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A topology preserving non-rigid registration algorithm with integration shape knowledge to segment brain subcortical structures from MRI images

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ABSTRACT

A new non-rigid registration method combining image intensity and a priori shape knowledge of the objects in the image is proposed. This method, based on optical flow theory, uses a topology correction strategy to prevent topological changes of the deformed objects and the a priori shape knowledge to keep the object shapes during the deformation process. Advantages of the method over classical intensity based non-rigid registration are that it can improve the registration precision with the a priori knowledge and allows to segment objects at the same time, especially efficient in the case of segmenting adjacent objects having similar intensities. The proposed algorithm is applied to segment brain subcortical structures from 15 real brain MRI images and evaluated by comparing with ground truths. The obtained results show the efficiency and robustness of our method.

1. Introduction

In recent years, the analysis of anatomical structures and substructures from medical images develop rapidly [1,2] due to the widespread research on brain functions and brain disorders. Brain internal structures play a central role in the intellectual capabilities of the human brain. Additionally, these structures are also relevant to a set of clinical conditions, such as Parkinson's and Creutzfeldt-Jakob diseases. However, segmenting these structures from MRI images remains a challenging task due to their complex shapes, partial volume effects, anatomical variability, and the lack of clearly defined edges.

A variety of computer-assisted methods have been studied to automatically segment brain internal structures [3–9]. We can cite deformable models or active contour evolution based methods [4,5,7], which can be good solutions to the problem because of their abilities to capture the information of the shapes or structures of interest. Although combining a registration process would be good solutions to the initialization problem [7], such methods still suffer from poor image contrast and missing boundaries. Methods based on expert or atlas knowledge are very attractive to make segmentation automatic [8,10]. In [8], the authors use information fusion to combine medical expertise with fuzzy maps of morphological, topological, and tissue composition data for anatomical structures segmentation in brain MRIs. In [10], a fuzzy model was introduced to represent more appropriately the knowledge of distance, shape and relationship of structures mainly derived from an anatomic atlas. Then a precise labeling of the desired structures is achieved using GAs followed by a voxel-wise amendment using parallel region growing. The published experiment results confirmed the value of knowledge integration in image segmentation and labeling. Another crucial technology is registration based image segmentation methods [1,6,9,11,12], referred to as registration-segmentation. These methods rely on a reference image volume with a corresponding atlas in which structures of interest have been carefully segmented by experts. To segment a new image volume, a transformation that registers the reference volume to the target volume is computed, which gives a spatial correspondence between the two image volumes. Then regions labeled in the atlas can be projected onto the volume of interest using the obtained transformation. Hence the segmentation problem is converted to a registration problem. These methods take advantage of the prior knowledge provided by the atlas (structure shape, relative positions between the structures and so on). Such strategy is helpful to the segmentation of the anatomical structures which are not clearly defined in the input images. The proposed method is based on this type of method.

The key of such registration-segmentation methods is to ensure the obtained spatial transformation accurate, robust and physically reasonable, where the topology preservation is an important constraint. Topology preservation means the unchanged connectivity inside a structure and the relationships between the neighboring structures in the deformed image. There is no tearing, no folding and no appearance or disappearance of structures. By adding this constraint on the deformation field, the optimal solution space can

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be limited to physically accepted ones. Topology preservation can be generally implemented by ensuring a positive Jacobian of the transformation [13–16]. One way to enforce topology preservation consists in adding further constraints on the deformation model such as penalization of small Jacobian values [9,15–17]. Another way is to track the Jacobian during the registration procedure [18,19]. Here we preserve the topology of a transformation using a local displacements correction method based on analyzing the geometrical features of a vector field.

In this paper, a new non-rigid registration method based on optical flow theory combining both image intensity and structure shape information is proposed to segment the brain MRI internal structures. The main contributions of the proposed method are twofold: (1) a new designed cost function, which combines *a priori* shape knowledge with the intensity information, and is represented efficiently by a distance map; and (2) a topology correction strategy, which ensures the consistency of the vector field obtained by optical flow based registration. This paper is organized as follows. In Section 2 the principle of the intensity based non-rigid registration is described. Based on this principle, the proposed method is presented in detail in Section 3. Then experimental results on MRI images are shown in Section 4. In Section 5, the conclusion is finally given.

2. Intensity based non-rigid registration

Image registration is a well studied problem [20–24]. This problem can be described as finding an optimal spatial transformation $\boldsymbol{T}^*$ for matching the transformed reference image to the target image. In addition to intensities, the positions should be considered for image data in image processing. A transformation $\boldsymbol{T}$ is a spatial mapping that relates the position of features in one image or coordinate space with the position of the corresponding features in another image or coordinate space. In general the optimal transformation $\boldsymbol{T}^*$ is acquired by minimizing the overall cost function E:

$$\boldsymbol{T}^* = \arg\min_{\boldsymbol{T}\in\Gamma}\{E(\boldsymbol{T})\} = \arg\min_{\boldsymbol{T}\in\Gamma}\{E_{sim}(B, A\circ\boldsymbol{T}) + E_{reg}(\boldsymbol{T})\} \tag{1}$$

where A and B denote the reference image and the target image respectively. The set Γ is the space of admissible transformations. $E_{sim}(B, A\circ\boldsymbol{T})$ as the first part of E denotes the data similarity measure and $E_{reg}(\boldsymbol{T})$ as the second part denotes the regularization term to penalize the undesirable transformations.

