Automatic multi-label segmentation of the preterm brain with the use of adaptive atlases

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Background

Brain growth between 25 weeks gestational age (GA) and term is rapid and encompasses changes in signal intensity in white matter, brain volume and cortical folding. MRI is being used increasingly to assess brain development in preterm infants. However, the significant changes in shape and size associated with development present a challenge for accurate segmentation of MR images obtained in the preterm period. Automatic segmentation of brain MR data sets can be achieved in an atlas-based fashion when authoritatively segmented atlases are available. In atlas-based segmentation methods, the MR images of the atlases are non-rigidly registered to the subject's image and their labels are propagated to it. When multiple atlases are used, their labels can be combined by vote fusion [1]. Alternatively, the transformed labels can be averaged to yield probabilistic priors. Using a probabilistic framework the priors can then be utilised for intensity-based segmentation, e.g. by using Expectation-Maximization (EM) [2] or graph-cut segmentation [3]. A major limitation is the inaccuracy when segmenting brains that deviate significantly from manually labelled atlases. This is because atlas-based segmentation techniques rely on the registration process to propagate their labelling. To account for such registration errors prior relaxation techniques have been proposed [4,5] that adapt the atlases' priors according to the image intensities. We present an automatic segmentation technique for segmenting the developing preterm brain with the use of EM and adaptive atlases.

Materials and Methods

In this study we adopt an EM scheme that combines an atlas prior with intensity information from the image to be segmented. The source atlases were manual labellings by an expert of T1w brain MRIs from 20 neonates of median GA 40^{+6} (range: 36^{+4} to 44^{+6}) weeks (Ioannis Gousias PhD thesis, [6]). The atlases divide the brain into 50 cortical and subcortical regions. The atlas labels are propagated to each subject's image and are used to form a probabilistic spatial prior for each structure. The intensities of the target image being labelled are modelled as a mixture of Gaussians, with one Gaussian characterizing each structure. As the manual segmentation protocol does not provide a differentiation of the cortical structures into white matter (WM) and gray matter (GM), these structures contain both tissues. Therefore, for a single Gaussian intensity model to describe each structure, we divided each cortical structure into its corresponding tissue parts (WM, GM) in the subject space. The tissue types were parcellated using the automatic tissue segmentation approach described in Xue et al [7]. This technique further models and removes the partial volume effect caused by the presence of unmyelinated WM in the neonatal brain images. This is important as in neonatal T2 images many voxels on the borders of cerebrospinal fluid (CSF) and GM have similar intensities to WM and can be incorrectly classified as the latter. The final structures included 18 subcortical structures and 32 cortical structures divided into WM and GM, as well as the CSF and background which are both removed after the initial segmentation (they are not regions of interest in this study). This forms a multi-label segmentation problem of dividing the brain into 84 structures of interest.

The initial labelling by the atlases is not generally highly accurate in this population, particularly when term-equivalent and late preterm atlases are propagated to early preterm brains, which have grossly different anatomy, especially around the cortex. To compensate for this, the priors are adapted with a relaxation process that uses the image intensities. The adaptation is performed by employing a Dirichlet prior for the described intensity model [4,5].Our probabilistic framework further includes intensity non-uniformity correction [8] and imposes spatial label constraints with a Markov Random Field model as described in [4]. Results from our EM approach were presented to an observer blinded to the processing method who compared them visually to those from a label fusion approach.

Subjects

The proposed segmentation scheme was applied to 39 subjects with age ranging from 27^{+6} to 32^{+3} weeks GA (30^{+4} weeks median GA).

Results

The experiments showed significant improvement over label fusion. Figure 1 presents example segmentations of neonates at 28 weeks (A) and 32 weeks GA (B). The propagated labels within our framework are clearly refined in terms of intensity (more visible around the cortical boundary of the brain, white arrows) and at the same time regions that are problematic for the registration are corrected (more visible around the ventricles, purple arrows). The method produced segmentations that were judged more accurate than simple label fusion in all cases.

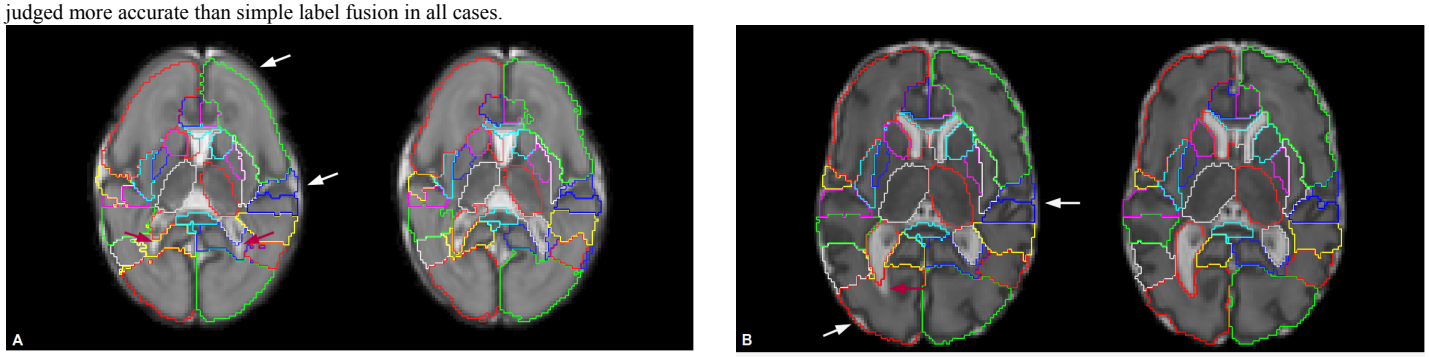

Fig.1.T2 MRIs of a 28 and 32 weeks GA brain with labels overlaid.The labels are estimated with label fusion(left images) and the proposed EM scheme (right images).

Conclusion

We have presented a EM segmentation approach that allows expert manually defined labels at term equivalent age to be propagated onto brain MR images obtained at younger GAs, which will allow the assessment of regional brain growth and development in this vulnerable population.

References

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