White matter hyper-intensities automatic identification and segmentation in magnetic resonance images

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A B S T R A C T
A methodology for automatic identification and segmentation of white matter hyper-intensities appearing in magnetic resonance images of brain axial cuts is presented. To this end, a sequence of image processing technics is employed to form an image where the hyper-intensities in white matter differ notoriously from the rest of the objects. This pre-processing stage facilitates the posterior process of identification and segmentation of the hyper-intensity volumes. The proposed methodology was tested on 55 magnetic resonance images from six patients. These images were analysed by the proposed system and the resulted hyper-intensity images were compared with the images manually segmented by experts. The experimental results show the mean rate of true positives of 0.9, the mean rate of false positives of 0.7 and the similarity index of 0.7; it is worth commenting that the false positives are found mostly within the grey matter not causing problems in early diagnosis. The proposed methodology for magnetic resonance image processing and analysis may be useful in the early detection of white matter lesions.

1. Introduction

Nowadays, magnetic resonance imaging (MRI) is an important tool widely used in different medical applications. Among the different types of possibly disorders detected with MRI images are those of brain axial cuts used to detect various diseases characterised by white matter abnormalities; their accurate detection is a challenging problem (Gordillo, Montseny, & Sobrevilla, 2013).

White matter lesions are described as white matter hyper-intensities (WMH) that can be found within normal white matter tissue regions as brighter image objects when MRI uses T-2-weighted and fluid attenuated inversion recovery (FLAIR) (Raniga et al., 2011). The problem of WMH segmentation is difficult due to small differences in brightness between normal and injured regions that might vary in an entire image. Manual segmentation is possible, but is a time-consuming task and subject to operator variability; reproducing a manual segmentation result is difficult and the level of confidence ascribed suffers accordingly (Withey, Koles, software. NFSI-ICFBI, & heart, 2007). For these reasons, automatic WMH segmentation is preferable, but this task is rather difficult and it remains an active research area (Gordillo et al., 2013; Khademi & Venetsanopoulos, 2012; Ong, Ramachadam, Mandalava, & Shuaib, 2012; Samaille et al., 2012). Recently, a number of methods for WMH segmentation were proposed in literature. A comprehensive study of state-of-the-art MRI tumour segmentation techniques can be found in Gordillo et al. (2013), El-Dahshan, Mohsen, Revett, and Salem (2014), Llady et al. (2012), Ma, Tavares, Jorge, and Mascarenhas (2010), Withey and Koles (2007).

The most efficient, in our opinion, technique that does not refer to specific lesions and describe the automatic WMH segmentation using T-2 weighted FLAIR images is the completely automatic adaptive technique proposed by Ong et al. (2012) for brain lesions detection. According to this technique, the presence of WMH is found using an adaptive approach for outlier detection in FLAIR images. The algorithm has three main stages: pre-processing, which includes skull stripping and inhomogeneity correction; the white matter segmentation; and post-processing stage, which includes normal brain tissue classification and morphological processing to remove false positives (FP). At the pre-processing stage an additional T1-weighted image as well as FLAIR input image is used for skull stripping. Then, outliers are determined by the box and whisker plot using the intensity distribution of the grey matter and white matter voxels. Next, extreme outliers are computed and removed. The feature that we want to detect is the intensity distribution of the grey matter and white matter voxels. Thus, false positives can be removed using the box and whisker plot. At the post-processing stage, the algorithm is run on the pre-processed image to remove false positives (FP).
2. WMH segmentation methodology

We propose a novel methodology for WMH segmentation in magnetic resonance images, which consists of several steps that may be divided in two stages: image preparation and final processing. At the first stage, the image is pre-processed for the following treatment, such as skull stripping and brain grey tissue separation. Once the image is prepared, at the final processing stage the different types of brain tissues are analysed and white matter is separated to detect and segment the hyper-intensities in white matter. The method does not require different MRI weighting and might be useful for radiologists dealing with cerebral disorder diagnosis without the need of the expensive multispectral scan slices and different weighting techniques that produce several volumes per patient.