Different features can be used to construct the similarity measure among which the sum of squared differences (SSD) is a simpler one. The formulation of such metric is

$$E_{sim}(B, A\circ\boldsymbol{T}) = E_{SSD}^{intensity}(B, A\circ\boldsymbol{T}) = \tfrac{1}{2}\|B - A\circ\boldsymbol{T}\|^2 \tag{2}$$

The SSD forms the basis of the intensity-based image registration algorithms and the optimal solution can be obtained by classical optimization algorithms. Among many different intensity based non-rigid image registration algorithms, the Demons algorithm (using SSD metric) [25] and its variants [26–28] are proved to be one of the most efficient methods. As is well known, a simple optimization of Eq. (2) over the space of non-parametric transformations leads to unstable and non-smooth solutions. The added regularization term $E_{reg}(\boldsymbol{T})$ is exactly used to overcome such problem. Here the defined regularization term is

$$E_{reg}(\boldsymbol{T}) = q||\nabla\boldsymbol{T}||^2 \tag{3}$$

where q controls the amount of regularization. Therefore, the cost function can be written as

$$E = E_{sim}(B, A\circ\boldsymbol{T}) + E_{reg}(\boldsymbol{T}) = E_{SSD}^{intensity}(B, A\circ\boldsymbol{T}) + E_{reg}(\boldsymbol{T}) = \tfrac{1}{2}\|B - A\circ\boldsymbol{T}\|^2 + q||\nabla\boldsymbol{T}||^2 \tag{4}$$

However, Eq. (4) will in general lead to computational intensive optimization steps. Ref. [25] provides a very ingenious scheme that optimizes the data similarity measure and the regularization term alternately. In this scheme, the deformation field is regularized by simple Gaussian smoothing. The details of the regularization problems can be found in [20]. On the other hand, the optimization of the data similarity term can be studied from the viewpoint of optical flow theory. Under the assumption of intensity preservation, the image moving velocity $\boldsymbol{v}$ is computed. Generally $\boldsymbol{v}$ is considered simply as a displacement vector field $\boldsymbol{u} = -\boldsymbol{v}$ in image registration problem. Then at each point $\boldsymbol{p}$ of the image, the displacement vector is

$$\boldsymbol{u}(\boldsymbol{p}) = -\frac{(A\circ\boldsymbol{T}(\boldsymbol{p}) - B(\boldsymbol{p}))}{(A\circ\boldsymbol{T}(\boldsymbol{p}) - B(\boldsymbol{p}))^2 + \|\nabla B(\boldsymbol{p})\|^2}\nabla B(\boldsymbol{p}) \tag{5}$$

The detailed derivation of the displacement vector field can be found in [25].

In summary, the optimization process of the spatial transformation is an alternately iterative process. The main steps can be described by the following iterations:

(a) Given the current transformation $\boldsymbol{T}(n)$, compute the displacement field $\boldsymbol{u}(n)$.
(b) Smooth the displacement field $\boldsymbol{u}(n)$: $\boldsymbol{u}(n) \leftarrow G_\sigma * \boldsymbol{u}(n)$, where G_σ is Gaussian smoothing filter.
(c) Compute the new transformation $\boldsymbol{T}(n+1) \leftarrow \boldsymbol{T}(n) + \boldsymbol{u}(n)$.

3. Method

It can be seen from Eq. (4) that only image intensity information is used in the cost function for matching under the constraint of a smooth deformation field. It is enough in some applications when the multi homologous objects in the two images do not have a large deformation. However it is insufficient in some situations. For example, if only a narrow gap exists between two objects with very similar intensities in the target image, and if one of the corresponding objects in the reference image overlaps with both the two target objects, a split problem will occur. Such situation is not a particular case and is common especially for brain deep gray structures. The final registration result might be good in visual inspection for such cases if we only see image intensities. However, if we follow up the displacements of the points on the structures, the corresponding points after the transformation could not correctly represent the structures. Therefore some complementary information must be taken into account. Features extracted by special feature extraction algorithms, such as points, lines and surfaces, are commonly used as the complementary information. The hybrid intensity and feature based techniques integrate the strengths of both intensity and feature based registration method, which would be favorite to many applications [28–30].

3.1. Combined intensity with shape non-rigid registration

An atlas of the structures superposed on the reference image, can provide a priori knowledge, such as the shapes of the structures, the relative positions between them. In common sense, homologous subcortical structures among normal subjects should have similar shapes. Therefore adding a shape similarity term in the cost function would be reasonable. To achieve the goals, an appropriate representation for the shapes of interest is important. Inspired by [10,31,32], we choose the distance transform to represent the shape of interest. The role of a distance function in improving registration quality has been mentioned in