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3D-brain Segmentation using Deep Neural Network and Gaussian Mixture Model

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Introduction

- Automatically segmenting important brain tissues such as gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) from high-quality magnetic resonance images (MRI) has played a crucial role in clinical diagnostics and neuroscience research for helping to assess many diseases.
- We propose a novel method utilizing Gaussian Mixture Model (GMM), Convoluion neural network (CNN) and Deep Neural Network (DNN) to classify each voxel of 3D MRI brain images.
- The empirical results on the dataset IBSR 18 [4] show that our proposed method outperforms 13 states-of-the-art algorithms, surpassing all the other methods by a significant margin.

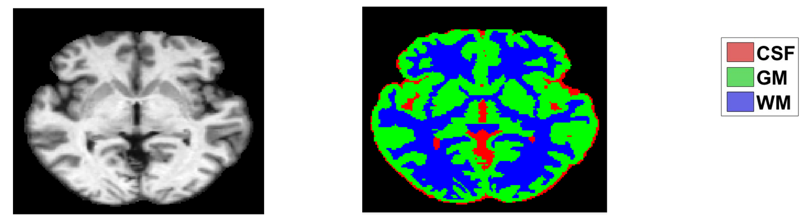

Figure 1. Left: Input MR image. Right: Output brain tissues segmented.

Proposed method

System overview

- We divide voxels into two groups of certain (easy-to-classify) voxels and uncertain (hard-to-classify) voxels using the uncertain-voxel detector.
- The certain voxels are classified using the GMM.
- The uncertain voxels are classified using a DNN.

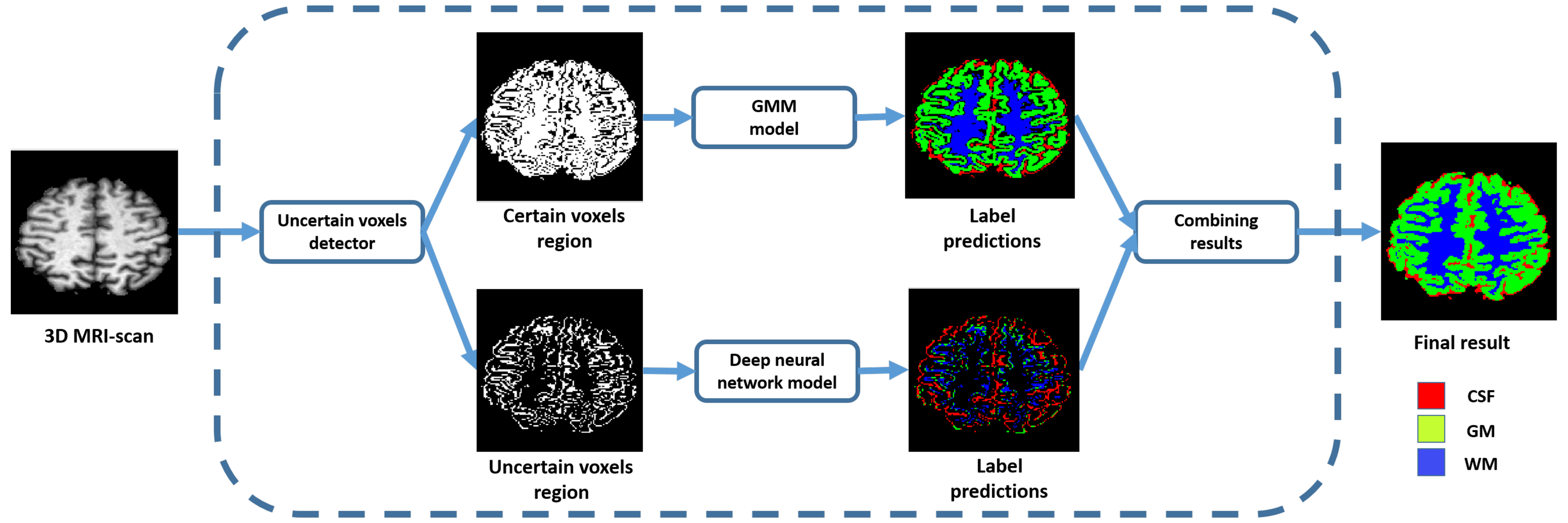

Figure 2. The system's flow chart.

