Segmentation for MS Lesions Based on 3D Volume Enhancement and 3D Alpha Matting

Ziming Zeng[1,2]
zzz09@aber.ac.uk
Reyer Zwiggelaar[1]
rrz@aber.ac.uk

[1]Department of Computer Science
Aberystwyth University, Aberystwyth, UK
[2]Faculty of Information and Control Engineering
Shenyang Jianzhu University, Shenyang, China

Abstract

This paper presents a novel approach for segmentation of Multiple Sclerosis (MS) lesions in T1-weighted (T1-w), T2-weighted (T2-w), and fluid-attenuated inversion recovery (Flair) Magnetic Resonance (MR) images. The proposed approach is based on three-dimensional (3D) enhancement followed by false positive reduction methods and 3D alpha matting technique. The experiments on real MRI data shows the unsupervised segmentation method can obtain better result than some state-of-the-art methods.

1 Introduction

Multiple Sclerosis is an inflammatory demyelinating disease of the central nervous system which is the most common non-traumatic neurological disease in young adults. In clinical practice, physicians use the segmentation results of MS lesions to analyze and estimate the growth process of MS lesions and evaluate effects of some pharmaceutical treatments by measuring various quantities. Some semi-automated and automated segmentation methods have been proposed. Zeng et al. [1] proposed a two dimensional joint histogram modelling for MS lesions to deal with the density overlap between normal and abnormal tissues. Souplet et al. [2] combined EM and morphology post-processing of resulting regions of interest to extract MS lesions. Geremia et al. [3] employed spatial decision forests to segment the region of interests. However, most segmentation methods are still not accurate enough because of the noise, density inhomogenity, and partial volume effects in the MR images. As a partial solution, we propose a segmentation method to segment MS lesions based on 3D volume enhancement and 3D alpha matting.

2 Methodology

In the preprocessing, a mutual information based method [4] is used to register MRI T1-w, T2-w and Flair images. Then a single slice with MS lesions is selected from the volume by an expert. In the first step, the MS lesions in the fusion volume (T2-w and Flair) is enhanced by using the enhancement function which is driven by the segmentation results. In the second step, false positive VOIs are removed and potential MS lesions are detected. In the third step, a 3D alpha matting method is utilized to achieve more accurate segmentation results.

2.1 3D Volume Enhancement

Due to the MS lesions exhibiting hyper-intensity compared with other tissues in T2-w and Flair, and the density of MS lesions in Flair can be better distinguished from CSF than in T2-w, we fuse the T2-w and Flair volumes by using different weights ($(1/2)T2+Flair$) in order to enhance the density of MS lesions. Then the grey level values of the fusion volume is normalized from 0 to 255. Considering the computing speed of the proposed algorithm, a single slice with MS lesions is selected by an expert and utilized as a benchmark to enhance the whole MRI volume. Specifically, the non-brain tissue of the single slice is removed by using the BET toolkit [5]. Then the HMRF-EM method [6] is used to segment the brain tissue with four groups which corresponding to cerebrospinal fluid (CSF), white matter (WM), grey matter (GM), and background (BG), respectively. Then the group centers of WM and GM defined as C_{WM} and C_{GM} can be estimated. Subsequently, the MS lesions in this slice are enhanced by using an enhancement function $E(x)$ which is defined as:

$$E(x) = \left(\frac{1}{2}\left[1+\frac{2}{\pi}arctan\left(\frac{I(x)-T}{\varepsilon}\right)\right]\times I(x)\right) * K_{\sigma} \tag{1}$$

where I denotes the single MR image/volume, K_{σ} is a Gaussian kernel, ε is a constant, T is defined as $(C_{WM}-C_{GM})/2$. This function is also used to enhance the whole fusion volume. With each iteration, the enhanced slice is segmented again, and the new parameter T is estimated by using the new group centers. In each iteration, the enhancement function which is driven by segmenting the enhanced slice is affecting the whole fusion volume. The mutual information [7] which is estimated by using the enhanced slice in successive steps is utilized as the iteration stopping criteria using an empirically determined threshold value (δ). Finally, the binary VOIs of MS lesions are obtained by using a small threshold value in the enhanced 3D volume.

