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Automatic segmentation of neonatal images using convex optimization and coupled level sets

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ABSTRACT

Accurate segmentation of neonatal brain MR images remains challenging mainly due to their poor spatial resolution, inverted contrast between white matter and gray matter, and high intensity inhomogeneity. Most existing methods for neonatal brain segmentation are atlas-based and voxel-wise. Although active contour/surface models with geometric information constraint have been successfully applied to adult brain segmentation, they are not fully explored in the neonatal image segmentation. In this paper, we propose a novel neonatal image segmentation method by combining local intensity information, atlas spatial prior, and cortical thickness constraint in a single level-set framework. Besides, we also provide a robust and reliable tissue surface initialization for the proposed method by using a convex optimization technique. Thus, tissue segmentation, as well as inner and outer cortical surface reconstruction, can be obtained simultaneously. The proposed method has been tested on a large neonatal dataset, and the validation on 10 neonatal brain images (with manual segmentations) shows very promising results.

Introduction

Accurate segmentation of neonatal brain magnetic resonance (MR) images into white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) has important implications for normal brain development studies, as well as for the diagnosis and treatment evaluation of neurodevelepmental disorders such as autism. Manual segmentation of neonatal brain structures is tedious, time consuming, and also lacks of reproducibility. Therefore, it is necessary to develop automatic techniques for neonatal brain segmentation. However, despite of the success of segmentation methods developed for adult brain images, it still remains challenging to segment neonatal brain images due to poor spatial resolution, ambiguous tissue intensity distributions (Prastawa et al., 2005; Shi et al., 2010a), as well as different levels of inverted contrast between WM and GM at different parts of neonatal brain (Xue et al., 2007).

To obtain reliable segmentation results, atlas-based methods are widely used (Cocosco et al., 2003; Prastawa et al., 2005; Shi et al., 2010a; Warfield et al., 2000; Weisenfeld and Warfield, 2009). For example, (Prastawa et al., 2005) proposed an atlas-based approach for neonatal brain segmentation. They generated an atlas by averaging three semi-automatic segmented neonatal brain images and then adopted the expectation–maximization (EM) scheme with inhomogeneity correction to achieve tissue classification of GM, CSF, myelinated and unmyelinated WM. (Warfield et al., 2000) proposed an age-specific atlas from multiple subjects and an iterated tissue-segmentation-and-atlas-alignment strategy to improve the neonatal tissue segmentation. (Shi et al., 2010a) proposed a new framework for performing neonatal brain tissue segmentation by using a subject-specific tissue probabilistic atlas generated from the follow-up data of the same subject. Comprehensive reviews on the atlas-based segmentation methods can be referred to (Kuklisova-Murgasova et al., 2011). Most of the above-mentioned neonatal segmentation methods are voxel-wise, although neighborhood information is incorporated in some studies. Geometric information, which describes the boundary between tissue structures and also constrains the relative locations of different boundaries, is not fully explored. In fact, the geometric information can be used in tissue segmentation to manage the ambiguous tissue distributions, especially for neonatal brain images.

One of the most effective ways of incorporating geometric information for tissue segmentation is to use active contour/surface models (Gooya et al., 2008; Shi and Karl, 2008; Shi et al., 2007). These models are able to provide smooth and closed contours/surfaces as final segmentation, which is not guaranteed in voxel-based segmentation methods. In fact, geometrically, the human cerebral cortex is a thin, folded sheet of GM, with a nearly constant thickness at a range of [1 5]mm for neonatal brains. To obtain a detailed geometric representation of the cortex, many algorithms have been proposed using

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explicit or implicit surface representation (Goldenberg et al., 2002; Han et al., 2004; MacDonald et al., 2000; Xu et al., 1999; Xue et al., 2007; Zeng et al., 1999). In these methods, adaptive fuzzy c-means (AFCM) algorithm (Pham and Prince, 1999) or EM–MRF segmentation scheme (Xue et al., 2007) are typically used to obtain an initial tissue classification, or local boundary indicator functions to derive the inner and outer interfaces of cortex (Zeng et al., 1999). Then, the tissue classification or interfaces of cortex are transformed into surface tessellation and the surfaces are further deformed with a self-intersection checking, smooth regularization, or thickness constraint. However, there are two main drawbacks for these methods. First, the initial segmentation is crucial to the final result. If the initial segmentation is not good enough, the errors are difficult to be corrected during the surface evolution procedure. In this way, the final result can be not accurate as well. Second, the AFCM algorithm and EM algorithm are sensitive to the initialization and typically converge to a local optimum (Dempster et al., 1977; Vovk et al., 2007), and also the local boundary indicator functions are sensitive to the image noise.

