Validation of an automatic method for change detection in serial scalar images characterizing diffusion properties

H. Boisgontier[1,2], V. Noblet[1], F. Heitz[1], L. Rumbach[3], and J-P. Armspach[2]

[1]Laboratoire des Sciences de l'Image, de l'Informatique et de la Télédétection, UMR CNRS-ULP 7005, Illkirch, France, [2]Laboratoire d'Imagerie et de Neurosciences Cognitives, UMR CNRS-ULP 7191, Strasbourg, France, [3]Service de Neurologie, CHU Minjoz, Besançon, France

Introduction

Magnetic Resonance (MR) imaging plays an important role in Multiple Sclerosis (MS) diagnosis and for monitoring the evolution of the disease over time [1]. The advent of new quantitative MR techniques and the constant improvement in spatial resolution yield an increasing amount of 3D image data, whose interpretation is a tedious and error-prone task. A challenging issue of medical image processing is to design reliable methods for automatic detection of changes between two or more images. Bosc *et al.* [2] proposed a fully automatic scheme for detecting MS lesion evolution between images taken at different time in several MRI modalities. Diffusion Tensor Imaging (DTI) is a relatively recent MRI modality allowing to characterize the diffusion properties of cerebral tissues. Studies have already highlighted diffusion property alterations induced by MS [1], thus making DTI an attractive modality for monitoring the evolution of MS. This paper investigates the feasibility of extending Bosc's detection scheme to scalar indices computed from DTI. Results obtained with three different scalar indices – Mean Diffusion (MD), Fractional Anisotropy (FA) and Lattice Index [3] (LI) – are compared.

Methods

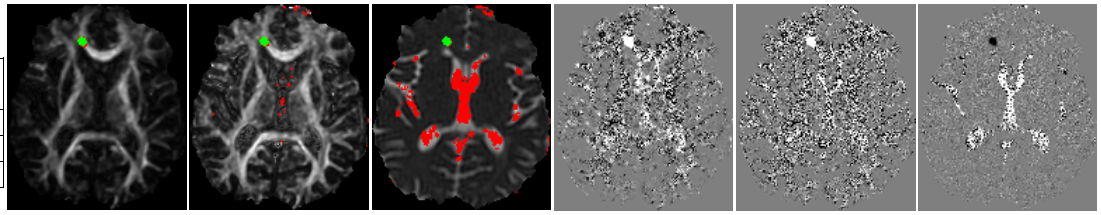
The proposed detection scheme between two DTI acquisitions is composed of the following steps: eddy-current distortion correction of raw DT-images, tensor estimation, scalar index computation, brain extraction, affine registration of the scalar indices computed from both DTI acquisitions, generalized likelihood ratio test [4] (GLRT) computation and thresholding. For GLRT computation, we assume that the intensity within a window of 3x3x3 voxels is modeled as a constant value with independent and identically distributed zero mean additive Gaussian noise, whose variance is supposed to be constant throughout the image [2]. To validate this approach and to compare the impact of the scalar index used, we resort to synthetic simulations. MS lesion appearance and evolution are related to demyelization processes. Studies have shown that demyelization leads to an increase of the radial diffusivity in DT-images [5]. To simulate this process, we consider the DTI acquisition (33 directions) of a healthy subject (the baseline) and a second exam obtained by adding a Gaussian noise to each raw DT-image of the baseline (several Signal-to-Noise Ratio (SNR) are considered: 10dB, 20dB and 30dB). Tensor images are computed and the two last eigenvalues (corresponding to the radial diffusion) of the second exam are increased in a small Region Of Interest (ROI of 173 voxels) in the following way: $\lambda_i'(x,y,z) = \lambda_i(x,y,z) + \alpha(x,y,z).(\lambda_1(x,y,z)-\lambda_i(x,y,z))/2$, where $i=\{2,3\}$, $\lambda_i(x,y,z)$ and $\lambda_i'(x,y,z)$ being the *i*-th original and updated eigenvalues and $\alpha(x,y,z) \in [0,1]$ being a coefficient allowing to account for a smooth spatial modification of the eigenvalues. This formulation ensures that λ_1 remains the highest eigenvalue after the update of λ_2 et λ_3. Since the ground truth of the expected detection is known, the threshold of the GLRT image is set to minimize false positive rate, while detecting the whole ROI where changes have been simulated.

Results and discussion

Table 1 presents the false positive rate of the detection for each index with respect to the level of noise in the raw DT-images. Figure 1 also illustrates some detection results for the different indices. Unsurprisingly, the results show that the LI is less sensitive to noise than the FA, since it is computed using neighborhood information (26-neighborhood is considered). Besides, it is interesting to see how poor the specificity of the detection using the MD index is. This is mainly due to the fact that, although the data have been generated using a Gaussian additive noise, the variance of noise in MD index is not constant anymore (see Figure 2), resulting in a huge number of false alarms in the cerebrospinal fluid. On the contrary, the assumption of additive Gaussian noise with constant variance throughout the image is further verified – to some extent – for the FA and LI indices (see Figure 2). Experiments carried out on real data (two acquisitions one year apart for 12 MS patients) have also led to similar conclusions.

noise / Indices	30dB	20dB	10dB
LI	0.04%	0.25%	3.74%
FA	0.36%	1.10%	34.31%
MD	2.65%	6.10%	31.59%

Table 1: false positive rate of the detection for LI, FA and MD with respect to the level of SNR in the raw DT-images.



a. b. c.

Figure 1: Detection results for (a) LI, (b) FA and (c) MD: false alarms are represented in red and true positives in green (noise: 20dB).

a. b. c.

Figure 2: Row difference between (a) LI, (b) FA and (c) MD of the two acquisitions (noise: 20dB).

Conclusions and perspectives

This validation study highlights that statistical comparison between DTI-derived indices may depend on the index considered, since the nature of noise varies from one index to the other. The proposed extension of Bosc's detection scheme to indices computed from DTI exhibits promising results when considering the FA or the LI indices, but leads to disappointing performances when considering the MD index. Some works have already been done to characterize the noise in DTI-derived indices [6]. We will carry out further work to incorporate these *a priori* on the noise in the GLRT formulation, in order to improve the performances of the proposed detection scheme, in particular when considering the MD index.

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