2.2 False Positive Removing

In the previous results, some false positive VOIs, such as skull, GM and areas between ventricles, are also enhanced because of the hyper-intensity and density inhomogenity. False positive VOIs are removed in this step. Firstly, we use the brain symmetry plane [8] to logical *and* with the 3D enhanced VOIs in the previous steps. Then the skull and VOIs between ventricles are removed by discarding the label which is connected with the symmetry plane. Secondly, as 95% of MS lesions occur within white matter tissue [9], the MS lesions contained in WM is only considered in this work. Most of the WM segmentation methods are time-consuming, because these methods need to remove the skull slice by slice before segmenting the WM, such as [2]. In addition, these methods fail to consider the whole volume information, and the density overlap between WM and other tissues may lead to false positives in the WM segmentation results. In this work, a novel color segmentation scheme is used to segment the WM volume. Specifically, we generate a color MR volume by using T1-w, T2-w, and Flair volumes. Each R, G, and B channel corresponds to $T1-w$, $T2-w$, and $Flair$ MR image, respectively. Anatomic brain tissues can be better distinguished in T1-w than the other MRI modalities [1], and the middle slice in the T1-w MRI volume is selected. Then the non-brain tissue is removed [5] and the HMRF-EM method [6] is utilized to segment the selected brain tissue without brain skull into four groups which represents CSF, WM, GM, and BG, respectively. Subsequently, the WM group is used as a mask and morphology is utilized to erode the WM mask in order

to reduce false positives in WM caused by the segmentation errors. Then the eroded $Mask$ region are used as mask to extract the corresponding pixels of the same slice in the color MR volume. Subsequently, we calculate the average value R_μ, G_μ, and B_μ in each color channel. For each color pixel $I(R_i, G_i, B_i)$, we can calculate the distance ΔE_i between the pixel and average color value as $\Delta E_i = \sqrt{(R_i - R_\mu)^2 + (G_i - G_\mu)^2 + (B_i - B_\mu)^2}$. Then we define a threshold $T_{tolerance} = mean(\Delta E_i \times Mask) + std(\Delta E_i \times Mask)$, where $mean(\cdot)$ and $std(\cdot)$ denote the mean and standard deviation values, respectively. Subsequently, we use the RGB color in the corresponding region to estimate all other similar color regions. The acquired values (R_μ, G_μ, B_μ) are used to calculate ΔE_i for the other voxels in the whole volume. If $\Delta E_i \leqslant T_{tolerance}$, the voxel will be segmented as WM. Finally, we remove all the VOIs outside of the WM volume segmented by using the color segmentation scheme.

2.3 Refining the Segmentation Results

Another big challenge of lesion segmentation, along with the eliminating of false negatives, is the uncertainty boundary of VOIs. This may be caused by partial volume effects and the limitation on image resolution. We observe that the uncertainty boundary of a VOI is caused by the fact that the boundary pixels are a mixture of foreground tissue (tumours) and background tissue (normal tissue). In order to extract the MS lesions from the other tissues, we introduce a 3D alpha matting technique [10] into the segmentation pipeline. Instead of generating a 0 and 1 segmentation label, the alpha matting technique can generate a fractional alpha value between 0 and 1 for these voxels, which can be viewed as more accurate soft segmentation. In this work, the color MR volume is used to refine the segmentation results. For each color voxel i, it would be convex combination of the foreground (F) and background (B), which can be modelled as $I_i^c = \alpha_i F_i^c + (1-\alpha_i) B_i^c$, where α is the transparency parameter, c denotes the RGB color channel representing $T1-w$, $T2-w$, and $Flair$ MRI. In [10], the 3D alpha matting was solved by using $J(\alpha) = \alpha^T L \alpha$, where the L referred to as the *matting Laplacian*. It is a square matrix of size $N \times N$ which captures the local color properties of the input image containing N voxels. Its $(i,j)^{th}$ element is given as

