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Biomedical image segmentation using geometric deformable models and metaheuristics

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ABSTRACT

This paper describes a hybrid level set approach for medical image segmentation. This new geometric deformable model combines region- and edge-based information with the prior shape knowledge introduced using deformable registration. Our proposal consists of two phases: training and test. The former implies the learning of the level set parameters by means of a Genetic Algorithm, while the latter is the proper segmentation, where another metaheuristic, in this case Scatter Search, derives the shape prior. In an experimental comparison, this approach has shown a better performance than a number of state-of-the-art methods when segmenting anatomical structures from different biomedical image modalities.

1. Introduction

Image segmentation is commonly defined as the partitioning of an image into non-overlapping regions that are homogeneous with respect to some visual feature, such as color or texture [1]. In many medical imaging applications, segmentation algorithms play a crucial role by automatically identifying anatomical structures and other regions of interest. Such algorithms are nowadays in the core of multiple tasks, like quantification and measurement of tissue volumes, localization of pathologies or computer-integrated surgery. It is important to highlight that manual segmentation is not only tedious and time consuming but, sometimes, also inaccurate, hence the importance of developing automatic and accurate segmentation methods.

In particular, medical imaging segmentation is usually challenging due to poor image contrast, noise, diffuse organ/tissue boundaries, and artifacts. These problems can cause considerable difficulties when applying traditional segmentation techniques, such as edge detection or thresholding. Consequently, an intelligent way of proceeding is to incorporate as much prior knowledge as possible about the particular object and image modality to segment. To address these difficulties, deformable models have been extensively studied and widely used in medical image segmentation with interesting results [2,3].

A single source of prior knowledge is usually not enough to satisfactorily tackle medical image segmentation problems. Therefore, the development of hybrid approaches combining different sources of information has been a major focus in the field of image segmentation [4–6]. In this work, the search/learning abilities of metaheuristics and the capability of geometric deformable models to handle topological changes are combined. Three sources of information (a region term, a shape prior, and an edge term) are used to accurately segment the organs of interest in different medical image modalities: microscopy, X-ray computed tomography (CT), and magnetic resonance imaging (MRI). In our proposal, metaheuristics [7] have capital importance in two stages. First, during the training process of the new model, the tuning of the parameters is carried out by a Genetic Algorithm [8]. Second, in the proper segmentation stage, the shape prior is obtained by a deformable registration process guided by Scatter Search [9].

Every image modality has its own peculiarities, thus the training phase allows our model to learn the most suitable parameters for a specific modality/anatomical district using few images as paradigmatic examples. In turn, the segmentation phase uses only one manually segmented reference image to generate the prior shape

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knowledge that will guide, together with the region- and edge-based terms, the evolution of the moving contour.

To assess the quality of the new approach, we developed an experimental comparison including seven state-of-the-art segmentation methods. The study was carried out on four different datasets, for a total of 22 microscopy, 11 MR, and 5 CT images.

This paper is structured as follows: in Section 2 we provide the theoretical foundations necessary to understand our work. In Section 3, a general overview of the method is presented, providing details about the different terms used in our deformable model. Finally, Section 4 presents the results and the statistical analysis of the experimental comparison, followed, in Section 5, by some final remarks and a discussion about possible future developments.

2. Theoretical background

In this section, an overview of the main techniques applied in our approach (geometric deformable models, image registration and metaheuristics) and previous related work are presented.

2.1. Deformable models

The term "deformable models" (DMs) was first used in the late eighties [10] with reference to curves or surfaces, defined within the image domain, that are deformed under the influence of "internal" forces, related with the curve features, and "external" forces, related with the features of the image regions surrounding the curve. Internal forces enforce regularity constraints and keep the model smooth during deformation, while external forces are defined to attract the model toward features of the object of interest.

DMs are segmentation techniques that use prior information about the shape of the object to be located or segmented. They start with some initial boundary shape represented in the form of a curve, and iteratively modify it by applying various shrink/expansion operations according to some energy function. DMs can either be region-based or edge-based approaches, depending on the feature they rely on to segment the object of interest. Region-based methods usually proceed by partitioning the image into connected regions by grouping neighboring pixels with similar features. Edge-based methods, instead, are focused on contour detection, relying on discontinuities in image values between distinct regions.