The paper is organised as follows: after the Introduction, Section 2 describes the WMH segmentation methodology; in Section 3 the results are discussed, and finally the conclusions are given in Section 4.

2.1. Image preparation

At this stage different treatment is performed before the MRI image enters the final processing stage. This treatment may be divided in three steps: pre-processing, skull stripping and grey matter extraction.

2.1.1. Pre-processing

The pre-processing step permits disposing the image for skull stripping. The treatment results in a labelled image, whose objects are brain and skull parts that will be stripped after. The pre-processing consists of the thresholding according to the Otsu method (Otsu, 1979), morphological filtering by opening and closing, sliding mean smoothing and labelling of the connected components.

The Otsu method searches for the optimal threshold that minimizes the weighted sum of within-class variances of the foreground and background image points (Sezgin & Sankur, 2004):

\[ T = \arg \min |P_1 \cdot \sigma_1^2 + P_2 \cdot \sigma_2^2|, \]

where \( P_1 = \sum_{i=0}^{T} p_i \), \( P_2 = \sum_{i=T+1}^{L} p_i \), are zeroth-order cumulative moments of the original image \( f(x, y) \) histogram up to the maximal level of the image background \( T \) and objects \( L \), respectively; \( \sigma_1^2 = \sum_{i=0}^{T} (i - \mu_1)^2 p_i \), \( \sigma_2^2 = \sum_{i=T+1}^{L} (i - \mu_2)^2 p_i \) are the variances of the two classes (background and objects), \( \mu_1 = \int_{0}^{T} y f(y) dy \), \( p_i \) are first-order cumulative moments of the original image; the histogram \( p_i \) is calculated for the entire dynamic range of image levels \( i \) from 0 to \( L \).

We choose this technique because of its ability to segment image objects that obviously are separated from the background, that is, brain and cranial cavity in MRI images as is shown in Fig. 2. The original image in this figure was chosen in an illustrative manner because it presents undesired unions between objects after thresholding.

After thresholding, three image enhancing filters are applied: opening and closing filters (Soille, 2010), and sliding mean filter.
Opening and closing filters use a structuring element of $4 \times 4$ voxels size.

The justification of this structuring element size is as follows: the morphological opening operation applied to the image removes the small objects (Soille, 2010), and Otsu thresholding leaves a number of small objects. According to Bricq, Collet, and Armpspach (2008), the volumes less than 3 mm$^3$ may be excluded. In our experiments, MRI images were of $600 \times 600$ voxels size, so the image objects to be excluded smaller than $4 \times 4$ voxels corresponds approximately to the volumes less than 1.5 mm$^3$. The structuring element of $4 \times 4$ size removes such objects but leaves the greater objects. It was established experimenting with various MRI images that the opening filter with the structuring element of $4 \times 4$ voxels size eliminates sufficiently the undesired unions between objects after Otsu thresholding and separates in MRI images the skull and the artefacts those having a volume much less than the brain one. The closing filter with structuring element of the same $4 \times 4$ voxels size allows to restore the original shape of the rest of image structures (Soille, 2010) by smoothing the brain contour and filling the holes.

Next, the image is smoothed by the sliding mean filter. The size of this filter has to match the image data correlation radio (Gonzalez & Woods, 2008; Pratt, 2007). Bricq et al. (2008) mention that in their case of $512 \times 512$ images, a strong correlation exists within $4 \times 4$ area, so in our case of $600 \times 600$ image size the data within the vicinity of $5 \times 5$ voxels can be considered as correlated. We found by experiments that the sliding mean filter of $5 \times 5$ voxels size smoothes the images and replenishes well the lost points at the squares resulted from the previous open-closing morphological processing.

