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A joint shape evolution approach to medical image segmentation using expectation–maximization algorithm

Mahshid Farzinfar[a,*], Eam Khwang Teoh[a], Zhong Xue[b]

[a]School of Electrical and Electronic Engineering, Nanyang Technological University, 639798 Singapore
[b]The Center for Bioengineering and Informatics, The Methodist Hospital Research Institute, Weill Medical College of Cornell University, Houston, TX 77030, USA

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Abstract

This study proposes an expectation–maximization (EM)-based curve evolution algorithm for segmentation of magnetic resonance brain images. In the proposed algorithm, the evolution curve is constrained not only by a shape-based statistical model but also by a hidden variable model from image observation. The hidden variable model herein is defined by the local voxel labeling, which is unknown and estimated by the expected likelihood function derived from the image data and prior anatomical knowledge. In the M-step, the shapes of the structures are estimated jointly by encoding the hidden variable model and the statistical prior model obtained from the training stage. In the E-step, the expected observation likelihood and the prior distribution of the hidden variables are estimated. In experiments, the proposed automatic segmentation algorithm is applied to multiple gray nuclei structures such as caudate, putamens and thalamus of three-dimensional magnetic resonance imaging in volunteers and patients. As for the robustness and accuracy of the segmentation algorithm, the results of the proposed EM-joint shape-based algorithm outperformed those obtained using the statistical shape model-based techniques in the same framework and a current state-of-the-art region competition level set method.

Keywords: Statistical shape model; Active contours; Level set methods; Expectation–maximization algorithm

1. Introduction

Numerous automatic and semi-automatic magnetic resonance (MR) brain image segmentation algorithms have been introduced over the last two decades [1,2]. Generally, the segmentation problem is defined as the estimation of the observed intensity model of the original images. According to the information level used to build various generative models, MR brain image segmentation can be categorized into two alternative groups. The first group is voxel-based labeling, which utilizes intensity classification methods aiming at assigning each voxel to a specific tissue type. Voxel-wise approaches were used for segmenting MR brain images into three common tissue types, that is, white matter, gray matter and cerebra-spinal fluid. In these algorithms, one can adopt the probability-based approaches based on the either maximum a posteriori [3] or the maximum-likelihood estimation [4,5]. Statistical atlas can also be used as the prior information in the segmentation by combining with an image registration algorithm [6–8]. In order to ensure spatial smoothness, the Hidden Markov Random Field (HMRF) was adopted to model the neighborhood relationship among voxels [6,9,10]. Most recently, both the prior knowledge-based and the HMRF modeling can be combined together [10]. In brief, the advantage of voxel-wise segmentation is that it is straightforward to apply local statistical methods to model tissue intensity and spatial information. One drawback of such methods is that the statistical information is voxel based or local, and they are venerable to noise, low image contrast and diffused boundaries.

* Corresponding author.
E-mail addresses: mahs0002@e.ntu.edu.sg (M. Farzinfar), eekteoh@ntu.edu.sg (E.K. Teoh), zxue@tmhs.org (Z. Xue).

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The second group of segmentation methods is based on deformable shape matching or curve/surface evolution. Energy functions are derived from both the image data and shape constraints in order to drive a deforming shape to the desired object in the image. In these methods, object shapes are characterized by different model parameters and extracted using both the intrinsic properties of the shape and the image information from the image [11–13]. Explicit shape descriptors can be easily implemented but cannot naturally handle topological changes (e.g., local shape topology might be different among subjects). This limitation can be addressed by using implicit shape descriptors also known as the level set method [14]. Typical level set methods include the geometric and the geodesic active contours introduced in [15,16], and extensions of the geodesic active contours can be achieved using the split schemes like the Additive Operator Splitting scheme [17] and the multigrid techniques [18]. The boundary-based geodesic active contour model was also improved by generating the model using the information of the entire image [19,20]. Compared to the voxel-based segmentation algorithms, shape evolution methods incorporate relatively global shape information and provide more robust segmentation of objects in medical images [21–26].

In shape evolution methods, maximizing the posterior distribution of the desired parameters is not analytical due to the limitation of the observation process and lack of information to construct statistical models and generative models from the observation data. To deal with such estimation complexity, additional features can be used as hidden variables for compensating the incomplete observation data. One can utilize the elaborate techniques such as the expectation–maximization (EM) algorithm in which the distributions of the incomplete observation data are identified with help of the estimation of hidden variables. The hidden variables are unknown and are associated with missing information and presented as the underlying local voxel labeling.

In the literature, it has been illustrated that voxel-wise segmentation techniques can utilize the EM algorithm for learning the generative models due to the direct dependencies between the estimation variables of the models and the hidden variables. However, in the shape evolution techniques, it is more challenging to find the relationship between the hidden variables and the shape model variables. In Ref. [27], the dependency between the learning data from the EM algorithm and the shape model parameters is defined by an explicit space-conditioned probability model, where the shape model parameters are represented by a level set function. In Ref. [28], the evolving boundary is constrained by the normalized difference (using least squares fitting) between the expected value and the actual value from current boundary using an adaptive EM model. Thus, our focus herein is to study an effective approach to improve the shape-based segmentation using hidden variables in the EM framework.

A new shape evolution approach is proposed in the probabilistic framework using the EM algorithm, wherein additional features are used as the hidden variables for compensating the incomplete observation data. Building upon the EM shape-based framework, our scheme can be considered as a statistical shape-based segmentation method combined by the hidden variable model. The object shape is represented by both parametric and nonparametric level set functions proposed in Ref. [29], and the hidden variable is defined as the underlying voxel labeling. The object shapes can be solved using the EM algorithm. In the E-step, the expected likelihood is computed, which includes two terms: the observation likelihood and the prior distribution of the hidden variables given the shape-based model and image information. In the M-step, the parametric and nonparametric level set functions are updated by maximizing their posterior distributions, weighted by the results of the E-step. The two steps can be iteratively performed until the evolving shape converges.

According to the joint curve evolution [29], the object shape can be represented by both parametric and nonparametric curves. Parametric shape can be easily embedded with statistical models so that the shape is well constrained, and nonparametric shape could match object boundary better due to its relatively higher degree of freedom. Thus, the object shape is deformed in two different domains: the image domain, which adopts the nonparametric curve evolution, and the statistical shape domain, which adopts the parametric curve evolution using a new Principal Component Analysis (PCA) analysis. Similar to the Active Appearance Model, in the training stage, the covariance matrix is defined by not only the object shapes but also the image intensity patterns inside the objects. It is worth noting that Pohl et al [27] also used the prior probability values of the missing parts variables under the level set function model. However, one important difference is that in Ref. [27], although the hidden variables and the shape-based model parameters are related, the estimation of the observation likelihood is independence under the shape model. Here, we utilize this fact that the shape-based parameters have effects on both the estimation hidden model variables and the estimation of the observation likelihood. Additionally, the use of joint parametric and nonparametric shapes could not only preserve robustness by using statistical models but also yield more accurate segmentation by taking advantage of the nonparametric shape matching.

The remainder of this article is organized as follows. Section 2 gives an overview of the segmentation algorithms modeling the relationship between image data and statistical shape distribution. In Section 3, we describe the combination of the hidden variable model and the statistical shape-based model, which is then used in the several segmentation applications described in Section 4. Finally, the discussion and conclusion are presented in Section 5.