Gaussian Mixture Model for certain voxels

- The histogram of intensity of voxels of each brain region (as shown in Figure 3) has the shape of a normal distribution and peaks of these three histograms are obviously seperated.
- Using GMM to capture the shapes of intensity distribution of three brain regions' voxels. The parameters are optimized by the Expectation Maximization algorithm.
- Applying the trained model to classify new voxels.

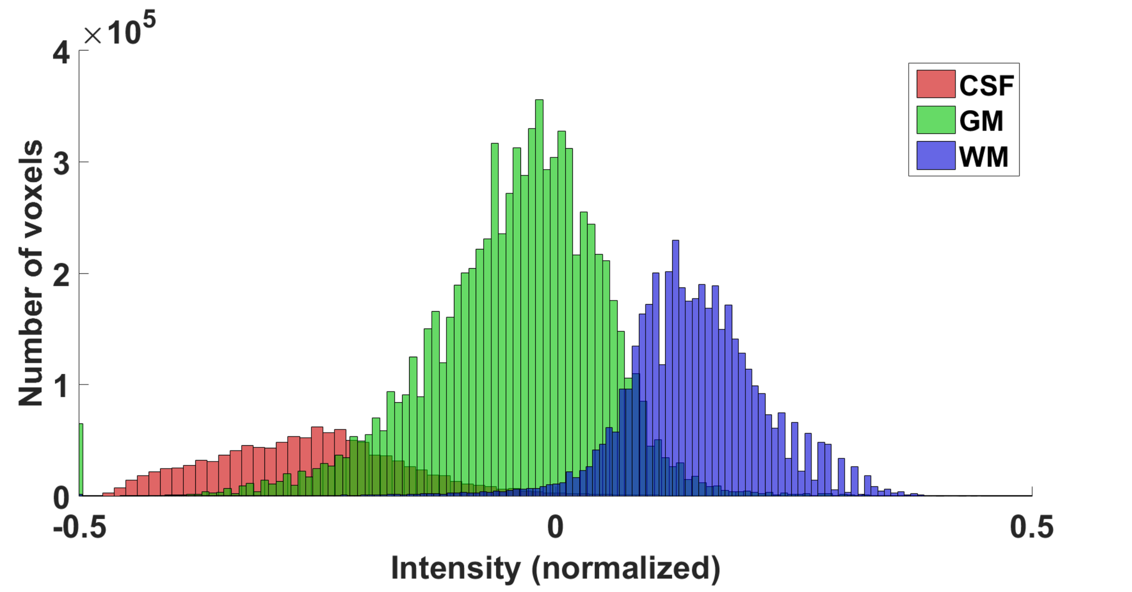

Figure 3. Intensity histograms of each tissue type collected from the training dataset.

Uncertain-voxel detector

- A combination of CNN and DNN is used to classify a voxel to be certain/uncertain voxel based on the information including intensity and coordinates of itself and its surrounding voxels in the grayscale MRI.
- "Certain"/"Uncertain" label is assigned to voxels that are correctly/incorrectly predicted by the GMM.
- Training dataset is created by applying the GMM on training data to determine voxels predicted correctly / incorrectly.
- The architecture of this combination can be described in Figure 4. The input features are the intensity of surrounding voxels (along 3 axes) and normalized coordinates of the predicted voxels. The output layer has the size of two, indicating the prediction of certain/uncertain voxels.
- Usually, a testing brain is predicted to has approximately 78% of certain voxels and 22% of uncertain voxels.