$$\sum_{k|(i,j)\in w_k} \left(\delta_{i,j} - \frac{1}{|\, w_k \,|} (1 + (I_i - \mu_k) \left(\sum_k + \frac{\varepsilon}{|\, w_k \,|} I_3 \right)^{-1} (I_j - \mu_k)) \right). \tag{2}$$

where $\delta_{i,j}$ is the Kronecker delta [10], μ_k and σ_k^2 are the mean and variance of the vector of the colors in the window w_k around k which is usually $3 \times 3 \times 3$, and $|\, w_k \,|$ is the number of pixels in the 3D window. If the size of the Laplace matrix L is too large when calculating the whole volume, it will result in a large number of calculations. Therefore, the subcube is used to segment the MS lesions instead of segmenting the whole volume. Before segmenting, a trimap of MS lesions has to be generated at first, this separates the image into three regions as shown in Fig. 1 Step 3: definite foreground F (show in color), definite background B (show inside the pink rectangle, but not include the other color), and the unknown region U (show in color, but not including the foreground). Our system automatically generates this trimap. Specifically, we use 3D morphology to erode the previous segmentation result with a spherical structuring element to obtain the foreground, then we dilate the 3D VOIs and calculate its maximum bounding box. The rectangle region without the foreground is used as the background. The unknown area can be generated by logical *and* the foreground with the dilated VOIs. The details of the energy minimization process can be found in [10]. Solving the matting problem leads to a soft segmentation of VOIs in color MR volumes.

3 Experiments

We evaluated the proposed method on the patient volumes from the CHB datasets [11]. The ground truth of all the images is publicly available from the MS Lesion Segmentation Challenge 2008 website [11]. For each case, three MR modalities are made available (T1-w, T2-w and Flair volumes) which are co-registered. Each modality contains 512 slices. The voxel size is $0.5mm^3$. We take CHB case 01 as an example which is shown in Fig. 1. In the first step, the T2-w and Flair volumes are fused by using $(1/2)T2+Flair$. Then a slice with MS lesions in the MR volume is selected by an expert, and the non-brain areas are removed (see Fig. 1a). Subsequently, the brain tissue is segmented by using HMRF-EM [6] (see Fig. 1b). According to the segmentation results, the parameters T in Eq. 1 is estimated as 0.8. Then the 3D volume and the slice are enhanced (see Fig. 1c and Fig. 1d). In Eq. 1, the parameters $\varepsilon = 10$ and $\sigma = 7$. In the second iteration, the enhanced image is segmented again (see Fig. 1e). Fig. 1f is the enhanced volume and slice in the second iteration. As the iteration increase, we calculate the mutual information of the enhanced slices in the successive iterations, and the threshold value $\delta = 0.9$ is used as the stopping criterion. In this case, the processing of 3D volume enhancement is stopped at the fifth iteration. Fig. 1g and Fig. 1i are the final enhanced result and the final enhanced volume, respectively. In the second step, the symmetry plane (see Fig. 1j) is estimated and used to remove false positive regions, such as the skull. Then the WM (see Fig. 1l) is segmented by using the color segmentation scheme. Then the 3D labels outside of the WM are removed. Fig. 1m shows the false positive removed VOIs. In the third step, a trimap which contains foreground (see Fig. 1n), background (see Fig. 1o), and unknown region (see Fig. 1p) is automatically generated. Subsequently, the alpha matting method is utilized to refine the previous segmentation results by using the color MR volume (see Fig. 1q). To compare against the ground truth (see Fig. 1t) which is a binary VOIs, we threshold the soft segmentation (see Fig. 1r) generated by matting at half the maximum value for this volume, which leads to the final binary segmentation of VOIs (see Fig. 1s). Fig. 2 shows our results for frontal, midsagittal, and sagittal views, respectively.

