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An efficient Self-Organizing Active Contour model for image segmentation

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ABSTRACT

Active Contour Models (*ACMs*) constitute a powerful energy-based minimization framework for image segmentation, based on the evolution of an active contour. Among *ACMs*, supervised *ACMs* are able to exploit the information extracted from supervised examples to guide the contour evolution. However, their applicability is limited by the accuracy of the probability models they use. As a consequence, effectiveness and efficiency of supervised *ACMs* are among their main real challenges, especially when handling images containing regions characterized by intensity inhomogeneity. In this paper, to deal with such kinds of images, we propose a new supervised *ACM*, named *Self-Organizing Active Contour* (*SOAC*) model, which combines a variational level set method (a specific kind of *ACM*) with the weights of the neurons of two Self-Organizing Maps (*SOMs*). Its main contribution is the development of a new *ACM* energy functional optimized in such a way that the topological structure of the underlying image intensity distribution is preserved – using the two *SOMs* – in a parallel-processing and local way. The model has a supervised component since training pixels associated with different regions are assigned to different *SOMs*. Experimental results show the superior efficiency and effectiveness of *SOAC* versus several existing *ACMs*.

1. Introduction

Image segmentation is the problem of partitioning the domain Ω of an image $I(x)$, where $x \in \Omega$ is the pixel location within the image, into different subsets Ω_i, for i belonging to an index set $\mathcal{I}$, where each subset has a different characterization in terms of color, intensity, texture, and/or other features used as similarity criteria. Segmentation is a fundamental component of image processing, which plays a significant role in computer vision, object recognition, and object tracking. Image segmentation can also be expressed as a contour extraction problem [1]. Active Contour Models (*ACMs*) constitute a powerful energy-based approach to segmentation. Such models usually deal with the segmentation problem as a functional (also called infinite-dimensional) optimization problem, which tries to partition a given image into regions on the basis of the maximization/minimization of a suitable energy functional. Starting from an initial contour, the optimization of the functional is performed iteratively, evolving the current contour with the aim of approximating better and better the actual object boundary (hence the term "active contour" models, which is used also for models that evolve the contour but are not based on the explicit minimization of a functional). Among *ACMs*, those based on variational level set methods [2] are particularly interesting, as they represent the current contour as the zero level set of a function, instead of a parametric curve. For this reason, they are able to model arbitrarily complex shapes, and to handle topological changes of the object boundary, such as merging and splitting. *ACMs* also allow the integration of boundary and regional information within the energy framework, and also information coming from a learning process [3]. A challenge for current *ACMs* consists in handling images with complex foreground/background intensity distributions (e.g., containing objects characterized by many different intensities), and intensity inhomogeneity (e.g., when there are no visible intensity changes around the true object boundary). Such a challenge is exacerbated when the amount of overlap between the foreground/background intensity distributions is hard to be estimated. An effective solution to deal with this issue is to incorporate prior knowledge in the image segmentation framework, e.g., by learning how to model the complexity of object shape and intensity distributions, when training examples are available.

In general, *ACMs* can be classified into three categories: edge-based, region-based, and hybrid models. Edge-based models make use of an edge-detector (in general, the gradient of the image intensity), to stop the evolution of the contour on the true

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boundaries of the objects of interest [4–11]. As a result, this kind of models has in general the ability to handle only images with well-defined edge information. Indeed, in case of images with ill-defined edges, the contour evolution usually does not converge to the correct object boundaries. An alternative solution is to use statistical information about the regions to be segmented (e.g., intensity, texture, color distribution, etc.) to construct a stopping functional that is able to stop the evolution of the contour on the boundary between two different regions, as in region-based models [12–14]. Compared to edge-based models, region-based models usually perform better in images with blurred edges, and are also less sensitive to the contour initialization. Moreover, in order to improve the robustness with respect to the choice of the initial contour, also hybrid models have been proposed, which combine the advantages of edge-based and region-based models, including both kinds of information in their level set energy functional framework [15–18].

All the above-mentioned models are usually not able to handle images with intensity inhomogeneity and/or images having an intensity overlap between the foreground/background intensity distributions (or even containing objects characterized by many different intensities). One possible way to deal with such issues consists in including local information in the variational level set framework. A number of techniques have been proposed to introduce terms related to local and global intensity information in the so-called *Signed Pressure Force* (*SPF*) function to handle the case of images characterized by intensity inhomogeneity and containing objects with many different intensities [19–22]. However, these models are sensitive to contour initialization and high levels of additive noise. Furthermore, when the initial contour is close to the object boundary, the influence of the global intensity force included in such models may move the contour away from the true object boundary, leading to object leaking (i.e., the presence of a final blurry contour and/or the appearance of holes in the final segmentation) [23]. In order to deal with images containing intensity inhomogeneity, Liu and Peng proposed in [23] the Local Region-based Chan–Vese (*LRCV*) model, which showed high accuracy when handling such kinds of images.