Note that the employed sizes of the mentioned spatial filtering techniques are determined to be adequate to process MRI skull images of $600 \times 600$ voxel size by evaluating the processing results. However, these sizes must be increased in the case of the images with higher spatial resolution, or contrary, reduced for smaller images. Alternatively, the MRI images of different sizes can be downscaled/upscaled to perform the spatial processing with the indicated sizes of the used spatial filters.

Continuing the pre-processing, the connected components are labelled. For this purpose, the iterative algorithm of 8-connectivity (Cheng, Peng, & Hwang, 2009) is employed. This type of connectivity is used because it takes into consideration all the treated voxel neighbours that generate a greater probability of correct labelling of the entire object. The purpose of labelling is to distinguish the objects within the image by their labels in order to count them later to determine their respective volume. Fig. 3 illustrates the labelling: the pre-processed image has assigned a label for each different grey level object.

### 2.1.2. Skull stripping and grey matter separation

Skull stripping is accomplished using the fact that the brain volume is much greater than artefacts resulting from the image pre-processing. To this goal, the objects are first counted, the labels are stored and the volume of each object is determined. Secondly, the greatest volumes are selected and the small volumes are eliminated, thus separating brain tissue objects from the rest. As a result, the image of two brain lobes is obtained.

At the next step only some parts of the grey matter are extracted because it is not well defined in the original image and it can be recognised only when the contrast is enhanced. This fact is illustrated in Fig. 4(a), where the emphasised grey matter regions after contrast enhancing must be eliminated because they present grey matter hyper-intensities that can be confused with the white matter hyper-intensities, resulting in a wrong WMH identification.

To extract an informative part of grey matter, the fill-hole algorithm (Soille, 2010) is applied first to brain volumes because in some cases WMH are found on gap edges. Then, we apply a special algorithm of volume/percentage, which we developed to eliminate a percentage of the volume external to the brain.

Fig. 2. Otsu thresholding: (a) original image; (b) image resulting from the thresholding. Arrows indicate the undesired unions between objects.

Fig. 3. Brain image with labelled connected components.
2.2.2. WMH identification and segmentation

At this stage, the regions of interest first are generated on the basis of the brightest voxel having the maximal values because they represent the most significant regions in the image. Once the regions of interest are determined, the centroid of each region is found. The resulting centroid voxels are the seeds for the following process of region growing and they form the seed matrix \( S(x,y) \). Fig. 7(a) shows the result of this process where for each region only one voxel seed is associated (more than one pink points are used to represent one seed voxel).

The centroid voxels of the regions of interest in the image resulted from WMH identification are the seeds for the region growing algorithm. Here, we briefly describe the basic algorithm for region growing of 8-connectivity. The segmentation process starts from the input image \( f(x,y) \) resulting from a previous contrast enhancing step; the seed matrix (image) \( S(x,y) \) has logical ones in the seed points and zeros in other points. The algorithm for region growing (Gonzalez & Woods, 2008) scans seed image \( S(x,y) \) to find a seed.
When a seed is found, the region growing is performed from this point over the input image $f(x, y)$. Region growing stops when a significant difference between the seed and the neighbour voxels is found. The region growing produces the image $g(x, y)$ depicted in Fig. 7(b), where the WMH regions are marked with pink points.

3. Results and discussion

In this section we present an evaluation of the processes of skull stripping, extraction of a part of the grey matter, WMH identification and segmentation, and also the complete processing. To evaluate the quality of these processes, 55 T2 weighted FLAIR images of six patients with multiple sclerosis, kindly provided by Instituto Nacional de Rehabilitación, were used. These grey scale images of brain axial cuts are of $600 \times 600$ voxels size. The images were manually segmented extracting the skull and dark brain volumes by a radiologist. The manually segmented images were compared to the automatically segmented ones using the proposed methodology described in Section 2.