Table 1: TPR, PPV and Dice index for MS lesions segmentation on CHB MRI datasets

Patient	*Ch. winner* [2]			*Context-rich RF* [3]			Our method		
Cases	TPR	PPV	DSC	TPR	PPV	DSC	TPR	PPV	DSC
CHB01	0.22	0.41	0.29	0.49	0.64	0.55	0.68	0.65	0.66
CHB02	0.18	0.29	0.22	0.44	0.63	0.51	0.54	0.53	0.53
CHB03	0.17	0.20	0.19	0.22	0.57	0.31	0.32	0.59	0.41
CHB04	0.12	0.55	0.20	0.31	0.78	0.44	0.39	0.68	0.50
CHB05	0.22	0.42	0.29	0.40	0.52	0.45	0.48	0.51	0.49
All	0.18	0.38	0.24	0.37	0.63	0.46	0.48	0.59	0.52
SD	0.04	0.13	0.05	0.11	0.10	0.09	0.14	0.07	0.09

To evaluate the accuracy of a segmentation result, three measures (true positive rate (TPR), positive predictive value (PPV), and Dice similarity coefficient (DSC)) are used to evaluate the spatial accuracy of the segmentation result compared to the results of state-of-the-art methods [2, 3] which are also test with CHB datasets [11]. When DSC=1, TPR=1, or PPV=1 denotes exact overlap with the ground truth. We compare the TPR, PPV and DSC of our method and segmentation methods [2] and [3] for real patient data in Tab. 1, which also shows the overall mean (All) and standard deviation for all the cases (SD). In all the cases,

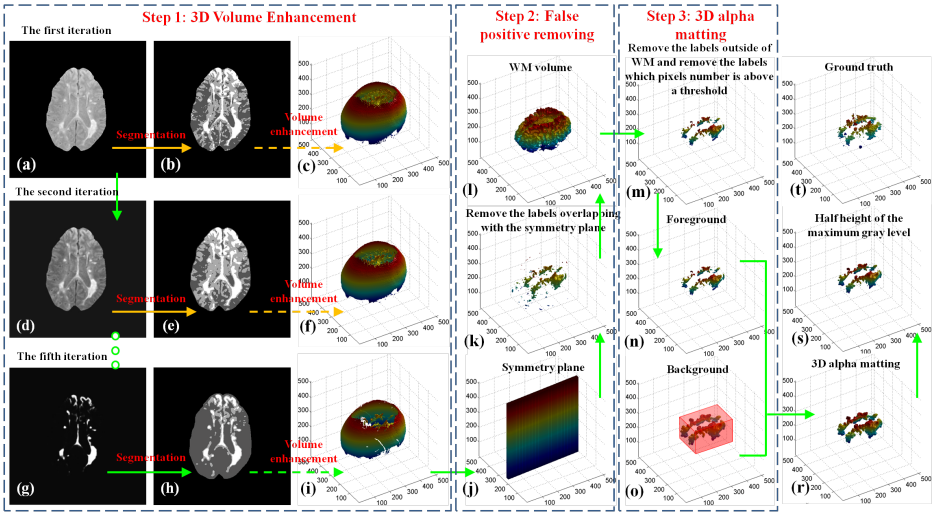

Figure 1: A T1-w, T2-w, Flair example (Case 01) of MS lesions segmentation based on the 3D enhancement and 3D alpha matting.

