Indian Journal of Science and Technology, Vol 9(28), Doi: 10.17485/ijst/2016/v9i28/94245, July 2016
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Hybrid Method for Brain Tissue Classification in Magnetic Resonance Images of Children

Chelli N. Devi[1*], Anupama Chandrasekharan[2], V. K. Sundararaman[3] and Zachariah C. Alex[1]

[1]School of Electronics Engineering, VIT University, Vellore - 632014, Tamil Nadu, India; chelli@rocketmail.com, zcalex@gmail.com

[2]Department of Radiology, Sri Ramachandra University, Chennai - 600116, Tamil Nadu, India; radanupama@yahoo.com

[3]Philips Innovation Centre, Bangalore - 560045, Karnataka, India; vk_sundar@rediffmail.com

Abstract

Background: Automatic brain tissue classification in children is tedious owing to motion artifacts, rapid brain maturation, etc. Considering this, we propose a hybrid approach for tissue classification. **Methods:** This approach utilizes atlas-free technique for brain extraction and labeling of Cerebrospinal Fluid and subsequent atlas-based method for classification of Gray and White Matter tissues. The results for brain, Gray Matter, White Matter and Cerebrospinal Fluid are validated quantitatively using Dice ratio. **Findings:** Mean Dice values of 0.9767 for brain, 0.8503 for Gray Matter, 0.7850 for White Matter and 0.8224 for Cerebrospinal Fluid are achieved. This signifies excellent agreement since Dice values for all tissues are much above the accepted similarity level of 0.7. **Applications:** The automatic tissue classification can be used to carry out volumetric tissue computations to understand brain maturation in childhood.

Keywords: Child's Brain, Hybrid Approach, Magnetic Resonance Imaging, Tissue Classification

1. Introduction

Automatic brain segmentation and tissue classification in Magnetic Resonance (MR) images is tedious, particularly in children. This is caused by numerous reasons like low contrast, motion artifacts, changing dynamics of the brain in children, etc. Further, the available brain tissue classification techniques in literature for children are typically atlas-based or atlas-free i.e., either they employ an atlas/template or are independent of brain atlases. Atlas-based techniques permit classification of tissues that have overlapping intensities and textural features; nonetheless, this approach best suits only the images with identical anatomy and age as the atlas. In contrast, atlas-free techniques have a broader scope for application including atypical and abnormal brain images but they entail several sequential operations making the process cumbersome. Hence, we have proposed a hybrid method i.e., integrating atlas-based and atlas-free techniques for classifying brain tissue in children.

Nevertheless we sum up the important aspects of other available techniques to provide an overview of the literature. It should be noted that though various researchers have explored different facets of adult brain classification[1–3], interest in brain tissue classification of children is fairly recent. Of these, Murgasova[4] described an atlas-based method combining registration and intensity-based approaches. Similarly, Aljabar[5] applied registration and segmentation techniques on serial brain image data of young children. Whereas Li et al.[6] reconstructed cortical surfaces from longitudinal data based on a deformable surface method. Wang et al.[7] presented a multimodal, level set based method for tissue segmentation in serial images. Later, Wang et al.[8] formulated the 'LINKS' method for integrating features from multi source images using the random forest method. Besides, following are the commonly employed brain atlases and templates for children. Sanchez et al.[9] constructed average, age-specific brain templates for children in the age

*Author for correspondence

range 2 weeks to 4 years. Further, Shi et al.[10] created atlases for neonates, 1 and 2 years old children based on longitudinal data. Additionally, Altaye et al.[11] constructed brain probability templates for infants aged between 9 to 15 months and Bhatia et al.[12] built average atlases of premature infants aged 1 and 2 years.

In this context, the proposed hybrid technique utilizesan atlas-free approach for brain extraction and Cerebrospinal Fluid (CSF) labeling, followed by atlas-based method for Gray Matter (GM) – White Matter (WM) tissue classification. The technique is explicated in the methodology section. Subsequently, we present the results and discussion and the conclusion.