3.1. Skull stripping results

To evaluate the quality of this process, 55 test images were used and the criterions were the correlation coefficient and the volume difference. The correlation coefficient is defined as (Pratt, 2007):
\[ \rho = \frac{\sum_{m,n}(f_{\text{aut}}(m,n) - \bar{f}_{\text{aut}})(f_{\text{man}}(m,n) - \bar{f}_{\text{man}})}{\sqrt{\sum_{m,n}(f_{\text{aut}}(m,n) - \bar{f}_{\text{aut}})^2 \cdot \sum_{m,n}(f_{\text{man}}(m,n) - \bar{f}_{\text{man}})^2}}, \]  

where \( f_{\text{aut}}(m,n) \) denotes the automatically segmented image, \( f_{\text{man}}(m,n) \) is the manually segmented image and \( \bar{f}_{\text{aut}}, \bar{f}_{\text{man}} \) are the means of the automatically and manually segmented images, respectively.

The volume difference is defined as (Ong et al., 2012):

\[ V_{\text{dif}} = \frac{V_{\text{aut}} - V_{\text{man}}}{V_{\text{man}}} \cdot 100\%, \]  

where \( V_{\text{aut}} \) is the volume of the automatically segmented image and \( V_{\text{man}} \) is the volume of the manually segmented image. The results of skull stripping in terms of the correlation coefficient are shown in Fig. 8.

From Fig. 8 it follows that the correlation coefficient mainly is in the range from 0.8 to 1; only one image has the correlation coefficient \( r = 0.733 \). In Fig. 9, the results of volume difference comparison in percentage are shown.

From Fig. 9 one can observe that most of the values lay in the range of \(-20\%\) and \(+15\%\) except two images having a volume difference of 24.5\% and 24.57\%. The negative percentage is equivalent to the volume that has been automatically segmented with the volume larger than the manually segmented one, and the positive percentage corresponds to the opposite case. The obtained maximal and minimal correlation values and the volume difference are presented in Table 1.

### 3.2. Extraction of grey matter informative part

To evaluate this process, the same 55 images as in the previous stages were used. The number of grey matter hyper-intensities (GMH) after the contrast enhancing were calculated in comparison to the number of such hyper-intensities eliminated by the proposed algorithm of informative part of grey matter extraction. The total number of GMH was 385, and 318 of them were eliminated, resulting in 83\% of the correct elimination of GMH. Besides, 67 of 385 GMH were not eliminated. This means that 17\% of GMH remained because the proposed algorithm of volume percentage erosion segments only a part of the grey matter due to the fact that the grey matter is not clearly differentiated in the processed images.

Fig. 10 illustrates the results of the extraction of the grey matter informative part. One can observe from Fig. 10(a) that this image has 11 GMH objects. Fig. 10(b) shows the volume to be extracted as a part of grey matter equal to 40\% of its total volume. In Fig. 10(c) the result of the informative grey matter part extraction...
is presented. In Fig. 10(d), one can observe that WMH segmentation is performed without taking into account GMH, i.e. GMH does not interfere in the process of WMH segmentation.

3.3. Results of WMH identification

For the evaluation of the WMH identification process, the WMH manually identified by an expert radiologist were compared to those obtained automatically by the proposed methodology. The manual and automatic identifications were calculated and compared, resulting in three types of identifications: “True”, where both the manual and automatic identifications were found; “Omitted”, where the manual identification was found and the automatic not; and “False”, where within the white matter the manual identification was absent but the automatic identification was found. In Table 2 the total values obtained in the process of WMH identification are presented.

The evaluation of WMH identification process resulted in 39 omitted identifications that correspond to 10.9% of WMH. These omissions can be explained by the fact that in the contrast enhancing, these omitted WMH did not achieve a contrast sufficiently high enough for their automatic identification. Moreover, the obtained results have 98 false automatic identifications from a total number of 401 that corresponds to 24.4% of WMH. This can be explained by the fact that during the contrast enhancing some volumes of grey matter are highly intensified but they are not WMH. Fig. 11 illustrates the process of WMH identification indicating false and omitted identifications.