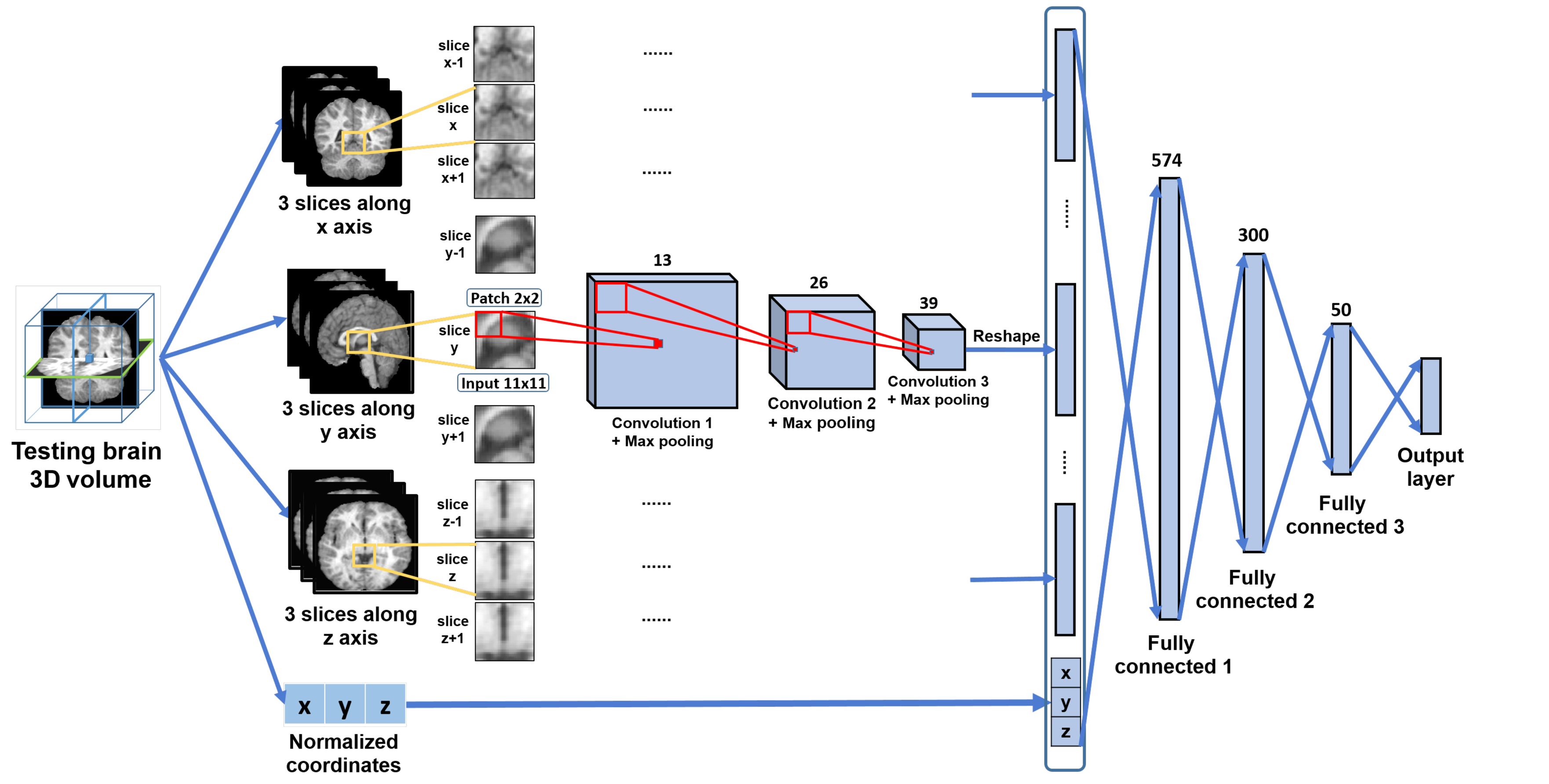

Figure 4. Feature extraction step and our deep neural network structure.

Deep Neural Network for uncertain voxels

- Another combination of CNN and DNN is used to classify a voxel to be in GM/WM/CSF class, also based on the information including intensity and coordinates of itself and its surrounding voxels in the grayscale MRI.
- The corresponding architecture is as same as the uncertain-voxel detector's. However, the output layer has the size of three (for GM/WM/CSF prediction).

Experiments and Results

- Evaluating on the dataset IBSR 18 [4] with Dice coefficients of the ground truth and predictions:

$$Dice(V_{gt}, V_{pd}) = \frac{2|V_{gt} \cap V_{pd}|}{|V_{gt}| + |V_{pd}|}$$

- Our method outperforms other 13 state-of-the-art methods [1-3] in the literature (Table 1).

