Lesions detection on 3D brain MRI based on Robust Hidden Markov Chain

S. Bricq[1,2], C. Collet[1], and J-P. Armspach[2]

[1]LSIIT - UMR CNRS 7005, Illkirch, France, [2]LINC - UMR CNRS 7191, Strasbourg, France

Introduction

In this paper, we present a new automatic robust method to estimate parameters to segment brain MR images (WM, GM, CSF) and MS lesions using the Hidden Markov Chain (HMC) model. For this aim, we use the Trimmed Likelihood Estimator (TLE) to extract outliers and propose to include a priori information brought by a probabilistic atlas. Tests on Brainweb images with MS lesions have been carried out.

Proposed Framework

To segment brain MRI, we propose to use Hidden Markov Chains (HMC) based on a 3D Hilbert-Peano scan of the data cube [1, 2]. Markov Chain methods for image segmentation are very interesting compared to 3D Markov Random Fields (MRF) models: based on 1D modeling, they result in lower computing costs with similar results. Neighborhood information is taken into account in the HMC model. Contrary to MRF, in the Markov chain model, the neighboring information is partially translated in the chain: two neighbors in the chain are neighbors in the grid, but two neighbors in the cube can be far away in the chain. However, due to strong correlation within the data cube, this scan will weakly influence the segmentation results. The first step of segmentation algorithms based on HMC consists in transforming the image into a vector using a 3D Hilbert-Peano scan [3]. Once all the processing has been carried out on the vector, the inverse transformation is applied on the segmented chain to obtain the final segmented image. Let us now consider two sequences of random variables $X=(X_n)_{n \in S}$ the hidden process, and $Y=(Y_n)_{n \in S}$ the observed one, with S the finite set corresponding to the N voxels of the image. Each X_n takes its value in a finite set of K classes $\Omega=\{\omega_1,\ldots,\omega_K\}$ and each Y_n takes its value in IR. In the case of brain MRI segmentation, each X_n takes its value in a set of K=3 classes Ω={WM, GM, CSF} (respectively white matter, gray matter and cerebrospinal fluid). The aim consists in finding the labels X_n knowing the observations Y in each voxel *n*. These observations could derived from different modalities (T1, T2, Flair, …), then Y_n is a vector $\mathbf{Y_n}$. Parameter estimation is performed using Expectation-Maximization (EM) [1].

A priori information brought by a probabilistic atlas is introduced in the model to drive the segmentation process. This atlas derived from 31 normal brains which were registrated using a non-rigid transformation [4] and then segmented using the HMC method described in [2]. Then these different segmentations were averaged to obtain the atlas. This atlas contains probability information about the expected location of WM, GM and CSF. The different probabilities in every voxel *i* calculated during the HMC algorithm were multiply by the prior probability of this voxel to belong to class *k* given by the atlas in the HMC modeling.

We detect MS lesions as outliers with respect to a statistical model for normal brain images. To extract these outliers and to estimate the parameters of the different classes in a robust way, the Trimmed Likelihood Estimator (TLE) was used [5]. The main idea lies in finding *h* observations from N samples for which the likelihood is maximum and thus in removing the N-*h* observations whose values would be highly unlikely to occur if the fitted model was true. We adapted this estimator to estimate parameters in a robust way in the HMC framework and thus to extract the potential outliers.

However outlier voxels also occur outside MS lesions. Thus, to remove these outlier voxels which do are not MS lesions, a post-processing step was added. Outliers detected in the CSF were removed and lesions with a small volume were excluded.

Results

To validate this approach, tests have been carried out on Brainweb images. The Brainweb database offers phantoms of MR brain images with MS lesions with different noise and non-uniformity levels. From these phantoms, the tissue classification in white matter, gray matter, cerebrospinal fluid and lesions is known. To evaluate the performance of our algorithm, we use the Kappa index (KI). The method was tested at value of the trimming parameter *h* of 99.5% on T1/T2 images with 3 and 5% of noise and 20% inhomogeneity level. Comparisons of the results obtained with and without atlas information are presented in Tab. 1 and Fig. 1. Using atlas information provides better results in the segmentation of MS lesions. Segmenting multimodal Brainweb images and extracting lesions takes approximately 10 minutes for volumes of size 181*217*181.

Conclusion and Perspectives

We have described a robust framework for tissue classification of multimodal brain MR images and lesions detection such as MS. Hidden Markov Chains were used to include neighborhood information in the model. This spatial regularization is required to overcome the disturbance added during the MRI formation. Moreover a priori information was introduced using a probabilistic atlas and lesions extraction was carried out using the Trimmed Likelihood Estimator. This method has been validated on 3D brain phantoms with MS lesions. This method will be applied to segment real brain images and compared to manual expert segmentation.

References

[1] W. Pieczynski, Statistical image segmentation, *Machine Graphics and Vision*, vol. 1 (2), pp. 261-268, 1992.

[2] S. Bricq, C. Collet and J.-P. Armspach, Triplet Markov Chain for 3D MRI Brain Segmentation Using a Probabilistic Atlas, in *IEEE 2006 International Symposium on Biomedical Imaging*, April 6-9, 2006.

[3] Y. Bandoh and A. Kamata, An address generator for a 3-dimensional pseudo-Hilbert scan in a cuboid region, in *Proc. of IEEE Int. Conf on Image Process*., 1999.

[4] V. Noblet, C. Heinrich, F. Heitz and J.-P. Armspach, 3-D Deformable Image Processing: A Topology Preservation Scheme Based on Hierarchical Deformation Models and Interval Analysis Optimization, *IEEE Transactions on Image Processing*, vol. 14 (5), pp 553-566, May 2005.

[5] N.M. Neykov and P.N. Neytchev, A robust alternative of the MLE, *Compstat'90*, pp. 99-100.

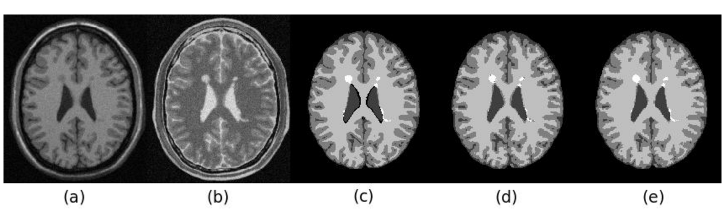

Fig. 1: Results obtained on a Brainweb image with 5% of noise and 20% inhomogeneity. (a) and (b) correspond to the T1 and T2 image. (c) corresponds to the ground truth, (d) and (e) correspond respectively to the results obtained without and with atlas.

Noise	Without Atlas	With Atlas
3%	70.7	75.9
5%	69.3	75.6

Tab. 1: Kappa Index for lesions, obtained on T1/T2 Brainweb images with different noise levels, with a value of *h* of 99.5%.