AUTOMATIC DETECTION AND SEGMENTATION OF CORTICAL LESIONS IN MULTIPLE SCLEROSIS

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Abstract

The purpose of this project is to develop robust algorithms for detection, segmentation and determination of different stages of MS cortical lesions in brain MR T2* images. The proposed approach is to improve existing approaches according with the new requirements, specially the subtle signal variations between normal and lesion tissues.

Problem

The in vivo study of cortical lesions in Multiple Sclerosis (MS) is constrained by the technical limitations of currently available Magnetic Resonance (MR) techniques including limited image resolution and low contrast between small cortical lesions and surrounding normal cortical GM[1].

Cortical multiple sclerosis lesions are difficult to detect in 7T T2* becouse:

a)To be required three independent scans to form an data set, Fig 1.

b) Poor contrast between grey and white matter, Fig 2;

c) Spatial variation in healthy and lesion grey matter, Fig 2;

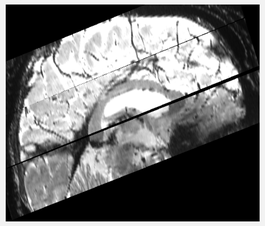

Figure 1: Three independent scans to form an data set.

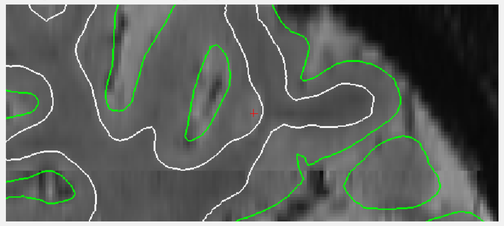

Figure 2: Poor contrast between grey and white matter and Spatial variation in healthy and lesion grey mattert.

Methods

For the detection, evaluation and segmentation of cortical lesions in MS we propose the MAP scheme previously described with the following changes:

1) Instead usinng all brain for segmentation for segmentation MS lesions [2][3], we selected only the cortex data by using FreeSurfer http://surfer.nmr.mgh.harvard.edu based tools, Figura . This approach reduces the number of classes involved diminishing the confusability among classes and perhaps improving the classification performance. In this case only two different tissue classes exist; normal and lesion tissue.

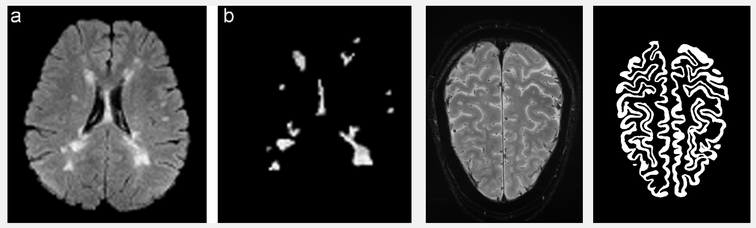

Figure 3: Result of applying the proposed algorithm in reference[3] to the image of a patient with moderate lesion load: (a) input image (b) segmentation of lesions. c) The original 37 T2* image. d) Application the Freesurfer tool to extract the cortex.

2)Using a Gaussian mixture Eq 1 with two or more components can model the entire cortex tissue.

$$P(x \mid \omega_j) = \frac{1}{(2\pi)^{l/2}\left|\sum_j\right|^{1/2}} \exp\left\{-\frac{1}{2}(x-u_j)^T \sum_j^{-1}(x-u_j)\right\} \qquad \text{(Eq 1)}$$

3) Based on a Bayesian classifier, utilizes the adaptive mixtures method (AMM) and Markov random field (MRF) model to obtain and upgrade the class conditional probability density function (CCPDF) and the a priori probability of each class.

Bayesian Classification

The Bayes rule, Eq 2 , indicates how the posterior probability of a class is calculated, given feature measurements.

$$P(\omega_j \mid x) = \frac{P(x \mid \omega_j).P(\omega_j)}{\sum_{j=1}^{K} P(\omega_j)} \qquad \text{(Eq 2)}$$

In this equation, ω_j refers to class *j*th and x is the feature vector. $p(x|\omega_j)$, $p(\omega_j)$ and $p(\omega_j|x)$ are the CCPDF, the *a priori* probability and the *a posteriori* probability of class j , respectively.

Markov random fields and Gibbs distributions

MRF models an image or a volume as a random field, a structured collection of random variables, Ω= {1, . . . ,m}, and defined on the set S.There are two conditions for considering a random field as MRF

1. $p(\omega_j) > 0, \forall \in \Omega$, Condition of positivity,

2. $p(\omega_j \mid \omega_{S-\{j\}}) = p(\omega_j \mid \omega_{Nj})$, Condition of Markovianity.

ω is a Gibbs Random Field (GRF) with respect to the neighborhood sytem if:

$$p(f) = \frac{1}{Z}\exp\left(\frac{1}{T}U(\omega)\right) \qquad Z = \sum_{\omega} \exp\left(\frac{1}{T}U(\omega)\right) \qquad U(\omega) = \sum_{C} V_C(\omega) \qquad \text{(Eq 4)}$$

Where Z is a normalization constant, T is the temperature parameter. U(ω) is the energy function where Vc(ω) is a potential function.

Model for Image Classification

Usinng a Bayesian classifer end Computation of the a priori probability by MRF model we can conver the product of the probability in a energy form:

$$E = E_r + \alpha E_f \qquad \text{(Eq 5)}$$

where is a weighting parameter to determine how much ER and EF individually contribute to the entire energy E[4]. For the model (5), the MAP may be any of the following:

$$\hat{\omega} = \arg \max_{\omega_j \in \Omega} \frac{1}{Z}\exp\left[-\frac{1}{T}E\right] \qquad \text{(Eq 6)}$$
$$= \arg \min_{\omega_j \in \Omega} E$$

Eq. (6) means that maximizing the posteriori conditional probability distribution or Gibbs distribution is equivalent to minimizing the energy of the model.

Data Set

Fourteen MS patients (nine with relapsing-remitting MS, RRMS; five with secondary progressive MS, SPMS; mean±SD age=38.9±12.9 years; median Expanded Disability Status Scale=3.0, range=1.0-6.5; mean±SD disease duration=10.2±7.7 years) and eight age-matched controls were scanned twice on a human 7T Siemens scanner using an in-house developed 8- or 32-channel phased array coil, and on a 3T Siemens Tim Trio scanner using the Siemens 32-channel coil.

Result Validation

The algorithm performance will be evaluated by comparing lesion volumes obtained by both; the algorithm and experimented radiologists.

[1] C. Mainero, A. van der Kouwe, T. Benner, G. Wiggins, B. R. Rosen, and R. P. Kinkel: In vivo characterization of cortical lesions in multiple sclerosis by 7T MRI. Proc. Intl. Soc. Mag. Reson. Med. 16 (2008).
[2] Admiraal-Behloul, F., van den Heuvel, D. M. J., Olofsen, H., van Osch, M. J. P., van der Grond, J., van Buchem, M. A., Reiber, J. H. C., (2005). Fully automatic segmentation of white matter hyperintensities in MR images of the elderly. NeuroImage, 28 607-617.
[3] Rasoul Khayati, Mansur Vafadust, Farzad Towhidkhah, S. Massood Nabavi (2008). Fully automatic segmentation of multiple sclerosis in brain MR FLAIR images using adaptive mixture method and markov random field model. Computers in Biology and Medicine 38, 379-390.
[4] Huawu Deng*, David A. Clausi:Unsupervised image segmentation using a simpleMRFmodel with a newimplementation scheme.Pattern Recognition 37 (2004) 2323 – 2335