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Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation

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ABSTRACT

The performance of the level set segmentation is subject to appropriate initialization and optimal configuration of controlling parameters, which require substantial manual intervention. A new fuzzy level set algorithm is proposed in this paper to facilitate medical image segmentation. It is able to directly evolve from the initial segmentation by spatial fuzzy clustering. The controlling parameters of level set evolution are also estimated from the results of fuzzy clustering. Moreover the fuzzy level set algorithm is enhanced with locally regularized evolution. Such improvements facilitate level set manipulation and lead to more robust segmentation. Performance evaluation of the proposed algorithm was carried on medical images from different modalities. The results confirm its effectiveness for medical image segmentation.

1. Introduction

The underlying objective of medical image segmentation is to partition it into different anatomical structures, thereby separating the components of interest, such as blood vessels and liver tumors, from their background. Computerized medical image segmentation is a challenging problem, due to poor resolution and weak contrast. Moreover the task is often made more difficult by the presence of noise and artifacts, due to instrumental limitations, reconstruction algorithms and patient movement. There is yet no universal algorithm for medical image segmentation. An algorithm's advantages and drawbacks often vary according to the problem under investigation.

The outcomes of most medical imaging modalities are of gray scale intensities. Suppose a medical image $\mathbf{I}(x,y)$, where $x(\in[1,N_x])$ and $y(\in[1,N_y])$ are spatial indices, and the pixel $i(x,y)$ quantifies the corresponding intensity. Image segmentation is to find a set of meaningful subclasses $\mathbf{S}_k$, where

$$\cup\mathbf{S}_k=\mathbf{I}; \tag{1}$$

$$\mathbf{S}_k\cap\mathbf{S}_j=\emptyset. \tag{2}$$

The indices k and j lie in the interval $[1,K]$ and K is the number of subclasses. Eq. (1) claims that an image segmentation should be complete, while Eq. (2) requires it to be non-overlapping.

There are two well-established concepts in image segmentation: pixel classification and tracking variational boundary [1]. The first one assumes that the pixels in each subclass have nearly constant intensities, which is true for the anatomical structures with similar physiological properties. Such algorithms may detect multiple components concurrently, but they are susceptible to environmental noise and image inhomogeneity. In contrast, methods that track variational boundaries make use of both intensity and spatial information. Therefore, a subclass has to be homogeneous and enclosed in a specific variational boundary. When applied to medical image segmentation, neither of them is universally robust due to intrinsic noise and artifacts [1–5].

Most segmentation algorithms in practice require radiologists, with their experience and knowledge, to adjust the segmentation parameters carefully for an optimal performance. Due to the complexity of medical image segmentation, most computerized systems run in a semi-automatic or interactive manner [6]; the radiologists initiate the segmentation, interrupt it when necessary, and finally stop the algorithm. Obviously such a procedure is quite subjective and labor-intensive. As a consequence, the ease of manipulation often determines the acceptance of a segmentation algorithm in clinics [7–9].

Level set methods, which are established on dynamic implicit interfaces and partial differential equations (PDEs), have been shown to be effective for medical image segmentation [9–11].

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However to employ those methods, clinical radiologists and even engineering practitioners are often overwhelmed by intensive computational requirements and complex regulation of controlling parameters [12]. Current state-of-the-art research is therefore oriented to facilitating the manipulation, while enhancing the quality of segmentation [7,10,12–14].

There have been many hybrid intelligent systems using fuzzy clustering to facilitate level set segmentation [9,10,13,14]. In short, such algorithms employ fuzzy clustering, based on an image intensity, for initial segmentation and employ level set methods for object refinement by tracking boundary variation. Our previous work on liver tumor segmentation [9] has shown that, fuzzy clustering, by approximately delineating tumor boundaries, not only relieves manual intervention, but also accelerates level set optimization. Ho and Suri, on the other hand, proposed to regularize level set evolution locally by fuzzy clustering, in order to alleviate the problems of noise sensitivity and weak boundaries [10,13,14]. Nevertheless, the operators still have to set several parameters carefully for an optimal level set segmentation.

In this paper, we propose a new fuzzy level set algorithm for automated medical image segmentation. Compared to our previous method [9], the new algorithm is significantly improved in the following aspects. Firstly, fuzzy clustering incorporates spatial information during an adaptive optimization, which eliminates the intermediate morphological operations. Secondly, the controlling parameters of level set segmentation are now derived from the results of fuzzy clustering directly. Thirdly, a new strategy, directed by fuzzy clustering, is proposed to regularize level set evolution, which is different from other methods [10,13,14]. Finally, we also verified the new fuzzy level set algorithm on general medical images, for example, ultrasound, computed tomography (CT) and magnetic resonance imaging (MRI).

The remainder of this paper is organized as follows. The next section describes fuzzy clustering and the algorithm with spatial restrictions. Section 3 elaborates on level set segmentation and a fast algorithm. Section 4 presents the new fuzzy level set algorithm in detail. Section 5 reports our experiments and the relevant discussion. Concluding remarks are drawn in Section 6.