3.4. WMH segmentation results

The WMH segmentations obtained automatically and the manual segmentations supervised by an expert were compared using the following parameters: the correlation coefficient (2), the volume difference (3), and the mean true positives’ rate (TPR), mean false positives’ rate (FPR), and similarity index (SI).

The TPR (Ong et al., 2012) in our terms is defined as

$$TPR = \frac{V(AS \cap MS)}{V(MS)}$$

where $V(\cdot)$ is the number of elements in a set, MS is the set of manually segmented WMH, and AS is the set of automatically seg-

<table>
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<tr>
<th></th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
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<tbody>
<tr>
<td>Correlation coefficient</td>
<td>0.9735</td>
<td>0.733</td>
</tr>
<tr>
<td>Positive volume difference</td>
<td>15.67%</td>
<td>0.2%</td>
</tr>
<tr>
<td>Negative volume difference</td>
<td>-24%</td>
<td>-0.17%</td>
</tr>
</tbody>
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Table 1 Extreme values of the correlation coefficients and the corresponding volume differences between automatically and manually skull stripped images.
mented WMH, \( \cap \) denotes intersection operator. The FPR (Ong et al., 2012) in our terms is defined as:

\[
FPR = \frac{V(AS \cup MS) - V(AS \cap MS)}{V(MS)},
\]

where \( \cup \) denotes union operator. The similarity index is defined as (Ong et al., 2012):

\[
SI = \frac{2(AS \cap MS)}{(V(AS) + V(MS))}.
\]

The obtained mean true positives’ rate is \( TPR = 0.9 \), which means that the majority of manually segmented WMH also were detected automatically: 86% of images have \( TPR \) in the range from 0.8 to 1, 7% have \( TPR = 0.7 \), and 7% have \( TPR \) in the range from 0.4 to 0.6. At the same time, the mean false positive rate is \( FPR = 0.7 \): 41% have \( FPR \) in

<table>
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<tr>
<th>Identification</th>
<th>Manual</th>
<th>Automatic</th>
<th>True</th>
<th>Omitted</th>
<th>False</th>
</tr>
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<tbody>
<tr>
<td>Value</td>
<td>346</td>
<td>401</td>
<td>304</td>
<td>39</td>
<td>98</td>
</tr>
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</table>

Table 2

Values obtained in the WMH identification process.

Fig. 11. WMH identification: (a) original brain image; (b) image resulted from manual identification, where pink WMH correspond to the lesions and cyan WMH represent reflections from brain folds; (c) resulted automatic identification image, where WMH are marked by yellow; (d) image with true automatic identifications rounded by pink circles; (e) omitted identifications are rounded by yellow circles; (f) false identifications are rounded by pink circles. (For interpretation of references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 12. Correlation \( \rho \) between manually and automatically WMH segmented images.
In the range from 0 to 0.5, 48% of images have FPR in the range from 0.8 to 1, and 2% had FPR in the range from 0.5 to 0.8. The obtained mean similarity index is $SI = 0.87$ that indicates a significant coincidence between two segmentations, manual and automatic. 70% of the images have $SI$ in the range from 0.7 to 1, and the remaining 30% have $SI$ in the range from 0.3 to 0.6.

To calculate the correlation coefficient (2) between manually and automatically segmented images, they were converted to a grey scale representation and then binarized. The results of the comparison are shown in Fig. 12. The correlation coefficient values were: 56% from moderate to significant ($q = 0.7 \ldots 0.9$) and 44% present partial correlation ($q < 0.7$).

Tables 3 and 4 present the results of WMH automatic segmentation in terms of $TPR$ (4) and $FPR$ (5) obtained with the proposed method and the results obtained by different methods (Bricq et al., 2008; Geremia et al., 2010; Huang, Abugharbieh, & Tam, 2009) described in literature and presented in the paper (Ong et al., 2012).

The WMH segmentation results in terms of the absolute values of the volume difference (3) are shown in Fig. 13. The mean, maximum and minimum volume difference values obtained by the proposed and other methods are presented in Table 5.