2. Methodology

2.1 Preprocessing

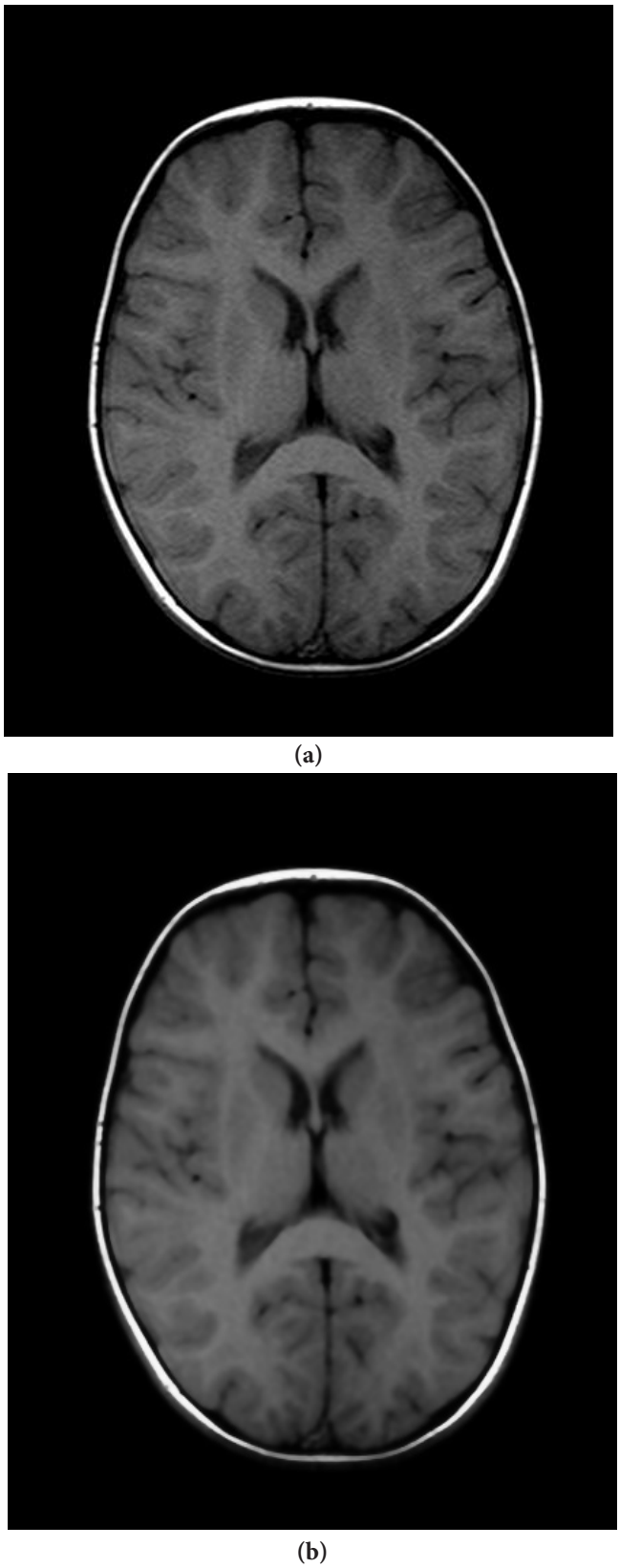
Axial T1 images from the Interactive digital MR atlas of the pediatric brain by[13] were employed as input. The images are preprocessed by anisotropic diffusion filtering; this filter preserves edges and favors within-region smoothing as opposed to across-boundary smoothing[14]. The input image and corresponding filtered image are portrayed in Figure 1.

2.2 Brain Extraction and CSF Labeling

The proposed hybrid method employs an atlas-free technique for brain extraction and CSF labeling based on intensity information. For this, we use the bi-level OTSU thresholding to separate the three tissue components or classes in the T1 image. The different components, in the order of increasing intensities, are given by: the CSF, brain tissue (i.e., GM and WM combined) and the skull. To isolate the skull, we obtain the pixels with intensity larger than the OTSU threshold . Subsequent to skull stripping, all pixels with intensity less than the OTSU threshold are labeled as the CSF. Successively, the brain is extracted by masking out the identified skull and CSF components. Figure 2 displays the result of skull, CSF and brain tissue labeling.

