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Bi-planar image segmentation based on variational geometrical active contours with shape priors

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A B S T R A C T

This work proposes an image segmentation model based on active contours. For a better handling of regions where anatomical structures are poorly contrasted and/or missing, we propose to incorporate a priori shape information in a variational formulation. Based on a level set approach, the proposed functional is composed of four terms. The first one makes the level set keep the important signed distance function property, which is necessary to guarantee the good level set evolution. Doing so results in avoiding the classical re-initialization process, contrary to most existing works where a partial differential equation is used instead. The second energy term contains the a priori information about admissible shapes of the target object, the latter being integrated in the level set evolution. An energy that drives rapidly the level set towards objects of interest is defined in the third term. A last term is defined on prior shapes thanks to a complete and modified Mumford–Shah model. The segmentation model is derived by solving the Euler–Lagrange equations associated to the functional minimization. Efficiency and robustness of our segmentation model are validated on synthetic images, digitally reconstructed images, and real image radiographs. Quantitative evaluations of segmentation results are also provided, which also show the importance of prior shapes in the context of image segmentation.

1. Introduction

Image segmentation is one of the most important tasks in the areas of image processing and computer vision. That is one of the reasons why new segmentation techniques are always being developed, and more elaborated models are still carried out. In medical imaging, despite it constitutes a crucial part, in most cases it is only a first step towards a real target application, which could be a study, an analysis or a therapeutic evaluation of segmented medical parts and structures.

One of the most known and easiest segmentation methods is the image thresholding. It is known that in the case of Computed Tomography (CT) images, that, most of the times, such an approach could be satisfactory to segment anatomical structures. Unfortunately, for most of other image acquisition techniques, an image thresholding and other low level segmentation methods are not efficient[1] enough, and most of times, at all, in order to get the objects and/or regions of interests. That were the major reasons of why much more elaborated and much more sophisticated techniques have been developed since then; particularly, the active contours or snakes methods Kass et al. (1987). Local contour deformations are obtained by minimizing a defined functional (or energy) such that its minimum is reached on the edges of the target object (or objects when dealing with many objects of interests) one would like to segment. Depending on the way to formulate and implement the active contours, different approaches were proposed. Indeed, the active contours methods can basically be grouped in two major classes: the parametric active contours (PACs) and the geometric active contours (GACs). PAC is defined in a Lagrangian domain, and explicitly formulated with a parametrized curve to be deformed afterwards. On the other hand, GAC are defined in an Eulerian domain, and represented implicitly with level sets of a bidimensional function. In addition to better robustness regarding the initialization of the active contour, GAC really brought noticeable improvements, in comparison to the PAC. Furthermore, besides more efficient and more robust numerical schemes, due mainly to the level set formulation, topological changes were allowed during GAC evolution. However, whatever the formulation and implementation that are used, one should keep in mind that (P/G) AC strongly rely on image gradients and other local features. And then, it appears clearly that if the image one would like to segment has low gradients, the active contours will not become stationary at object boundaries, and such approaches will be definitely inappropriate and inefficient to get good segmentations.

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[1] Here, "efficiency of the segmentation" refers to the segmented objects of interests themselves and the accuracy of the segmentations.

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Unfortunately, what we just described is truly the case in most medical images. Indeed, maybe except for CT images, the majority of medical imaging modalities; particularly, *X-rays* modality for which the bi-planar EOS system and images we are dealing with are also issued, presents generally many anatomical structures having sensibly the same gray level values (e.g., it is the case for bones). Also, images have weak contrast, and very often, many parts of anatomical structures boundaries are not salient or do not appear at all; this is also amplified by occlusions phenomena in bones joints. Furthermore, due to their complicated forms in many cases (the femur and tibia bones for instance), another issue regarding anatomical structures is about the fact that it is very difficult to describe or model them just by using parametric models. If that was possible, then, one could use Bardinet et al. (1996) approach where superquadrics were proposed, followed by some refinement formulated as an inverse problem. Therefore, it becomes clear that using only the local image features is definitely insignificant for characterizing an object (or objects) of interests in this kind of images. One known way to resolve this problem and obtain better accuracy in the segmentation of the desired structures, is to incorporate a priori information about the boundary of the target object shape.