There are basically two types of DM depending on the kind of shape representation used: parametric/explicit and geometric/implicit.

- *Parametric deformable models*: This type of DM represents curves and surfaces explicitly in their parametric forms during deformation, allowing direct interaction with the model and leading to a compact representation for fast real-time implementation. As examples of parametric DMs we could cite "snakes" or Active Contour Models (ACMs) [11], Active Shape Models (ASMs) [12], Active Appearance Models [13,14], and Topological Active Nets (TANs) [15].
- *Geometric deformable models*: Geometric DMs are based on curve evolution theory [16–18] and the Level set method [19,20]: curves and surfaces are adapted using only geometric measures, resulting in deformations that are independent of the parameterization but, as in parametric DMs, also rely on image data to delineate object boundaries. Since the adaptation is independent of parameterization, the evolving curves and surfaces can be represented implicitly as a level set of a higher-dimensional function and topological changes can be handled automatically.

Among geometric models, the Level Set (LS) method [19] relies on an evolving closed surface defined by a moving interface, the front, which expands into the image. The interface $\Gamma(t)$ can be characterized as a Lipschitz continuous function:

$$\begin{cases} \phi(t,\mathbf{x}) > 0 & \text{for } \mathbf{x} \text{ inside } \Gamma(t) \\ \phi(t,\mathbf{x}) < 0 & \text{for } \mathbf{x} \text{ outside } \Gamma(t) \\ \phi(t,\mathbf{x}) = 0 & \text{for } \mathbf{x} \text{ on } \Gamma(t) \end{cases}$$

The front or evolving boundary, denoted by Γ, is represented by the zero level $\Gamma(t) = \{\mathbf{x} \mid \phi(t,\mathbf{x}) = 0\}$ of a LS function $\phi(t,\mathbf{x})$. The dynamics of ϕ can be described by the following general form:

$$\frac{\partial \phi}{\partial t} + F|\nabla\phi| = 0$$

known as the LS equation, where F is called the speed function and ∇ is the spatial gradient operator. F can depend on position, time, the geometry of the interface (e.g., its normal or its mean curvature), or the different image features.

In any case, the definition of the LS function ϕ is essential. One common choice is the signed distance function $d(\mathbf{x})$, which gives the distance of a point to the surface and the sign: generally $d > 0$ if the point $\mathbf{x}$ is outside and $d < 0$ if it is inside the surface (assuming it is a closed surface). This definition is especially interesting to avoid numerical instabilities and inaccuracies during computations. But even with this definition, ϕ will not remain a signed distance function all the time and a reinitialization procedure to keep the LS intact will be needed [21].

2.2. Metaheuristics

The classic gradient search techniques perform efficiently when the problem under consideration satisfies tight constraints. But when the search space is discontinuous, noisy, high-dimensional and multimodal, then metaheuristics [7] have been found to consistently outperform traditional methods. Among the stochastic approaches to continuous optimization, Evolutionary Algorithms (EAs) and Swarm Intelligence (SI) algorithms, as well as other metaheuristics [22], offer a number of attractive features: no requirement for a differentiable or continuous objective function, robust and reliable performance, global search capability, virtually no need of specific information about the problem to solve, easy implementation, and implicit parallelism.

2.2.1. Genetic Algorithms

Genetic Algorithms (GAs) [8] are stochastic, parallel search algorithms based on the principles of natural selection. GAs were designed to efficiently search large, non-linear, poorly-understood search spaces where expert knowledge is scarce or difficult to encode and where traditional optimization techniques fail. They are flexible, robust, and try to exhibit the adaptiveness of biological systems.

These algorithms encode a potential solution to a specific problem into a chromosome-like data structure and apply recombination operators to preserve critical information. The main features of a GA are the encoding of individuals as strings of symbols, the individuals selection policy, and the use of both the mutation and recombination operators. The basic outline of a GA is shown in Algorithm 1.