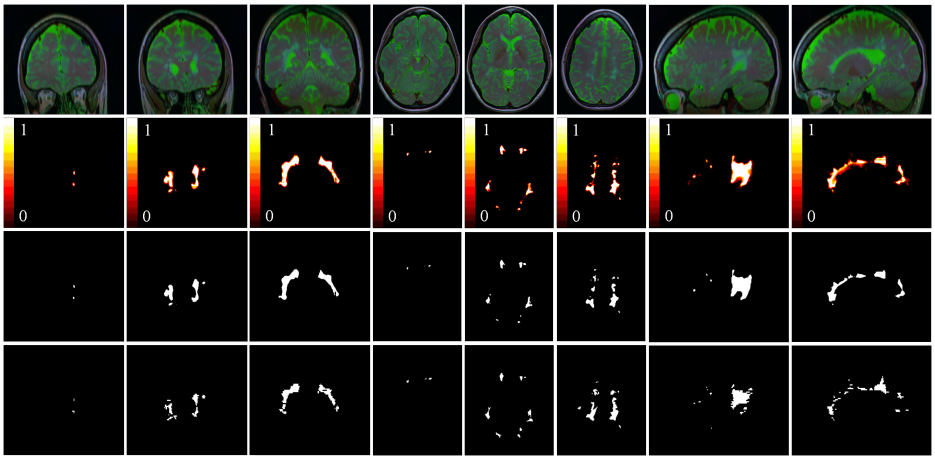

Figure 2: Examples of the results of the proposed method on MRI from different views. The first row shows the color MR images, the second row shows our segmentation results, the third row shows the half height probability of the segmentation results, the fourth row shows the ground truth.

our method shows improved results compared to the *Ch. winner*'s [2] method. In addition, our results in the overall mean of TPR and DSC are better than [3].

4 Discussion and Conclusions

This paper presents a novel segmentation scheme based on 3D volume enhancement and 3D alpha mating. The proposed method has three advantages. Firstly, the 3D enhancement method

can deal well with image noise, and density inhomogeneity within the MS lesions. Secondly, the 3D alpha matting technique is introduced for the first time to color MRI segmentation, which can effectively deal with partial volume effects. In the future, 3D bias field removal could be investigated in a large clinical datebase. In addition, it should be noted that the use of the CHB datasets [11] for evaluation is seen as positive, because the results taken from [3] are calculated with a lower resolution, so a direct comparison to the proposed method might be unfair. Therefore, we will further evaluate the proposed method with [1] on the same public databases.

References

[1] Zeng, Z., Zwiggelaar, R.: Joint histogram modelling for segmentation Multiple Sclerosis Lesions. Lecture Notes in Computer Science. 6930, 133–144 (2011)

[2] Souplet, J.C., Lebrun, C., Ayache, N., Malandain, G.: An automatic segmentation of T2-FLAIR multiple sclerosis lessions. In: The MIDAS Journal - MS lesion Segmentation (MICCAI 2008 Workshop). 1–5 (2008)

[3] Geremia, E., Menze, B.H., Clatz, O., Konukoglu, E., Criminisi, A., Ayache, N.: Spatial decision forests for MS lesion segmentation in multi-channel MR images. Lecture Notes in Computer Science. 6361, 111–118 (2010)

[4] Collignon,A., Vandermeulen, D., Marchal, G., Suetens, P.: Multimodality image registration by maximization of mutual information. IEEE Transactions on Medical Imaging. 16(2), 187–198 (1997)

[5] Stephen M.S.: Fast robust automated brain extraction. Human Brain Mapping. 17(3), 143–155 (2002)

[6] Kraskov, A., Stogbauer, H., Grassberger, P: HMRF-EM-image: Estimating mutual information. Physical review. E, Statistical, nonlinear, and soft matter physics. 69(6), 1–16 (2004)

[7] Wang, W.H., Feng, Q.J., Chen, W.F.: Segmentation of brain MR images based on the measurement of difference of mutual information and Gauss-Markov random field model. Journal of Computer Research and Development. 46(3), 521–527 (2009)

[8] Prima, S., Ourselin, S., Ayache, N.: Computation of the mid-sagittal plane in 3-D brain images. IEEE Transactions on Medical Imaging. 21(2), 122–138 (2002)

[9] Grosman, R.I., Mcgowan, J.C.: Perspectives on Multiple Sclerosis. AJNR. 19, 176–186 (1998)

[10] Shao, H.C., Cheng, W.Y., Chen, Y.C.: Colored muti-neuron image processing for segmenting and tracing neural circuits. In: Proceedings of IEEE International Conference on Image Processing, pp. 1–4. (2012)

[11] Styner, M., Lee, J., Chin, B., Chin, M.S., Commowick, O., Tran, H.H., Jewells, V., Warfield, S.: 3D segmentation in the clinic: A grand challenge II: MS lesion segmentation. MIDAS Journal. 1–5 (2008)