2.3 GM–WM Tissue Classification

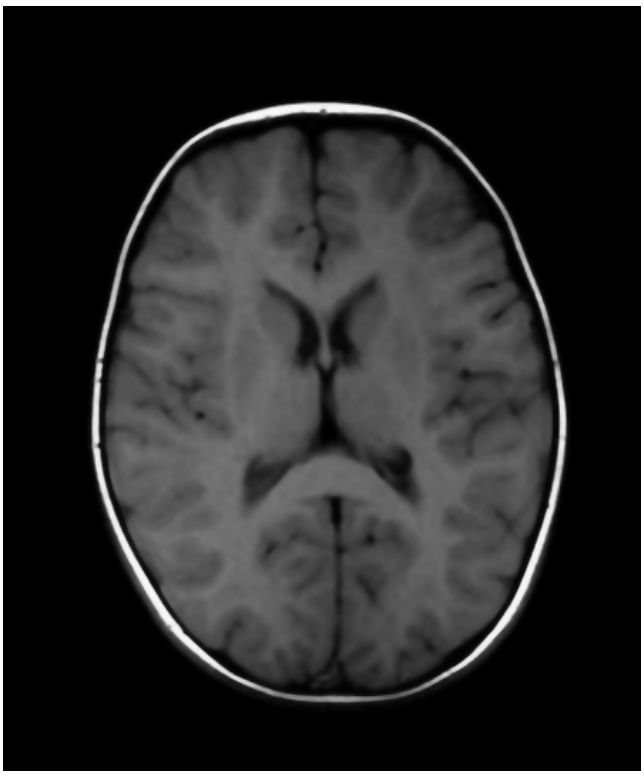
Following the atlas-free method of brain extraction and CSF labeling, we perform an atlas-based GM–WM tissue classification. For this, the 1 and 2 years old atlases of[10] are used. The atlas that closely matches the subject's



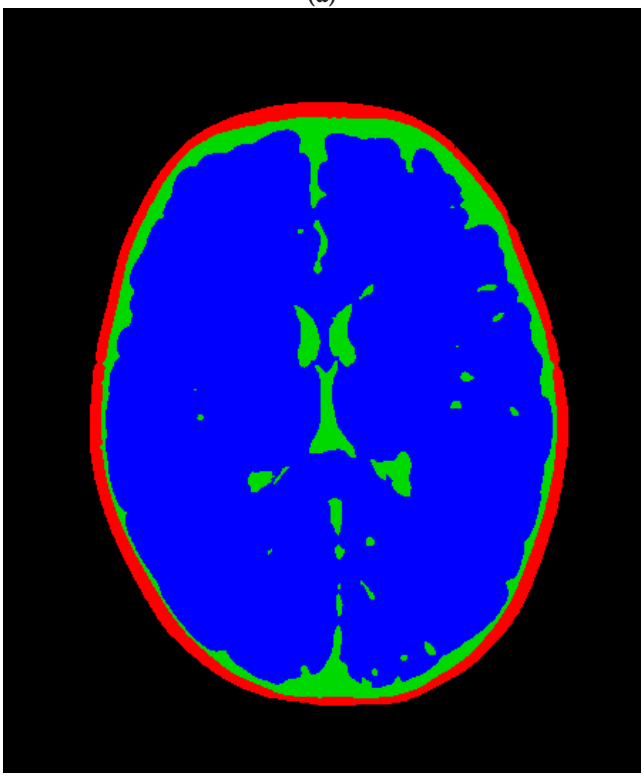
(a)

(b)

Figure 1. **(a)** Input image. **(b)** Corresponding preprocessed image.



(a)



(b)

Figure 2. **(a)** Preprocessed T1 image. **(b)** Corresponding labeled image (red – skull, green – CSF, blue – extracted brain).

age is chosen and non-rigidly registered based on mutual information[15]. Subsequently, the probability maps for GM and WM are warped onto subject space. This is followed by hard segmentation to assign distinct labels to each brain pixel. Figure 3 indicates the extracted brain and corresponding segmented image.

2.4 Validation of Results

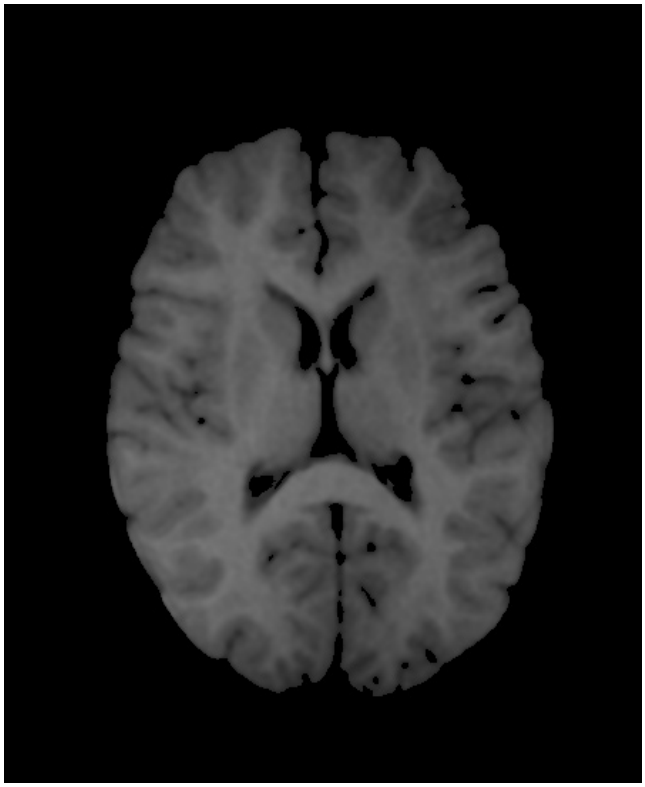
The tissue classification results are validated visually by radiologists. Furthermore, quantitative validation is achieved based on corresponding manual segmentations using Dice ratio. The Dice ratio between automatic and manual segmentations is represented as:

$$Dice\ ratio = \frac{2\,|autoseg \cap manseg|}{|autoseg| + |manseg|} \quad (1)$$

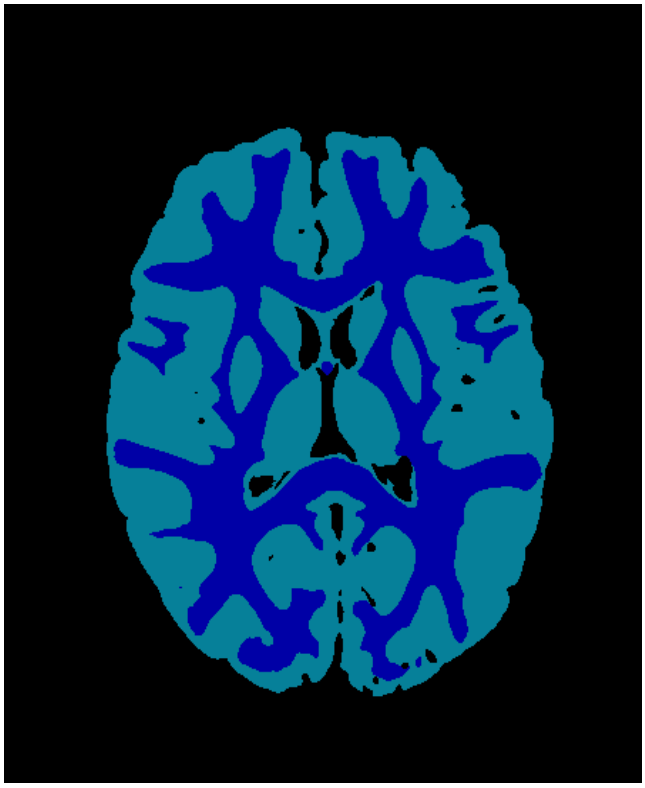
Dice ratios are computed for the brain tissue (i.e., GM and WM combined), GM, WM and CSF.

3. Results and Discussion

The results of hybrid tissue classification and manual segmentation are compared in Figure 4. Further, we present the quantitative results for hybrid classification by way

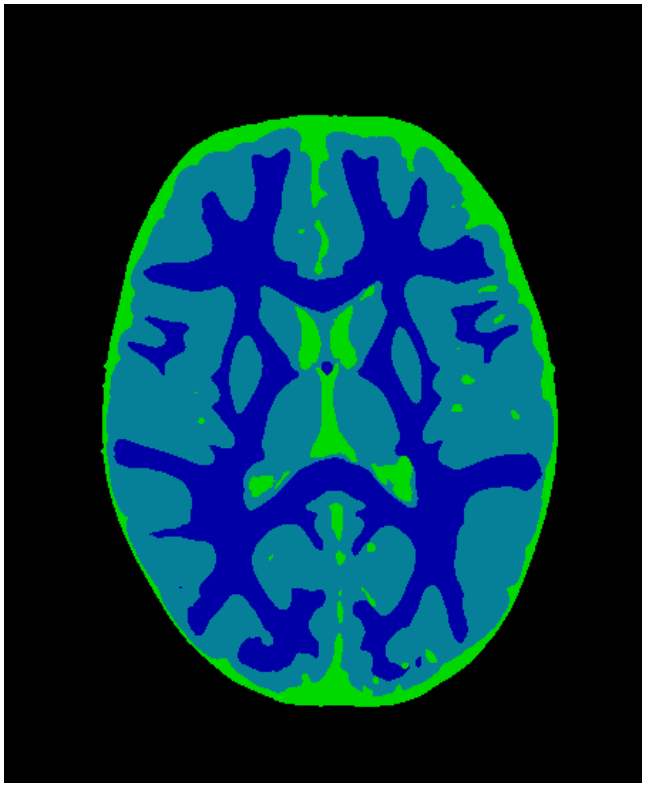


(a)

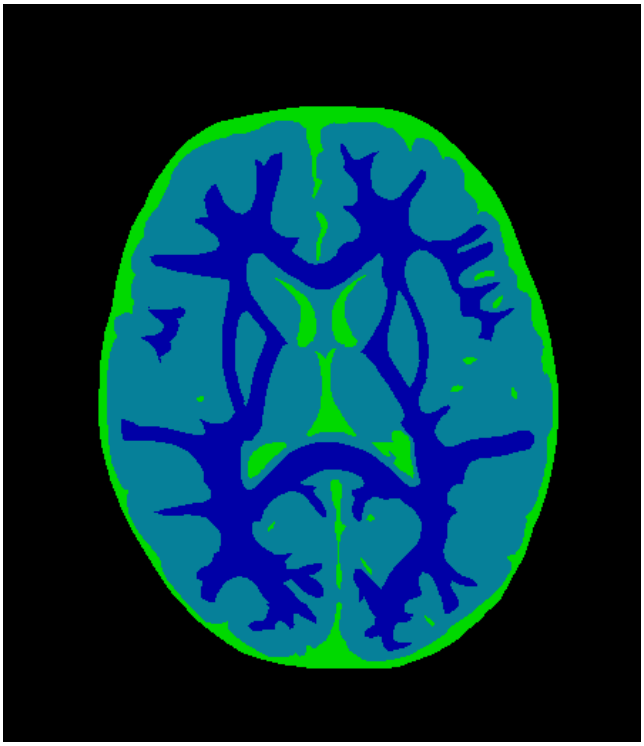


(b)

Figure 3. **(a)** Extracted brain. **(b)** Segmented image showing GM and WM (light blue – GM, dark blue – WM).



(a)



(b)

Figure 4. **(a)** Hybrid tissue classification. **(b)** Manual segmentation (green – CSF, light blue – GM, dark blue – WM).

of Dice ratios. The mean and standard deviations for the brain, GM, WM and CSF are provided in Table 1. It is seen that mean Dice ratios of 0.9767 for the brain (GM and WM put together), 0.8503 for GM, 0.7850 for WM and 0.8224 for CSF are achieved.

We interpret the results of hybrid tissue classification as follows. It is seen visually from Figure 4 that the brain, CSF, GM and majority of WM are classified accurately by the hybrid segmentation. Small differences in peripheral extensions of WM can be attributed to the slight age gap and possible structural dissimilarities between atlas and subject. This is also reflected in the numeric Dice values. We infer from Table 1 that larger mean Dice ratios are attained for brain, GM and CSF compared to WM. Nonetheless the mean Dice ratio for WM is larger than 0.7; this is noteworthy because similarity above 0.7 signifies excellent agreement[16].

4. Conclusion

Thus we have presented a hybrid approach for brain tissue classification in children. This method involves an

Table 1. Dice ratios for hybrid tissue classification

	Brain	GM	WM	CSF
Mean	0.9767	0.8503	0.7850	0.8224
Standard Deviation	0.0068	0.0152	0.0080	0.0188

atlas-free technique for brain extraction and CSF labeling and subsequent atlas-based procedure for GM–WM tissue classification. The hybrid approach achieves good results with mean Dice ratios above 0.7 at all tissues. In future, the proposed technique can be expanded to carry out volumetric tissue computations to better understand brain maturation in children.

5. References

1. Naik PPS, Gopal TV. Quantitative analysis and segmentation of metastasis brain images using hybrid mean shift clustering. Indian Journal of Science and Technology. 2015; 8(35):1–10.
2. Naveen A, Velmurugan T. Identification of calcification in MRI brain images by k-means algorithm. Indian Journal of Science and Technology. 2015; 8(29):1– 7.
3. Sasirekha N, Kashwan KR. Improved segmentation of MRI brain images by denoising and contrast enhancement. Indian Journal of Science and Technology. 2015; 8(22):1–7.
4. Murgasova MK. Segmentation of brain MRI during early childhood [PhD thesis]. Department of Computing, Imperial College London; 2008.
5. Aljabar P. Tracking longitudinal change using MR image data [PhD thesis]. Department of Computing, Imperial College London, University of London; 2007.
6. Li G, Nie J, Wang L, Shi F, Gilmore JH, Lin W, Shen D. Measuring longitudinally dynamic cortex development in infants by reconstruction of consistent cortical surfaces. IEEE 10th International Symposium on Biomedical Imaging: From Nano to Macro; San Francisco, CA, USA. 2013. p. 1380–3.
7. Wang L, Shi F, Yap PT, Gilmore JH, Lin W, Shen D. 4D multi-modality tissue segmentation of serial infant images. PLoS ONE. 2012; 7(9).
8. Wang L, Gao Y, Shi F, Li G, Gilmore JH, Lin W, Shen D. LINKS: Learning-based multi-source integration framework for segmentation of infant brain images. NeuroImage. 2015; 108:160–72.
9. Sanchez CE, Richards JE, Almli CR. Neurodevelopmental MRI brain templates for children from 2 weeks to 4 years of age. Dev Psychobiol. 2012; 54(1):77–91.
10. Shi F, Yap PT, Wu G, Jia H, Gilmore JH, Lin W, Shen D. Infant brain atlases from neonates to 1- and 2-year-olds. PLoS ONE. 2011; 6(4).
11. Altaye M, Holland SK, Wilke M, Gaser C. Infant brain probability templates for MRI segmentation and normalization. NeuroImage. 2008; 43(4):721–30.
12. Bhatia KK, Aljabar P, Boardman JP, Srinivasan L, Murgasova M, Counsell SJ, Rutherford MA, Hajnal J, Edwards AD, Rueckert D. Groupwise combined segmentation and registration for atlas construction. MICCAI 2007, Part I, Lect Notes Comput Sci. 2007; 4791:532–40.
13. Jelacic S, de Regt D, Weinberger E. Interactive digital MR atlas of the pediatric brain. Radio Graphics. 2006; 26(2):497–501.
14. Perona P, Malik J. Scale-space and edge detection using anisotropic diffusion. IEEE Pat Anal Mach Intel. 1990; 12(7):629–39.
15. Myronenko A. Non-rigid image registration: Regularization, algorithms and applications [PhD thesis]. Department of Science and Engineering, School of Medicine, Oregon Health and Science University; 2010.
16. Zijdenbos AP, Dawant BM, Margolin RA, Palmer AC. Morphometric analysis of white matter lesions in MR images: Method and validation. IEEE Trans Med Imag. 1994; 13(4):716–24.