Sampling area-based mixed model for T1-MRI Brain Tissues

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Introduction: In this paper we consider the segmentation problem of MR images. Of specific interest in the current work is the primary tissue constituents of the brain: gray (GM) and whit matter (WM) as well as cerebrospinal field (CSF). To improve the quantitative precision of the segmentation, we focus on the mixel model as well as the error classification problem, which is that the cortex voxels with low intensity are assigned to CSF in error. We make use of the fact that a voxel is mixed by the sampling area surrounding it in the image formation process, and consider the observed intensity of a voxel as a mixture of its sampling area in the image forming processing. An improved mixel model, called sampling area-based mixel mode, is proposed. The sampling area is separated into M discrete pure voxels. When M is selected, all probability cases are known. Then the segmentation task is to assigned a tissue combination to each voxel in the MRF-MAP framework.

Method: Suppose that the observed intensity of a voxel is meanly mixed by the sampling area surrounding it in the image formation process. If the area is discreted into M pure tissue voxels with each voxel belong to one pure tissue type j, we have

$$x_i = \frac{1}{M}\sum_{j=1}^{K} n_j b_j \quad \sum_{j=1}^{K} n_j = M \quad (i \in S, n_j \in [0, M], M = 1,2,\cdots) \qquad (1)$$

where K is the number of pure tissue types, n_j represents the voxel number of the pure tissue type j, n_j/M is called the PVC(partial volume coefficient) of type j, and S is the ROI, the brain. When K is known, PVCs are only related to M. The model of Eq.(1) for the formation of image intensity within MRI is simplified from of the actual situation[1][2]. From Eq.(1) an image intensity is dependent on the number of each pure tissue class in its sampling area. Suppose M is given, we may generate all possible combinations, the PVCs, using an enumeration method. In this paper a combination or PVC is noted by a K-dimension vector $\mathbf{V}$. The task for the PV classification is to assigned a specific combination of all the possible PVCs to each voxel. The MRF-MAP framework is adopted[3][4], and the second-order energy function is newly defined as for a clique $\{i, i'\}$

$$V_2(x_i, x_{i'}) = \begin{cases} r_{ii'} \left\| \mathbf{v}_{x_i} - \mathbf{v}_{x_{i'}} \right\|^2, i' \in S \\ \mathbf{v}_{x_i 1} C \qquad , otherwise \end{cases} \qquad (2)$$

It includes two terms. One is the distance between two configurations when $x_{i'}$ is not a background voxel. where $r_{ii'}$ is a value relative to the direction of the clique, and is the sampling resolution in corresponding image direction in this paper. Another is the newly introduced boundary constrained term (BCT), which is defined as the multiply of $\mathbf{V}_{x_i 1}$ and a biggish C when $x_{i'}$ is a background voxel, where $\mathbf{V}_{x_i 1}$ is the CSF part in the vector $\mathbf{V}_{x_i}$ Through this modification, it is able to prevent assigning a cortex voxel near the background to CSF.

Result: The classification with our algorithm was evaluated with IBSR data set(http://neuro-www.mgh.harvard.edu/cma/ibsr), but 6 data set whose bias field contamination is very heavy are not considered in the experiment. Before perform classification, first the all combinations must be generated. For a normal brain the main tissue classes are GM、WM and CSF, then K equals to 3. When M is given, the all configurations are generated by a enumeration method with K-1 loops. If M is 7, the all configurations are 36 kinds. We should remove these insignificant types for certain application. For example the probability of mixing more than two tissue in a voxel is very low and the mixture of WM and CSF is very poor in brain data. Finally only 15 types are remained. From the result showed as Fig.1, it is very obvious that the result with BCT is better than one without BCT. It is successful to prevent low intensity cortex voxels from being assigned into CSF. The Tanimoto coefficients (TCs) of PV segmentation results with BCT are computed. The mean value of the TCs is 0.5711 for the CSF, 0.8010 for the GM, and 0.7395 for the WM.

Discussion: An improved PV model by considering observed voxel as its sampling area in image formation process is proposed.. The experimental results using IBSR data set are comparable or superior to other published algorithms. When the area is discreted into M pure voxels and there are K tissue types in images, the PVCs can be gotten by an enumeration method. For the size of a sampling area, the experiment results show when M=7 is proper. When M is smaller than K, the model is a hard segmentation. When M is larger, the result is not better, and the efficiency changes lower. The segmentation is implemented in the MRF-MAP framework. Moreover, the spatial position information is embedded into the MRF potential energy for avoiding assigning cortical voxels to CSF. Though the RF field inhomogeneity is not considered in this PV model, it can be corrected using exited methods, for example [5].

Reference:

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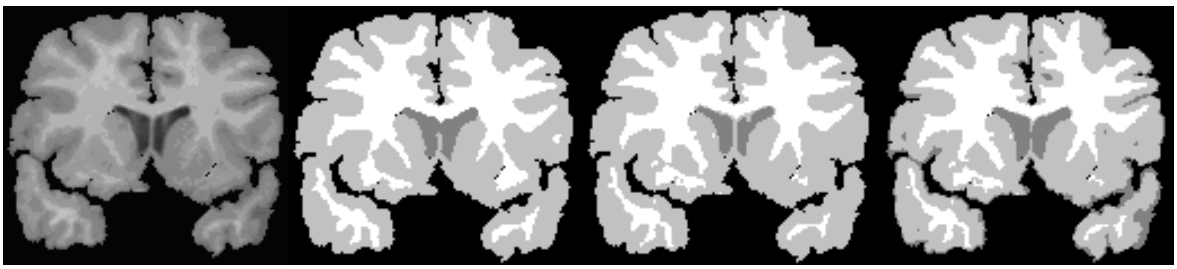

(1) (2) (3) (4)

Fig. 1 the local enlarged results (1) origin image;(2) the "true" segmentation;(3) segmentation with BCT; (4) segmentation without BCT