Improving lesion classification using an empirical knowledge of false classifications in multiple sclerosis

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Introduction:

Accurate classification or segmentation of lesions in multiple sclerosis (MS) is necessary for tracking their temporal changes. Classification of lesions based on automated techniques often result in false classifications. Anatomical knowledge of the brain can be exploited to minimize the false classifications to some extent but such an approach is sub-optimal in the presence of regions that mimic lesions. Based on the automated lesion classification and expert validation, we developed and implemented a false classification probability (FCP) map for improved lesion classification.

Image Acquisition:

Fifty seven MS subjects underwent MR brain imaging on a 3T Philips intera scanner with a dual quasar gradient system with a SENSE factor of 2. Volumetric magnetization-prepared rapid gradient echo (MPRAGE) T1-weighted (TR/TE = 8.1 ms/3.7 ms), T2-weighted (TR/TE = 2500.0 ms/362.9 ms), and fluid attenuated inversion recovery (FLAIR) (TR/TE/TI = 8000.0 ms/336.8 ms/2400 ms) images with 1 mm³ isotropic voxels were acquired in the sagittal plane covering the whole brain. T2-weighted images were acquired with fat-saturation technique for suppressing the fat/muscle surrounding the brain. All the images were later reformatted into axial plane for image processing and analysis.

Methods:

For each subject, T1-weighted (or T1) and FLAIR images were co-aligned with T2-weighted (or T2) image using rigid body registration. Extrameningeal tissues were removed from T2 images by exploiting the fat-sat technique and applying image histogram-based thresholds followed by the application of region connectivity and region labeling algorithms [1]. The brain mask obtained from the T2 image was subsequently applied to co-aligned T1 and FLAIR images for brain extraction. These images were processed for intensity non-uniformity correction and noise filtration. Non-parametric Parzen window classifier was applied to T2 and FLAIR images to extract lesions. Since lesions do not follow Gaussian distribution, they were removed from the T1 and T2 images and the images were then classified into gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) using parametric EM-MRF algorithm [2]. The intensity of cerebellar parenchyma was observed to be different from rest of the brain [2, 3]. Therefore the cerebellar parenchyma was isolated from the remaining part of the brain. The ICBM brain template (http://www.loni.ucla.edu/Atlases/) and the corresponding anatomical map were deformed to the T1 image volume of the subject's brain using symmetric non-linear registration, which were utilized to extract the cerebellum from the T1 image [2, 4]. Once isolated, the cerebellar tissues were classified into GM and WM separately. The rest of the brain was classified into GM, WM, and CSF. The classified tissues from the cerebellum and the remaining brain, and lesions from Parzen classification were combined for segmentation of the entire brain. False lesions classifications were minimized by masking the lesion class with WM mask obtained from the coaligned brain template and were delineated using fuzzy connectivity [1]. Due to the low contrast of deep GM structures compared to cortical GM, these structures are not generally well classified [5]. The accurate segmentation of thees

The subjects were classified into two groups based on their lesion load (LL) as obtained by the expert. Group I consists of 29 subjects with LL less than or equal to 10 cc and group II consists of 28 subjects with LL greater than 10 cc. It is observed from these two groups, that false classifications are more prevalent in group I and some of these false classifications are consistent in most of the subjects and appear to be located at the same regions. Hence, these known false classifications were utilized to further improve the lesion classification. Segmented and expert validated images of each subject was deformed to the template using the inverse deformation fields, that were generated while co-aligning template with subject T1 images, following which false classifications on each subject was obtained by subtracting the deformed validated lesions from deformed segmented lesions in the template space. FCP map was created by taking the average of false classifications from all subjects. The FCP was then deformed to each subject using respective deformation fields. A threshold was applied to FCP to eliminate lower probabilities of occurrence of false classifications which was then applied to segmented images to further minimize the false classifications thus improving the lesion classifications. The threshold was set based on the observation on a cohort of subjects and was kept same for all subjects.

Results and Discussion:

Figure 1 shows a schematic diagram of the work flow for improving the lesion classifications using FCP map. Figure 2 shows T1, T2, FLAIR, automated segmented, expert validated, and improved segmented images. As can be observed from this figure, false classification on segmented image (arrow) was successfully removed by the application of FCP map. The dice similarity indices (DSI = $2*(\text{Seg} \cap \text{Ref})/(\text{Seg} + \text{Ref})$; seg: obtained with automated technique and ref: validated lesions obtained by the expert) was calculated for all 57 subjects before and after the application of FCP. Average (\pm sd) similarity indices for all subjects, group I, and group II, when segmented images were compared with validated images were 0.791 (\pm 0.136), 0.699 (\pm 0.111), and 0.886 (\pm 0.082) respectively. These indices increased to 0.836 (\pm 0.106), 0.770 (\pm 0.094), and 0.904 (\pm 0.071) following the application of FCP. These improvements are significant on two-tailed paired t-test (fig. 3).

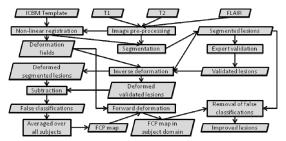


Fig. 1: Schematic diagram of the work flow for minimizing false classifications using FCP map.

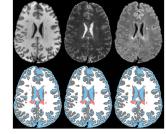


Fig. 2: 1st row: T1, T2, FLAIR; 2nd row: segmented, validated, improved images.

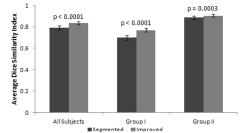


Fig. 3: Bar chart representing average DSI before and after the application of FCP map.

Conclusions:

We have presented an automated technique for improved lesion classifications retrospectively using an empirical knowledge of false classifications from each subject. The proposed scheme significantly improved the accuracy of lesion classification, as assessed by the DSI.

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References: [1] Datta and Narayana, JMRI 2011;33:822-829; [2] Datta et al., OHBM 2011; [3] Datta et al., JMRI 2009;29:1035-1042; [4] Xiao et al. MLMI LNCS 2010;6357:165-173; [5] Derakhshan et al., 2010;52:1261-1267.