alternative state-of-the-art textural representations, including directional representations [20], [21], as well as on various segmentation contexts.



(a) (b) (c) (d)

Fig. 5: (a) Original real-world photograph, (b) map of the region-based parameters, as calculated by the proposed method, (c) segmentation results obtained by the model of Wang et al., (d) segmentation results obtained by the application of the proposed method.

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