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Accurate and robust extraction of brain regions using a deformable model based on radial basis functions

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ABSTRACT

Brain extraction from head magnetic resonance (MR) images is a classification problem of segmenting image volumes into brain and non-brain regions. It is a difficult task due to the convoluted brain surface and the inapparent brain/non-brain boundaries in images. This paper presents an automated, robust, and accurate brain extraction method which utilizes a new implicit deformable model to well represent brain contours and to segment brain regions from MR images. This model is described by a set of Wendland's radial basis functions (RBFs) and has the advantages of compact support property and low computational complexity. Driven by the internal force for imposing the smoothness constraint and the external force for considering the intensity contrast across boundaries, the deformable model of a brain contour can efficiently evolve from its initial state toward its target by iteratively updating the RBF locations. In the proposed method, brain contours are separately determined on 2D coronal and sagittal slices. The results from these two views are generally complementary and are thus integrated to obtain a complete 3D brain volume. The proposed method was compared to four existing methods, Brain Surface Extractor, Brain Extraction Tool, Hybrid Watershed Algorithm, and Model-based Level Set, by using two sets of MR images as well as manual segmentation results obtained from the Internet Brain Segmentation Repository. Our experimental results demonstrated that the proposed approach outperformed these four methods when jointly considering extraction accuracy and robustness.

1. Introduction

Brain extraction is essential or beneficial to many neuroimaging applications. For example, removal of the non-brain tissues facilitates the correction of intensity non-uniformity for magnetic resonance (MR) images (Acosta-Cabronero et al., 2008). Tissue segmentation algorithms for separating brain regions into grey matter (GM), white matter (WM), and cerebrospinal fluid (CSF) usually incorporate brain extraction as a preprocessing step to simplify the segmentation problem (Dale et al., 1999; Zhang et al., 2001; Shattuck et al., 2001). Extraction of brain regions can improve the accuracy of brain image registration by avoiding the interference of inter-subject variation of non-brain structures (Woods et al., 1998), including affine and non-rigid methods (Jenkinson and Smith, 2001; Gholipour et al., 2007; Liu et al., 2008a). In the past decade, voxel-based morphometry (VBM) (Ashburner and Friston, 2000) has been extensively applied to statistically reveal regions with significant structural discrepancy between image groups (Good et al., 2001a, b; Beyer and Krishnan, 2002; Brenneis et al., 2003; Karas et al., 2003). Recent studies indicated that accurate brain extraction can improve the validity of VBM results because of better tissue segmentation and brain registration (Fein et al., 2006; Acosta-Cabronero et al., 2008).

Brain extraction algorithms can be classified into four major classes: (1) thresholding/clustering based methods, (2) boundary-based methods, (3) deformable model methods, and (4) hybrid methods. Thresholding/clustering based methods extract brain regions according to the phenomenon that intensities of the voxels belonging to the same tissue are similar. Lemieux et al. (1999) proposed a fine-tuned algorithm which utilizes several intensity thresholds and morphological operations to remove non-brain areas. Analysis of Functional NeuroImages (AFNI) fits a Gaussian mixture model to the intensity histogram of a brain image and estimates an intensity range to segment the brain areas in a slice-by-slice manner (Cox, 1996; Ward, 1999). Hahn and Peitgen (2000) presented a watershed algorithm which uses a connectivity criterion, pre-flooding height, to group image voxels with similar intensities and then regards the largest connected component as

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the brain volume. More examples can be found in Brummer et al. (1993), Lee et al. (1998), Worth et al. (1998), Hata et al. (2000), Stokking et al. (2000), and Huh et al. (2002). Methods of this type are usually sensitive to image scanning parameters and image artifacts, such as noise and intensity inhomogeneity. Therefore, user intervention is usually required to determine proper parameters.

Boundary-based methods locate brain boundaries using the edge information obtained from image derivatives. Bomans et al. (1990) presented a semi-automated algorithm in which the brain region was manually labelled from the connected components detected with the Marr–Hildreth operator. Brain Surface Extractor (BSE) method improved the work of Bomans et al. (1990) by adaptively smoothing the noisy regions, detecting structure edges, and automatically determining the brain volume (Sandor and Leahy, 1997; Shattuck et al., 2001). In contrast to the thresholding/clustering based approaches, these methods are less sensitive to intensity inhomogeneity and scanning parameters. However, automated methods of this type may encounter difficulties in differentiating true boundaries from the false ones. For example, the GM/WM edges are usually very close to the target boundaries, the CSF/GM edges, and thus may perplex the determination of the brain volume.