From a machine learning perspective, *ACMs* for image segmentation can be modeled in both an unsupervised and a supervised way. Both kinds of *ACMs* rely on parametric and/or nonparametric density estimation methods to approximate the intensity distributions of the given subsets (e.g., foreground/background). The main idea of such models, as mentioned above, is to make statistical assumptions on the image intensity distribution and to solve the segmentation problem by a Maximum Likelihood (*ML*) or Maximum A-Posteriori probability (*MAP*) approach. For instance, for scalar-valued images, in both parametric/nonparametric region-based *ACMs*, the objective energy functional has usually an integral form (see, e.g., [24]), whose integrands are expressed in terms of functions $e_i(x)$ having the form

$$e_i(x) := -\log(p_i(I(x))), \quad \forall i \in \mathcal{I}. \tag{1}$$

Here, $p_i(I(x)) := p(I(x) | x \in \Omega_i)$ is the conditional probability density of the image intensity $I(x)$, conditioned on $x \in \Omega_i$, so the log-likelihood term $\log(p_i(I(x)))$ quantifies how much an image pixel is likely to be an element of the subset Ω_i. In the case of supervised *ACMs*, the models $p_i(I(x))$ are estimated from a training set, one for each subset Ω_i. Similarly, for a vector-valued image $\mathbf{I}(x)$ with D components, the terms $e_i(x)$ have the form

$$e_i(x) := -\log(p_i(\mathbf{I}(x))), \quad \forall i \in \mathcal{I}, \tag{2}$$

where $p_i(\mathbf{I}(x)) := p(\mathbf{I}(x) | x \in \Omega_i)$.

Neural networks having the form of *Self-Organizing Maps* (*SOMs*) have been used explicitly to model the active contour and control its evolution by a learning scheme similar to Kohonen's learning algorithm [25,26], resulting in unsupervised *SOM*-based *ACMs*. The evolution of the contour in such models is guided by the feature space constructed by the *SOM* when learning the prototypes (weights) associated with the neurons of the map. For instance, Venkatesh et al. [27] proposed to integrate the advantages of *SOMs* and of an *ACM* known as the *Snakes* model [8], by making use of the gradient information about the image intensity in a local region to drive the evolution of the current contour. However, these models often lead to segmentation results containing discontinuities in the final contour, are very sensitive to contour initialization, and have the limitation of using *SOMs* only as unsupervised tools for segmentation, without any form of supervision.

In this paper, in order to deal with the issues described above, we propose a new supervised *ACM*, which we term *Self-Organizing Active Contour* (*SOAC*) model, and relies on *SOMs* trained in a supervised way, in the sense that different *SOMs* are trained on the basis of examples coming from different subsets Ω_i. The main idea is to use the sets of neurons belonging to different *SOMs* to model the intensity distributions of the associated subsets Ω_i. This is accomplished, for each *SOM*, by using a self-organizing learning procedure that preserves the topological structure of the intensity distribution of the associated subset Ω_i. Consequently, the learned prototypes of such neurons, which control the topological preservation procedure, are used to approximate the image intensity distribution, and to integrate it implicitly into the energy functional to guide the contour evolution. In particular, in the paper we focus on the case of two[1] subsets Ω_i, e.g., the foreground and the background, which corresponds to $|\mathcal{I}| = 1$ and has remarkable applications.

The contributions of this paper can be summarized as follows. We provide

- a novel formulation for supervised *ACMs* based on self-organizing neurons;
- the definition of a new energy functional to guide the evolution of the contour;
- new local regional descriptors (the learned prototypes of the neurons) to represent locally the image intensity distribution;
- a thorough experimental study pushing the boundaries of state-of-the-art techniques in terms of accuracy, efficiency, and robustness of the proposed model.

The paper is organized as follows. Section 2 discusses various kinds of region-based *ACMs*. In Section 3, we describe briefly *SOMs*, and a motivation for using this kind of networks in *ACMs*. Section 4 presents the formulation of our *SOAC* model in the case of scalar images, its extension to vector-valued images, and their numerical implementation. Section 5 presents some experimental results comparing *SOAC* with some well-known *ACMs*, focusing on the segmentation accuracy obtained on a number of synthetic and real images. Finally, Section 6 summarizes the results of the paper, and discusses possible future extensions.

2. Region-based *ACMs*

In this section, we briefly review some region-based *ACMs*, distinguishing between supervised and unsupervised image segmentation models.

Due to the possible lack of a precise prior information on the shape of the objects to be segmented, most *ACMs* deal with shape

[1] This is not a limitation, since the *SOAC* model is an *ACM* belonging to the class of variational level sets methods, which are able to deal with the case in which the sets Ω_i (here, the foreground and the background) are not necessarily connected internally.