In this paper, we proposed a novel framework for neonatal image segmentation based on convex optimization and coupled level sets. We first use a convex optimization to derive a preliminary segmentation, which then forms an initialization for the following coupled level sets. Finally, the coupled level sets are constructed by refining the surfaces defined on the boundaries among WM, GM, CSF, and background, which will further segment the neonatal brain image based on the local intensity information, atlas spatial prior, and cortical thickness constraint. In contrast to the methods in (Goldenberg et al., 2002; Han et al., 2004; MacDonald et al., 2000; Xu et al., 1999; Xue et al., 2007; Zeng et al., 1999), our framework allows for random initialization. Even when the preliminary segmentation is in question, the following coupled level sets can still robustly locate the correct boundaries.

Method

In this paper, we present a novel surface-based segmentation method, utilizing local intensity information, atlas spatial prior, and cortical thickness constraint, for segmentation of neonatal MR brain images in to GM, WM, and CSF. We adopt the local Gaussian distribution fitting (LGDF) energy (Wang et al., 2009), which describes local image intensities by Gaussian distributions with different means and variances. The means and variances of local intensities are spatially varying functions, which enable the model to deal with intensity inhomogeneities. A prior knowledge from atlases is then combined with the LGDF energy to regularize the segmentation and further increase the ability in handling the inhomogeneities. Based on the fact that the cortex has a nearly constant thickness, a constraint of cortical thickness can provide useful geometric information to guide more accurate segmentation. Accordingly, these three terms are finally incorporated into the coupled level sets in such a way that the surfaces are driven by the LGDF and spatial prior, while the distance between the inner and the outer surfaces of cortex remains within a predefined range by an additional cortical-thickness constraint term. We also propose a novel initialization method for this coupled level sets by using convex optimization, which allows for the random initializations. The contributions of this paper are two-fold:

a) we propose a novel coupled-level-sets based neonatal image segmentation method by combining local intensity information, atlas spatial prior, and cortical thickness constraint in a level-set framework.
b) we propose a robust initialization based on the convex optimization for the coupled level sets by using the global image statistical information and atlas spatial prior.

An overview of the proposed framework is shown in Fig. 1. The framework consists of three steps: (1) Preliminary segmentation for CSF, WM and GM, as shown in the left panel of Fig. 1; (2) Partial Volume (PV) removal and correction of the mislabeled CSF from WM, as shown in the bottom panel; and (3) Coupled level sets based segmentation, as shown in the top-right panel. Steps (1) and (2) form an initialization for the step (3). For better emphasizing our contribution, we will first introduce step (3) in Section 1, and then

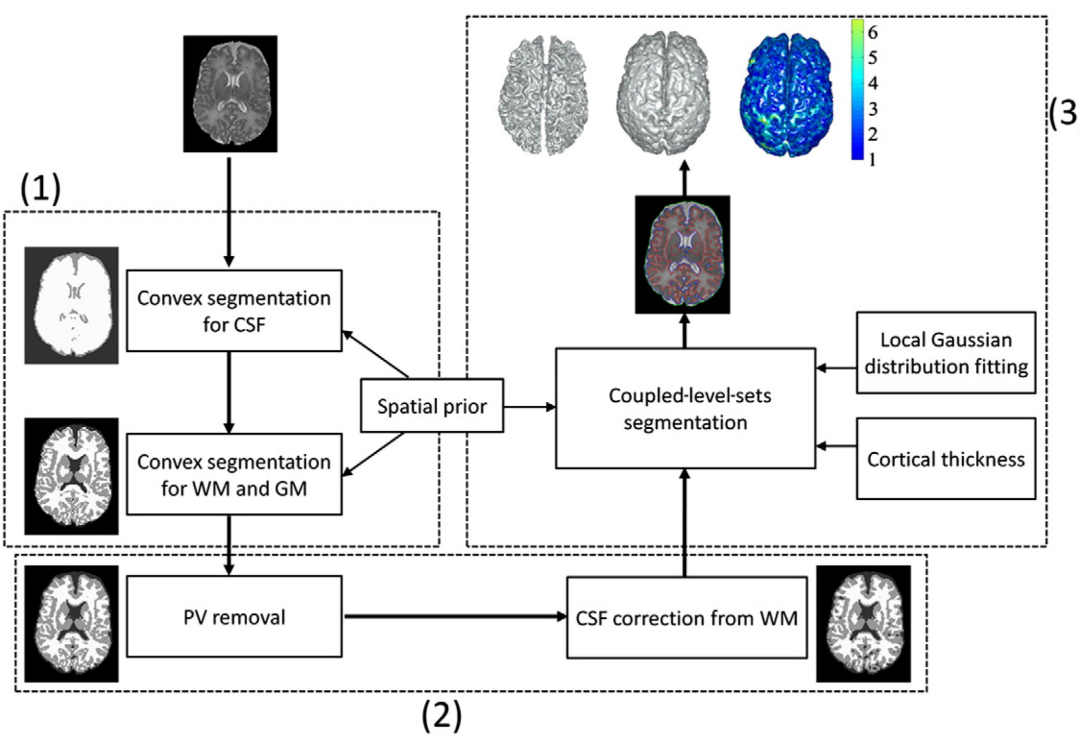

Fig. 1. The proposed framework for neonatal brain segmentation.