Paper:

Optimal Parameter Setting of Active-Contours Using Differential Evolution and Expert-Segmented Sample Image

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Generally, tissue extraction (segmentation) is one of the most challenging tasks in medical image processing. Inaccurate segmentation propagates errors to the subsequent steps in the image processing chain. Thus, in any image processing chain, the role of segmentation is in fact critical because it has a significant impact on the accuracy of the final results, such as those of feature extraction. The appearance of variant noise types makes medical image segmentation a more complicated task. Thus far, many approaches for image segmentation have been proposed, including the well-known active contour (snake) model. This method minimizes the energy associated with the target's contour, which is the sum of the internal and external energy. Although this model has strong characteristics, it suffers from sensitivity to its control parameters. Finding the optimal parameter values is not a trivial task, because the parameters are correlated and problem-dependent. To overcome this problem, this paper proposes a new approach for setting snake's optimal parameters, which utilizes an expert-segmented gold (ground-truth) image and an optimization algorithm to determine the optimal values for snake's seven control parameters. The proposed approach was tested on three different medical image test suites: prostate ultrasound (33 images), breast ultrasound (30 images), and lung X-Ray images (48 images). In the current approach, the DE algorithm is employed as a global optimizer. The scheme introduced in this paper is general enough to allow snake to be replaced by any other segmentation algorithm, such as the level set method. For experimental verification, 111 images were utilized. In a comparison with the prepared gold images, the overall error rate is shown to be less than 3%. We explain the proposed approach and the experiments in detail.

Keywords: image segmentation, object extraction, active contour (Snake), differential evolution (DE), ultrasound

1. Introduction

The identification of specific organs or tissues in medical images requires adequate knowledge and expertise, and therefore it is usually performed manually by an expert physician during treatment planning and diagnosis. Computer-aided methods can speed up this time consuming process, but due to the high level of noise and low quality of these images, targeting accurate results is highly challenging.

In medical images, segmentation can be used for extracting images of tumors or cancerous organs for volume measurement, computer-guided surgery, diagnosis, treatment planning, and the study of anatomical structural changes. There are many variant segmentation techniques, such as thresholding [1], clustering [2], histogram-based approaches [3], edge detection [4], active contour [5], level set [6], and graph partitioning methods [7]. Obviously, none of these is a universal method applicable to all kinds of image modality.

The active contour method (snake) tries to find the boundary of an object by minimizing the energy associated with the current contour, which is the sum of the internal and external energy. They have been applied in many various applications, such as, image segmentation [8, 9], detection of eye and cornea on IR images [10], and tracking video objects [11]. The drawback of this method is its high level of sensitivity to the control parameters. These parameters are correlated and problem-oriented. In practice, a trial-and-error approach to the adjustment of the parameters is used, which makes the process very time consuming, and frequently it cannot be guaranteed that optimal (or at least sub-optimal) values are obtained. The approach proposed in this paper is not limited to active contour algorithms and can be applied to other kinds of segmentation approaches, e.g., level sets. In this study, the Differential Evolution (DE) algorithm is utilized to optimize the snake's parameters, but it can be replaced with other global optimization techniques. In other words, the proposed scheme is general enough to be used to find the optimal parameter settings for other image processing tasks, such as image filtering and enhancement. The proposed scheme is a sample-based optimization method, which was inspired by the image processing chain optimization proposed by Rahnamayan et al. [12, 13].