Extraction methods using deformable models segment brain volumes by evolving contour or surface toward the target. Deformable model can be characterized by its representation method, implicit or explicit, and the evolution scheme (Xu et al., 2000; Montagnat et al., 2001). An explicit model directly describes the brain contour or surface and the fitting process is usually rapid (Davatzikos and Bryan, 1996; Kelemen et al., 1999; Dale et al., 1999; Smith, 2002). On the other hand, implicit model can easily change the model topology, for example, to split or merge objects, but the computational complexity is usually high. The level set method adopted in Zhuang et al. (2006) is an example of this kind of methods. Brain extraction using deformable model is generally more robust and accurate compared to the thresholding/clustering based and boundary-based methods (Smith, 2002; Ségonne et al., 2004; Zhuang et al., 2006). Moreover, incorporation of constraints or prior knowledge about the brain shape is relatively easy for this kind of methods. Therefore, they are more robust to both image artifacts and boundary discontinuities and can achieve subvoxel accuracy (Xu et al., 2000).

Hybrid approaches integrate the methods of different types with the anticipation to draw on the specific strengths at the expense of more computational cost (Atkins and Mackiewich, 1998; Aboutanos et al., 1999; Germond et al., 2000; Baillard et al., 2001; Rex et al., 2004; Mikheev et al., 2008). Ségonne et al. (2004) applied the watershed algorithm (Hahn and Peitgen, 2000) to generate an initial brain volume and incorporated the prior information of the brain shape into a deformable model to refine the extraction results. Rehm et al. (2004) integrated the extraction results obtained from atlas registration (Woods et al., 1998), intensity thresholding, and the BSE algorithm (Sandor and Leahy, 1997; Shattuck et al., 2001) by means of voting in the brain volume.

For large-scale studies, both accuracy and efficiency are important issues when considering brain extraction algorithms (Fennema-Notestine et al., 2006). The level set methods, which use implicit deformable models, are superior in accuracy and robustness, but the computational complexity of these methods is usually very high. On the contrary, methods using explicit models are generally more efficient. However, the discretization process in this kind of methods needs to compromise between the extraction accuracy and evolution efficiency. Finer (coarser) discretization employs more (fewer) sampling points to model object boundaries and can achieve more precise (rougher) results at a relatively slow (rapid) evolution speed.

In this work, we designed a new deformable model and developed an automated brain extraction method. The deformable model is implicitly represented by a set of Wendland's radial basis functions (RBFs) and can efficiently evolve toward the target boundary by iterative updates of RBF locations. Because of the use of RBFs, the new model can smoothly represent object boundaries though each RBF keeps a distance to the neighboring ones. Brain contours of 2D coronal and sagittal slices are individually fitted. The results of these two views are generally complementary and thus can be integrated to obtain accurate 3D brain volumes. According to our experiments, the proposed brain extraction method outperformed others when jointly considering extraction accuracy and robustness.

2. Methods

The proposed brain extraction method comprises three major steps, as shown in Fig. 1. Image intensity parameters and brain centroid are first estimated for the following segmentation procedures. Then the proposed deformable model is applied to extract the brain area on each of the coronal and sagittal slices. Complementary areas extracted from two different views are then integrated into a complete 3D brain volume.

2.1. Estimation of image intensity parameters and brain centroid

We estimate the effective intensity range and centroid of the head as the work of Smith (2002). An effective intensity range $[t_1, t_2]$ is determined to ignore the voxels with unusual intensities, such as noises or DC spikes, in which t_1 and t_2 are the intensity values in the histogram such that the accumulated number of voxels reaches 2% and 98%, respectively, as shown in Fig. 1. To roughly separate the head from the background, the threshold t is set to be 10% in the range of $[t_1, t_2]$. The brain centroid $\mathbf{O}$ is calculated by the first order image moment using the voxels with intensity value in the range of $[t, t_2]$.

An ellipsoid approximating the brain shape is determined by detecting the head bounding box from those voxels with intensity within $[t, t_2]$. The polar radius is set to the distance between the centroid and superior plane and the two equatorial radii are set to the halves of the distances between the opposite bounding planes, that is, the left-right and the anterior–posterior planes.

Difference of Gaussian (DOG) operator provides brain structure information which can be used for the detection of the mid-sagittal plane (MSP) of the brain (Liu et al., 2008b) and for the estimation of the brain tissue intensities. DOG performs image subtraction after the convolution with two Gaussian kernels $G(\sigma_1)$ and $G(\sigma_2)$, $\sigma_1 > \sigma_2$:

$$\mathrm{DOG}(I, \sigma_1, \sigma_2) = G(\sigma_1) * I - G(\sigma_2) * I, \tag{1}$$

where I is a T1-weighted MR image and "$*$" denotes the convolution operator. The voxels with DOG values smaller than zero are in the regions with relatively high intensities, which are mostly the WM areas in the brain. Therefore, the median intensity of these voxels within the brain-approximating ellipsoid estimates the global WM intensity, t_w. On the other hand, the regions with DOG values larger than zero indicate the tissues with relatively low intensities. These voxels within the ellipsoid are mostly the GM and CSF. We apply Otsu's algorithm (Otsu, 1979) to calculate an intensity threshold t_o for separating CSF voxels from GM voxels. The median intensity of the CSF voxels estimates the global CSF intensity, t_c.

2.2. Brain extraction on the slices in two views

Brain extraction using deformable model generally requires a constraint to keep the contour or surface smooth. Loosening this