









AUTOMATIC MULTIPLE SCLEROSIS BRAIN LESION LOCALISATION AND VOLUMETRY

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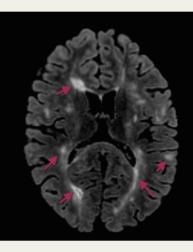
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ABSTRACT

The presence and location of white matter lesions on MRI are important criteria for diagnosing multiple sclerosis. Quantitative values such as lesion volumetry are expected to have high impact in clinical practice. Therefore, we propose an accurate, automatic method for lesion quantification based on T1 and FLAIR. The proposed method segments the lesions as an outlier to the normal brain. Finally, the number and volume of lesions is quantified for different brain regions.

INTRODUCTION

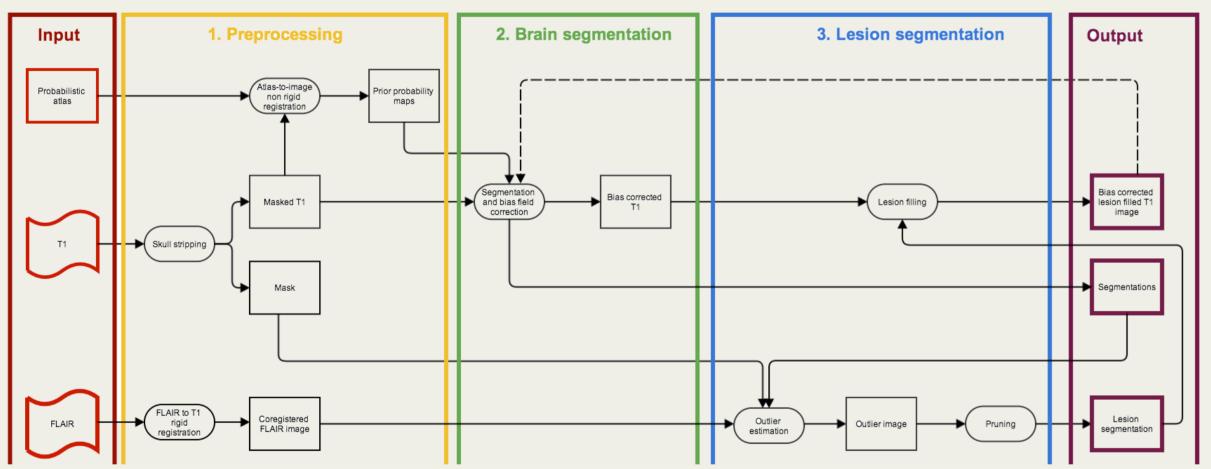
Multiple Sclerosis (MS) is a disease that affects the central nervous system and results in lesions formation. Manual lesions delineation and count on MR image is time-consuming. Therefore, many automatic lesion segmentation methods have been developed. They are broadly classified into supervised and unsupervised methods. The supervised methods need training images to segment lesions and unsupervised methods segment lesions based on the pixel intensity distribution.



Lesions on FLAIR

METHOD

Our method classifies the brain into three classes, namely, GM, WM and CSF. In addition, by using a healthy brain atlas, MS lesions are detected as an outlier to the normal brain [1]. This idea is embedded into an iterative approach where FLAIR image is used for lesion segmentation, while lesion-filled T1 image is used for obtaining brain segmentation.



Architecture of the proposed method

1. Preprocessing

The preprocessing step has three stages:

- Skull strip the T1 image.
- Register FLAIR to T1.
- III. Transfer the GM, WM and CSF probabilistic tissue priors non rigidly from the MNI to T1 image space.

2. Brain segmentation

- Using the probabilistic priors together with the skull stripped T1 image, the brain is segmented using an expectation maximization (EM) algorithm [2].
- The EM models the intensities of each tissue class as a normal distribution, it assumes a Gaussian distributed bias field and it contains a spatial consistency model.
- The algorithm iteratively estimates the parameters of each tissue class, the bias field parameters, and maintains the spatial consistency until convergence. After the convergence of the algorithm, the T1 image is bias corrected and segmented into the three tissue classes, i.e., GM, WM and CSF.

3. Lesion segmentation

- The three tissue class segmentations together with the registered FLAIR image are used to estimate the outliers in the FLAIR image. The outlierness is defined as the deviation of each intensity from normal tissue distributions and are detected using an EM algorithm [2].
- However, not every outlier is a MS lesion (e.g. partial volume effect). Therefore, an extra a priori information about the location (dominantly in WM) and the appearance (hyper intense in FLAIR) of the lesions is incorporated to filter true MS lesions.

Step 2 and 3 of the algorithm are repeated until convergence for better tissue and lesion segmentation.

RESULTS

Data

20 multiple sclerosis patients participated in a study at VU University Medical Center (VUmc), Amsterdam, the Netherlands. They were scanned on a 3T whole body scanner (GE Signa HDxt, Milwaukee, WI, USA). Expert lesion identification and manual segmentation was performed based on the FLAIR images by a highly trained neuroradiological team [3].

The total lesions volume is computed for both our method's segmentation and the expert lesion segmentation. We report the mean and standard deviation of the total lesion volume over all patients, as well as the overlap between both segmentations. The consistency between the two methods is assessed by the intraclass correlation coefficient (ICC).

The number and volume of the brain lesions for different regions, such as the frontal lobe, etc, is quantified using a brain parcellation registered to the T1 image.

Qualitative results



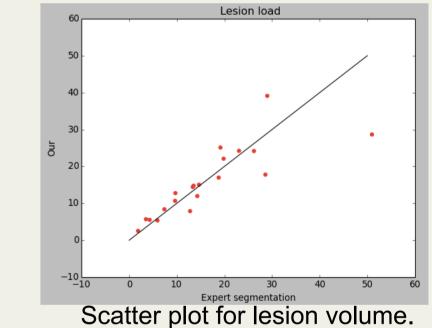
Lesion segmentat ion.

(A) original image (B) expert segmentat ion (C) our result

Quantitative results

Metric (μ ± σ)	Expert	Our
Lesion volume (mL)	16.33 ± 11.48	15.66 ± 9.30
Dice (%)	62.30 ± 9.00	
ICC (%)	81.16	

Accuracy of method over the dataset.



CONCLUSIONS & FUTURE WORK

Conclusions

We propose a fully automatic method that is generally applicable and allows consistent and reliable volumetry of lesions in the whole brain or in different brain regions. Complementary information is thus provided to the MS clinicians, supporting early diagnosis.

Future work

- 1. Juxta cortical lesion segmentation.
- 2. Separation of dirty WM from true lesions.
- 3. Segmentation of new lesions and volume changes of old lesions over time.

ACKNOWLEDGEMENTS & REFERENCES

Acknowledgements

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- 2. The dataset creation was supported in part by the Dutch MS Research Foundation through a program grant to the VUmc MS Center Amsterdam (grant number 09-358d).

References

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[2] Cardoso, M. J., (2012), NiftySeg: Statistical Segmentation and Label Fusion Software Package, http://niftyseg.sourceforge.net/index.html [3] Steenwijk D., Daams M., Willem J.V.D, Caan M., Richard E., Barkhof F., Vrenken H., 2013, Accurate white matter lesion segmentation by k nearest neighbor classification with tissue type priors (kNN-TTPs), NeuroImage: Clinical, pages 462-469.