1.1. Motivation

Images we are currently dealing with are obtained with the EOS acquisition system which provides very low dose *X-rays* radiographs, simultaneously in the frontal and profile positions, along with 3*D* bones reconstructions gained only from the already obtained 2*D* frontal and profile radiographs (see Laporte et al., 2003). However, in other positions different from the standing one, the 3*D* reconstruction of bones is impossible, and even if one can obtain a 3*D* reconstruction, and in an extremely difficult way, the latter one is very far away from the exact 3*D* bone. A 2*D*/3*D* image registration method, as proposed in Zosso et al. (2008) and Jerbi et al. (2009), is a way to overcome that issue. Indeed, the registration provides a way to find the positions of the structures reconstructed in the bi-planar radiographs of other positions, from the standing position. However, that approach works if and only if the only structures present in the bi-planar radiographs, are the structures of interests; this is in fact not the case at all for real radiographs. The algorithm proposed in Jerbi et al. (2009) was successfully applied on digitally reconstructed radiographs (*DRRs*) images. The case of real radiographs is more complicated though, and results are not actually satisfactory. This is mainly due to the presence of various structures in real radiographs, in addition to problems related to gray level image intensities between structures in the image, shadings, gaps in object edges, contours saliency, occlusions phenomena in bones joints, etc. Segmentation results will be used to make the 2*D*/3*D* registration more robust and more accurate, in order to perform better analyses of the hip and knee joint pathologies. Therefore, the accuracy and computation time are essential factors to be taken into account.

1.2. Main contributions

We propose a new segmentation model formulated in a variational framework with a functional composed of four terms. For each of the energy terms, the explanation of its potential advantages on the active contour evolution is provided. The first term allows the level set to keep during its evolution the essential property of SDF. This way, instead of solving periodically a PDE as it is done classically, this first term eliminates the re-initialization procedure. Shape prior information is defined in the second term and incorporated in the level set evolution. We define in the third term an energy that drives quickly the level set towards the boundaries of the target object. The last term is a complete and modified Mumford–Shah functional. Integrating all the four terms together allows us to provide a theoretical explanation of the good behaviors of the segmentation method, which is shown to be robust in the presence of occlusions and missing parts.

1.3. Paper organization

The outline of the paper is as follows. In Section 2, we present a brief review of some shape prior-based image segmentation methods. Our proposed model based on geometric active contours is detailed in Section 3. Qualitative and quantitative results are presented in Section 4, for both synthetic, *DRRs* and real radiographs images. Concluding remarks and perspectives of this work are proposed in Section 5.

2. Brief review on shape prior-based segmentation

In this section, we propose a review of some segmentation approaches based on active contours and a priori shapes information. The active contours are formulated either in a parametric way as for PAC or in geometric form as for GAC. In either case, prior shapes are incorporated in the active contour evolution model, or are performed in an independent stage of the segmentation process. We first quote the work of Leventon et al. (2000) who proposed to integrate a set of deformable shapes during the level set evolution. Prior shapes were obtained by defining a probability distribution on variances of the training set elements. The proposed shape model was based on a Principal Components Analysis (PCA), which was then applied on SDFs built with the training set composed of target objects contours. Then, at each step of the proposed segmentation algorithm, the level set evolved locally thanks to the intrinsic image features, such as the gradients and curvature, but the evolution was also guided by the estimations of the maximum a posteriori of the shape prior position and shape. However, as pointed out in Bresson et al. (2006), due to the fact that a posteriori probability is maximized at each iteration of the algorithm through an independent optimization process, then, the final evolution equation is no more a PDE. In fact, two independent steps are mandatory to evolve the level set. Proposed evolution equation in Leventon et al. (2000) is defined as follow:

$$u(t+1) = u(t) + \lambda_1(g(c+\kappa)|\nabla u(t)| + \nabla u(t) \cdot p\nabla g) + \lambda_2(u^\star(t) - u(t)). \quad (1)$$

Chen et al. (2002) proposed a different method to integrate the shape prior information in the active contours evolution. In fact, contrary to the work of Leventon et al. (2000) where the shape prior was obtained in a probabilistic manner, Chen et al. proposed to construct it as the mean of the training contours, which were primarily rigidly aligned. Also, the proposed evolution equations are truly PDEs, and authors also proposed a theoretical proof of the existence of the minimum of their functional; the proof was based on bounded variations functions. The following functional was proposed:

$$E(C,\mu,R,T) = \int_0^1 \left\{ g(|\nabla I|(C(p))) + \frac{\lambda}{2} d^2(\mu R C(p) + T) \right\} |C'(p)| \mathrm{d}p. \quad (2)$$

Following the same principle, Thiruvenkadam et al. (2008) proposed to resolve the segmentation issue in the case where occlusions appeared specifically in edges. The problem was then formulated as a segmentation with depth; the objectives being to find objects contours, object intensities and spatial order. The following functional was proposed: