

# Robust automatic rodent brain extraction using pulse-coupled neural networks in 3D

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## Introduction

Brain extraction is an important preprocessing step for registration and morphometric analyses [1]. Due to the time-consuming nature of manual extraction, development of automated or semi-automated methods is essential for large-scale studies. While automatic methods are available for the human brain, they often perform poorly on rodent brains due to differences in shape and size of the brains. There is a growing need for algorithms that are optimised for rodent brains in the study of animal models of disease. Yet to date, little work has been done on rodent brain-extraction [2,3].

The pulse-coupled neural network (PCNN) is a neural-network based binary classification algorithm which iteratively ‘links’ pixels with similar intensity. Recently, Murugavel et. al. applied a PCNN algorithm to successive coronal slices of rat head MRI, showing improved performance over existing brain-extraction algorithms [2]. However, this method is cumbersome when applied to 3D datasets and fails in anterior slices, where the eyes are larger than the olfactory lobe. We introduce a 3D PCNN method that overcomes this limitation while improving performance.

## Method

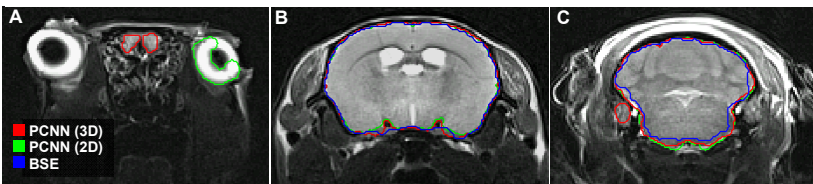
MRI of five C57BL6 mice were acquired on a Bruker 7T ClinScan using a 2D T2w TSE sequence (TR/TE=2710/42ms, voxel size=100x100x300µm). The volume is first corrected for bias field using the N3 algorithm in MIPAV [4]. PCNN is then applied to the MRI volume, with each iteration including the pixels highlighted by earlier iterations. For each iteration, morphological opening is used to break narrow connections between regions, and the region with the largest volume is selected as the brain mask. A plot is made of region size against iteration number, known as the image signature (Fig 1). The optimal iteration can be found in the ‘plateau’ region just before a rapid increase in volume of the mask.

Three automated methods were compared: The PCNN algorithm in 2D (by coronal slices) and 3D mode (whole volume) and the Brain Surface Extraction (BSE) algorithm in BrainSuite09 [5]. Manually extracted brain-masks drawn with reference to the Paxinos & Franklin atlas [6] were used as a gold standard. Three indices were used to measure similarity between the automated methods ( $M_{auto}$ ) and the manual standard ( $M_{manual}$ ): the Jaccard index, True-positive rate (TPR) and False-positive rate (FPR), as defined below:

$$\text{Jaccard Index} = \frac{M_{auto} \cap M_{manual}}{M_{auto} \cup M_{manual}} \quad \text{TPR} = \frac{M_{auto} \cap M_{manual}}{M_{manual}} \quad \text{FPR} = \frac{M_{auto} - M_{auto} \cap M_{manual}}{\text{Total Vol} - M_{manual}}$$

## Results

Both the 3D and 2D PCNN methods performed better than BSE (Figs 2,3), with significantly higher Jaccard index and TPR ( $p < 0.006$ , paired 2-tailed t-test). The FPR (not shown) was comparable among the 3 methods. Compared to the 2D PCNN, the 3D mode had a higher TPR but also a slightly higher FPR. Although the t-test was not significant, we observed that the TPR of 3D mode was higher than 2D mode for all 5 datasets.

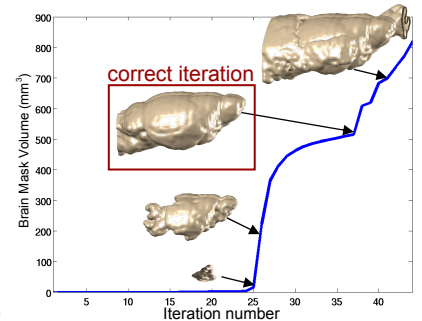


**Fig 2.** Outlines of brain masks in three coronal slices. **A.** *Olfactory bulb*: PCNN (2D) detects the eye instead of brain and BSE fails to detect anything. **B.** *Hypothalamus, thalamus, cerebral cortex*: PCNN methods show slight improvement over BSE. **C.** *Cerebellum & brainstem*: PCNN methods show significant improvement over BSE.

individual selection is required for every slice. Furthermore, in all but the center slices, the 2D image signature does not show a clear ‘plateau’ region, making it difficult to determine the correct iteration. In contrast, 3D mode in all cases gave a well defined image signature like the one shown in Fig 1, and knowledge of brain volume (e.g., 450-550 mm<sup>3</sup> for adult mice) can be used to further aid selection of the correct iteration. Although 3D PCNN inevitably has a higher computational complexity due to whole volume processing, it is still preferable to 2D mode due to its more consistent performance and minimal requirement for user intervention. This method will enable easy application of automatic registration and morphometric analysis methods to rodent brains.

## References

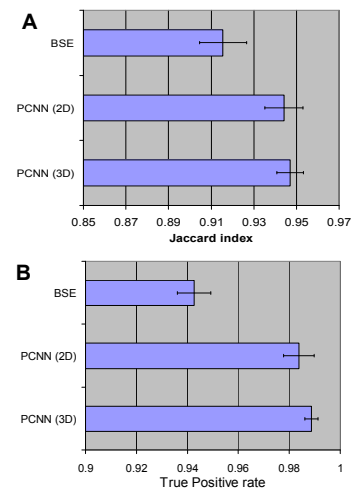
- [1] C.Fennema-Notestine *et al*, Human Brain Mapping. 27 (2006) 99-113 [2] M. Murugavel *et al*, Neuroimage. 45 (2009) 845-854 [3] M.G. Uberti *et al*, J. Neuroscience Methods. 179 (2009) 338-344 [4] J.G. Sled *et al*, IEEE TMI. 17 (1998) 87-97 [5] Shattuck *et al*, Medical Image Analysis. 6 (2002) 129-142 [6] G. Paxinos *et al* (2004)



**Fig 1.** Typical image signature of a mouse head volume. Surface plots of brain masks at selected iterations (25,26,37,41) are shown..

## Discussion

The 3D PCNN not only offers improvements over 2D mode in terms of TPR and Jaccard index, it has the added advantage that optimal extraction involves only one iteration selection for the entire volume. In 2D PCNN, an



**Fig 3.** Average (A) Jaccard index (B) True positive rate over 5 datasets.