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Biomedical image segmentation using variational and statistical approaches

Statistical region-based active contours for segmentation: An overview

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Abstract

In this paper we propose a brief survey on geometric variational approaches and more precisely on statistical region-based active contours for medical image segmentation. In these approaches, image features are considered as random variables whose distribution may be either parametric, and belongs to the exponential family, or non-parametric estimated with a kernel density method. Statistical region-based terms are listed and reviewed showing that these terms can depict a wide spectrum of segmentation problems. A shape prior can also be incorporated to the previous statistical terms. A discussion of some optimization schemes available to solve the variational problem is also provided. Examples on real medical images are given to illustrate some of the given criteria.

1. Introduction

Due to the rapid evolution of medical imaging systems, image segmentation faces various and increasingly difficult challenges. In order to cope with the growing variety of data encountered in medical imaging, segmentation tools must be able to handle different noise models and to provide a way to include geometric and photometric priors. To this end, geometric variational approaches that consider image segmentation as a continuous optimization problem are particularly well adapted (see for example [1–3]). Indeed, the computation of a given shape (i.e. segmentation) can be advantageously modeled as the optimum of a wisely chosen continuous energy functional. Continuous energy functionals allow the use of photometric image properties such as texture [4–8] and noise [9–12], as well as geometric properties such as the prior shape of the object to be segmented [13–18], see also [19] and more recently [20] for some reviews on deformable models and active contours in medical image segmentation.

In this paper, we propose to focus on region-based terms that take benefit of the probability density function of a given image feature inside the region of interest [1,9,21]. We more particularly review the optimization of divergences between pdfs which represent a general setting for both segmentation and tracking in medical images. When considering a segmentation framework, we aim at maximizing the distance between the pdf of the inside region and the pdf of the outside region. When considering a tracking application, we aim at minimizing the distance between the pdf of the region of interest and a reference one. The pdf can be considered as parametric (e.g. Gaussian, Rayleigh...) or non-parametric (no assumption is made on the law). In the literature, region tracking using non-parametric probability density functions has been first proposed in reference [22] for video and then developed for cardiac structures tracking in perfusion MRI (p-MRI) sequences in reference [23]. On the other hand, some authors [24] have also proposed to take benefit of the maximization of the Bhattacharya distance of non-parametric pdfs for segmentation. Concerning parametric pdfs, we restrict our study to the exponential family as first proposed in reference [9]. The rationale behind using the exponential family is that it includes, among others, Gaussian, Rayleigh, Poisson and Bernoulli distributions that have proven to be useful to model the noise structure in many real image acquisition devices (e.g. Poisson for photon counting devices such as X-ray or CCD cameras, Rayleigh for ultrasound images, etc). To cope with the occlusion and missing data and to alleviate initialization issues in medical image segmentation, a shape prior on the structure to be isolated can also prove necessary. For space reasons, we restrict our review to the use of the Legendre moments in a variational approach first proposed in reference [16] and applied to echocardiography

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in reference [25] and in cardiac segmentation on non-contrast CT images in reference [18].

One of the difficult point concerning variational approaches remains the associated resolution schemes. We propose here to review two main schemes. The first one is based on advanced and efficient optimization tools (e.g. originating from shape derivation tools [26] and the second one relies on efficient non-smooth convex optimization tools as proposed in reference [27]). Some segmentation examples of medical structures are taken (brain and cardiac MRI, echocardiography, MRI perfusion) to show the adaptability of such statistical segmentation methods.

2. Statistical region-based terms for segmentation

A region-based segmentation problem aims at finding a partition of the image domain Ω into n regions $\{\Omega_1,..,\Omega_n\}$ of respective boundaries $\{\partial\Omega_1,..,\partial\Omega_n\}$ that minimizes the following criterion:

$$E\left(\Omega_1, .., \Omega_n, \Gamma\right) = \sum_{i=1}^{n} E_{r_i}\left(\Omega_i\right) + \lambda E_b\left(\Gamma\right) \tag{1}$$

where E_{r_i} is the region-based term related to the domain Ω_i, and $\Gamma = \bigcup_{i=1}^{n} \partial\Omega_i$. The regularization term E_b is balanced with a positive parameter λ.