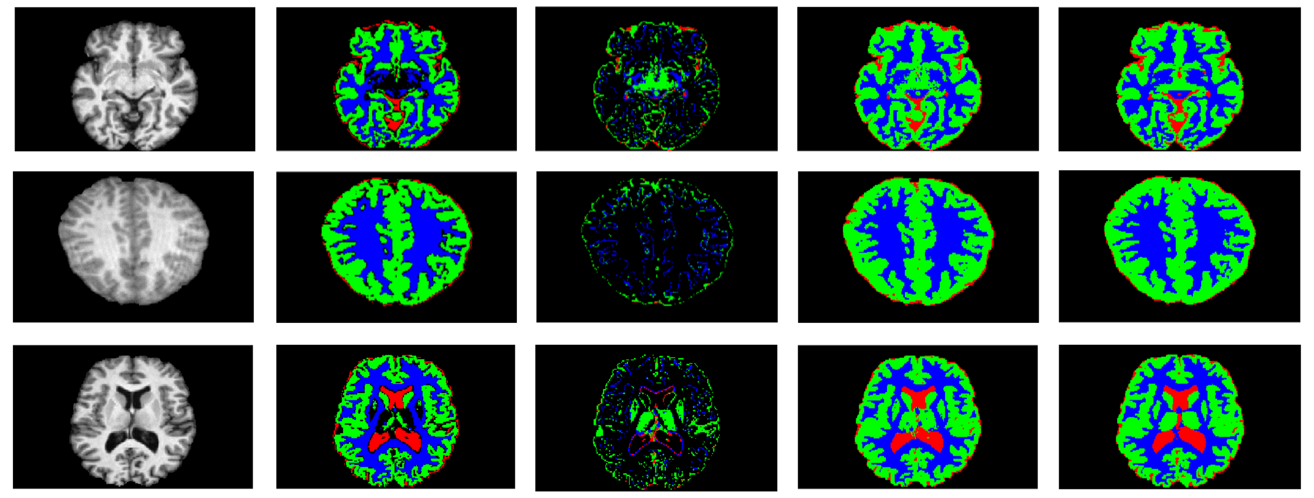

Figure 5. Examples of results of our method on the IBSR 18 dataset. From left to right: MRI, predictions from GMM for certain voxels, predictions from deep neural network for uncertain voxels, combinations of the two predictions, and the ground truth.

Table 1. Results of different methods in IBSR 18 dataset.

Method	CSF	GM	WM	Average
Proposed	0.79 ± 0.03	0.91 ± 0.03	0.90 ± 0.01	0.86
SITDS	0.67 ± 0.03	0.86 ± 0.01	0.89 ± 0.02	0.80
ITDS	0.60 ± 0.05	0.81 ± 0.03	0.86 ± 0.02	0.75
3L-GMM	0.57 ± 0.19	0.92 ± 0.02	0.87 ± 0.03	0.78
MI	0.52 ± 0.08	0.79 ± 0.04	0.80 ± 0.03	0.70
KNN	0.46 ± 0.16	0.87 ± 0.03	0.86 ± 0.03	0.73
SVPASEG	0.57 ± 0.13	0.90 ± 0.01	0.87 ± 0.02	0.78
SPM8	0.77 ± 0.08	0.91 ± 0.01	0.88 ± 0.01	0.85
WPNN	0.63 ± 0.03	0.83 ± 0.02	0.87 ± 0.03	0.77
GAMIXTURE	0.52 ± 0.15	0.89 ± 0.03	0.87 ± 0.02	0.76
ANN	0.52 ± 0.15	0.87 ± 0.03	0.88 ± 0.03	0.75
SPM5	0.79 ± 0.08	0.89 ± 0.02	0.87 ± 0.02	0.85
MRF	0.53 ± 0.06	0.76 ± 0.03	0.87 ± 0.03	0.72
FCM	0.52 ± 0.15	0.88 ± 0.02	0.88 ± 0.03	0.76
FANTASM	0.53 ± 0.15	0.88 ± 0.02	0.88 ± 0.03	0.76
PVC	0.52 ± 0.15	0.83 ± 0.08	0.84 ± 0.07	0.73
FAST	0.47 ± 0.18	0.88 ± 0.01	0.89 ± 0.02	0.74
KMEANS	0.51 ± 0.06	0.75 ± 0.06	0.78 ± 0.04	0.68

Conclusions

- We propose a novel and effective approach to automatically segment brain tissue for MR images.
- Future work involves applying our method to other datasets.

References

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- [3] S. Valverde, A. Oliver, M. Cabezas, E. Roura, and X. Llado. Comparison of 10 brain tissue segmentation methods using revisited ibsr annotations. Journal of Magnetic Resonance Imaging, 41(1):93–101, 2015.
- [4] https://www.nitrc.org/projects/ibsr.

NAFOSTED National Foundation for Science & Technology Development

For further information
http://www.math.hcmus.edu.vn/icip-lab/