Many works related to medical image segmentation have used active contour algorithms. However, because of the high noise level and low quality of many images, this algorithm should be enhanced or customized to tackle challenging images. An enhanced active contour algorithm was introduced by Liu et al. [14], who used a geodesic active contour algorithm, which they tested on CT images. The edge detector in their model ensures that the data on both sides of the contour is as dissimilar as possible, and it makes the interior of the interest region as homogeneous as possible. Another study was conducted by Wang et al. [15] in which the authors tried to intensify the energy in the active contour model for brain MR image segmentation. They defined an energy function with a local intensity fitting term, which induces a local force to attract the contour and stops it at object boundaries, and an auxiliary global intensity fitting term, which drives the motion of the contour far away from object boundaries. Another paper by McInerney and Terzopoulos [16] introduced a technique for the segmentation of anatomical structures in medical images using a topologically adaptable snake model. The model is set in the framework of domain subdivision using simplified decomposition. Boscolo et al. [17] proposed a segmentation technique that combines a knowledge-based segmentation system with a sophisticated active contour model. This approach exploits the guidance of a higher-level process to perform the segmentation of various anatomical structures robustly. Information about the anatomical structures to be segmented is defined statistically in terms of the probability density functions of parameters, such as location, size, and image intensity.

Many other attempts have been made to enhance the active contour model; however, these studies, such as that of Williams and Shah [18], focused mostly on the enhancing algorithm itself, not its parameters. The authors proposed a greedy algorithm for the active contour model, which makes the whole algorithm run faster. Another paper discusses the optimization of the shape that should be segmented [19]. For each of the landmarks that describe the shape, a distinct set of optimal features is determined. The selection of features is automatic, using training images and sequential feature forward and backward selections. In one study, a genetic algorithm was used to set the parameters for the active contour algorithm [20], which minimizes the energy related to the image. Therefore, in this approach the authors tried to use the snake algorithm as the fitness function and to find the parameters based on minimizing this function. For straightforward images, this approach performs better than others, but for noisy images, it is prone to fail because object boundaries are not necessarily in the minimized position of the total fitness function. Our approach uses a gold image, which is segmented by an expert, during the parameter optimization process. This approach enables us to set the parameters, which are embedded in the segmented image (called gold image), for any image based on the desired needs of a professional.

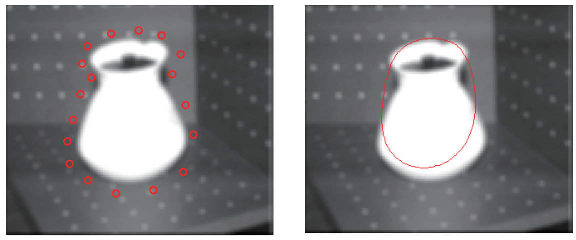

Fig. 1. A sample experiment that demonstrates that snake segmentation fails to segment an object when its parameters are set to non-optimal values. Left image: input image and initial outer seed points. Right image: failure of snake to segment the object.

The rest of this paper is organized as follows. A brief review of the active contour and Differential Evolution (DE) algorithms is presented in Section 2 as a background review. In Section 3, the proposed approach is explained in detail. Experimental verification results and a corresponding results analysis are provided in Section 4. Finally, the paper is summarized and concluded in Section 5.

2. Background Review

In this section, we briefly review the snake and the DE algorithm, which are utilized as the main components of the proposed approach.

2.1. Active Contours (Snakes)

The idea of active contour (snake) segmentation originated from Kass et al.'s 1988 study [5]. This method is one of the well-known segmentation methods. It extracts objects in 2D images using the concept of internal and external energies. This algorithm acquires a set of points near the object's boundary and builds an initial snake. However, the performance of the algorithm is highly sensitive to its control parameters, which control the behavior of the snake's movements toward the object's boundary. To achieve an accurate segmentation result, finding the optimal setting of these parameters is therefore a crucial task. **Fig. 1** illustrates the output of the snake segmentation algorithm for an easily segmented image: the algorithm fails to extract the object because of the non-optimal parameter settings. Generally, the optimal parameter settings are of utmost importance for any segmentation algorithm (including the snake algorithm) and it can affect the outcome drastically.

The performance of a snake algorithm is based on minimizing the energy of the snake, which is the sum of the internal and external energies.

$$\begin{aligned} E_{snake} &= \int E_{snake}[(V(s))]ds \\ &= \int E_{int}(V(s)) + E_{images}(V(s)) + E_{con}(V(s))ds, \quad (1) \end{aligned}$$

where E_{int} represents the internal energy, E_{images} gives rise to the image forces, and E_{con} gives rise to the external