We focus here on statistical region-based terms E_{r_i} that take advantage of the pdf of some image features $\mathbf{y}$ whose realizations take values in $\chi \subset \mathbb{R}^p$ within each region Ω_i (e.g. when considering the intensity in grey level images $y(\mathbf{x}) = I(\mathbf{x})$ with $\mathbf{x}$ the pixel location, $p = 1$ and $\chi = [0.255]$). This framework is then also adapted to the use of vectorial image features such as the coefficients of the wavelet transform or optical flow vectors. At this stage, we consider two main classes of region descriptors detailed in the two sections below. We also provide a comparison for brain MRI segmentation in Section 6.2.

2.1. Statistical descriptors based on regions integrals

For the first kind of region descriptors, we consider the minimization of region integrals of some well chosen functions of the pdf of the feature $\mathbf{y}$ within the region Ω_i, namely $p(\mathbf{y}(\mathbf{x}),\Omega_i)$. We then consider as a region-based term:

$$Eri\left(\Omega_i\right) = \int_{\Omega_i} \Phi\left(p\left(\mathbf{y}\left(\mathbf{x}\right), \Omega_i\right)\right) d\mathbf{x} \tag{2}$$

with Φ at least C^1 and Lebesgue integrable function. Let us note that when $\Phi(t) = -\log(t)$ the function ((2)) is known as the log-likelihood score function, used to describe the homogeneity of a region. It has been introduced in reference [1] using Gaussian pdfs and in reference [9] using parametric pdfs from the exponential family. In reference [12], we consider a general setting replacing the $-\log$ by any proper function Φ within the exponential family. We also elucidate the impact of the estimation method of the hyper-parameters on the shape derivatives of the criterion. Such a criterion has been also investigated using non-parametric pdfs and some functions Φ related to mutual information and entropy as developed in references [28,29].

2.2. Statistical descriptors based on features integrals

Another class of statistical region descriptors may be interesting since it can depicts both supervised and unsupervised segmentation. In this class of statistical descriptors, we consider integrals over the feature domain χ and so we do not make any assumption on the independence of the random variable $\mathbf{y}(\mathbf{x})$ on the contrary to the region descriptors described using [2]. Let us then introduce the following functional which represents the distance, or more generally the divergence, between the current pdf estimate $p(\cdot,\Omega_i)$ and another one $q(\cdot)$ for some appropriate function ψ comparing pdfs:

$$E_{r_i}\left(\Omega_i\right) = \int_{x} \Psi\left(p\left(\mathbf{y}, \Omega_i\right), q\left(\mathbf{y}\right)\right) d\mathbf{y} \tag{3}$$

We can introduce for example the Hellinger distance or the commonly used Kullback-Leibler divergence. Some other distances or divergences can be introduced to improve the accuracy and robustness of the segmentation such as the Wasserstein distance [30] or alpha-divergences [31]. Segmentation of complex regions can also take benefit of local estimation of the pdfs on small patches as proposed in reference [32].

Such divergences represent a general setting for both segmentation and tracking in medical images. Indeed, we may cast the segmentation problem as the maximization of the distance between the pdfs of the feature in the inside and outside regions. In order to fix ideas, let us consider a partition of an image in two regions Ω_1 and Ω_2. The segmentation may be formulated as the maximization of the following criterion:

$$E_r\left(\Omega_1, \Omega_2\right) = \int_{x} \Psi\left(p\left(\mathbf{y}, \Omega_1\right), q\left(\mathbf{y}, \Omega_2\right)\right) d\mathbf{y} \tag{4}$$

In the tracking problem, one aims at finding a consistent region Ω_i through a series of images. We can assume statistical similarity between the pdfs of the region in two consecutive images. We then search for the domain that minimizes the functional (3) where $q(\cdot)$ is a reference pdf that has been learned from the region of interest:

$$E_{r_i}\left(\Omega_i\right) = \int_{x} \Psi\left(p\left(\mathbf{y}, \Omega_i\right), q_{ref}\left(\mathbf{y}\right)\right) d\mathbf{y} \tag{5}$$

This framework may also be applied to supervised segmentation where a reference pdf is learned on the region of interest.

3. Statistical features description

For all the above criteria, the pdf can be either parametric or non-parametric. Parametric pdfs are useful for the segmentation and tracking of homogeneous regions. The pdf can then be chosen according to the noise model as detailed thereafter. However, parametric models may be subject to bias when the pdf model is only an approximation of the true noise model. In this case non-parametric pdfs may be useful as well as in the case of segmentation or tracking of non homogeneous regions.