2. Spatial fuzzy clustering and image segmentation

In fuzzy clustering, the centroid and the scope of each subclass are estimated adaptively in order to minimize a pre-defined cost function. It is thereby appropriate to take fuzzy clustering as a kind of adaptive thresholding. Fuzzy c-means (FCM) is one of most popular algorithms in fuzzy clustering, and has been widely applied to medical problems [4,5,15].

The classical FCM algorithm originates from the k-means algorithm. In brief, the k-means algorithm seeks to assign N objects, based on their attributes, into K clusters ($K \leq N$). For medical image segmentation, N equals the number of image pixels $N_x \times N_y$. The desired results include the centroid of each cluster and the affiliations of N objects. Standard k-means clustering attempts to minimize the cost function

$$J = \sum_{m=1}^{K} \sum_{n=1}^{N} ||i_n - v_m||^2, \tag{3}$$

where i_n is the specific image pixel, v_m is the centroid of the mth cluster, and $||\cdot||$ denotes the norm. The ideal results of a k-means algorithm maximize the inter-cluster variations, but minimize the intra-cluster ones.

In k-means clustering, every object is limited to one and only one of K clusters. In contrast, an FCM utilizes a membership function μ_{mn} to indicate the degree of membership of the nth object to the mth cluster, which is justifiable for medical image segmentation as physiological tissues are usually not homogeneous. The cost function in an FCM is similar to Eq. (3)

$$J = \sum_{n=1}^{N} \sum_{m=1}^{C} \mu_{mn}^{l} ||i_n - v_m||^2, \tag{4}$$

where $l(>1)$ is a parameter controlling the fuzziness of the resultant segmentation. The membership functions are subject to the following constraints:

$$\sum_{m=1}^{C} \mu_{mn} = 1; \quad 0 \leq \mu_{mn} \leq 1; \quad \sum_{n=1}^{N} \mu_{mn} > 0. \tag{5}$$

The membership functions μ_{mn} and the centroids v_m are updated iteratively

$$\mu_{mn} = \frac{||i_n - v_m||^{-2/(l-1)}}{\sum_{k=1}^{C} ||i_n - v_k||^{-2/(l-1)}}; \tag{6}$$

$$v_i = \frac{\sum_{n=1}^{N} \mu_{mn}^{l} i_n}{\sum_{n=1}^{N} \mu_{mn}^{l}}. \tag{7}$$

The standard FCM algorithm is optimized when pixels close to their centroid are assigned high membership values, while those that are far away are assigned low values.

One of the problems of standard FCM algorithms in an image segmentation is the lack of spatial information [4,5,9]. Since image noise and artifacts often impair the performance of an FCM segmentation, it would be attractive to incorporate spatial information into an FCM. Cai et al. [5] proposed a generalized FCM algorithm that adopts a similarity factor to incorporate local intensity and spatial information. In contrast to the above preparatory weighting, it is also possible to utilize morphological operations to apply spatial restrictions at the post-processing stage [9].

Chuang et al. [4] proposed another spatial FCM algorithm in which spatial information can be incorporated into fuzzy membership functions directly using

$$\mu'_{mn} = \frac{\mu_{mn}^{p} h_{mn}^{q}}{\sum_{k=1}^{C} \mu_{kn}^{p} h_{kn}^{q}}, \tag{8}$$

where p and q are two parameters controlling the respective contribution. The variable h_{mn} includes spatial information by

$$h_{mn} = \sum\nolimits_{k \in N_n} \mu_{nk}, \tag{9}$$

where N_n denotes a local window centered around the image pixel n. The weighted μ_{mn} and the centroid v_m are updated as usual according to Eqs. (6) and (7).

3. Level set segmentation

In contrast to FCM using pixel classification, level set methods utilize dynamic variational boundaries for an image segmentation [16,17]. Segmenting images by means of active contours is a well-known approach [2,18,19], but instead of parametric characterization of active contours, level set methods embed them into a time-dependent PDE function $\phi(t,x,y)$. It is then possible to approximate the evolution of active contours implicitly by tracking the zero level set $\mathbf{\Gamma}(t)$

$$\begin{cases} \phi(t,x,y) < 0 & (x,y) \text{ is inside } \mathbf{\Gamma}(t) \\ \phi(t,x,y) = 0 & (x,y) \text{ is at } \mathbf{\Gamma}(t) \\ \phi(t,x,y) > 0 & (x,y) \text{ is outside } \mathbf{\Gamma}(t) \end{cases} \tag{10}$$

The implicit interface $\mathbf{\Gamma}$ may be comprised of a single or a series of zero isocontours. The issue of an image segmentation is therefore converted to

$$\cup \mathbf{S}_k \cup \mathbf{\Gamma} = \mathbf{I}. \tag{11}$$