### Table 3
Percentage of true positives’ rate (4) calculated over the test image set of the proposed method in comparison to the results presented in the literature (more percentage for greater TPR rate is better, the best result is marked by bold).

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<tbody>
<tr>
<td>1–0.8</td>
<td>86%</td>
<td>4%</td>
<td>39%</td>
<td>13%</td>
<td>20%</td>
</tr>
<tr>
<td>0.8–0.66</td>
<td>7%</td>
<td>11%</td>
<td>52%</td>
<td>22%</td>
<td>17%</td>
</tr>
<tr>
<td>0.6–0.4</td>
<td>7%</td>
<td>37%</td>
<td>9%</td>
<td>43%</td>
<td>11%</td>
</tr>
<tr>
<td>0.4–0.0</td>
<td>0%</td>
<td>48%</td>
<td>0%</td>
<td>22%</td>
<td>52%</td>
</tr>
<tr>
<td>Mean TPR:</td>
<td><strong>0.9</strong></td>
<td>0.44</td>
<td>0.77</td>
<td>0.55</td>
<td>0.53</td>
</tr>
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### Table 4
Percentage of false positives’ rate (5) calculated over the test image set of the proposed method in comparison to the results presented in the literature (more percentage for lower FPR rate is better, the best result is marked by bold).

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<tr>
<td>0–0.5</td>
<td>41%</td>
<td>41%</td>
<td>0%</td>
<td>4%</td>
<td>9%</td>
</tr>
<tr>
<td>0.50–0.8</td>
<td>11%</td>
<td>41%</td>
<td>24%</td>
<td>61%</td>
<td>34%</td>
</tr>
<tr>
<td>0.8–1</td>
<td>48%</td>
<td>18%</td>
<td>76%</td>
<td>35%</td>
<td>57%</td>
</tr>
<tr>
<td>Mean FPR:</td>
<td><strong>0.7</strong></td>
<td>0.86</td>
<td>0.74</td>
<td>0.79</td>
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### Table 5
Absolute values of volume difference $V_{dif}$ between the manually and automatically segmented WMH images (the best results are marked by bold).

<table>
<thead>
<tr>
<th>Volume difference</th>
<th>Mean (%)</th>
<th>Maximum (%)</th>
<th>Minimum (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed method</td>
<td><strong>0.25</strong></td>
<td>50</td>
<td>0</td>
</tr>
<tr>
<td>Bricq et al. (2008)</td>
<td>61</td>
<td>420</td>
<td>0.9</td>
</tr>
<tr>
<td>Ong et al. (2012)</td>
<td>73</td>
<td>648</td>
<td>0.3</td>
</tr>
<tr>
<td>Geremia et al. (2010)</td>
<td>49</td>
<td>145</td>
<td>0.7</td>
</tr>
<tr>
<td>Huang et al. (2009)</td>
<td>115</td>
<td>682</td>
<td>3.2</td>
</tr>
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</table>

Fig. 13. Absolute values of volume difference $V_{dif}$ between manually and automatically WMH segmented images.

3.5. Discussion of segmentation results

From the results presented in Table 3, it can be seen that the proposed methodology best detects WMH in the magnetic resonance brain images in comparison to different methods: in 86% of case, true positives’ rate (4) is from 0.8 to 1 with the mean TPR is 0.9. Among other methods, only the outlier adaptive detection method (Ong et al., 2012) with $TPR = 0.77$, but at the same time, this method is the worst in terms of $TPR$, omitting approximately 50% of the existed lesions and only in 4% of cases better detecting WMH. At the same time, this method (based on hidden Markov chain...
segmentation in 3D $4 \times 4 \times 4$ volumes) in 41% cases shows the same low TPR < 0.1 as our proposal.

Fig. 13 shows the absolute values of volume difference (3). From this figure, one can see the proposed method produces in the majority of cases a low volume difference between automatically and manually segmented images. The overall superiority of the proposed method over the considered ones for the comparison is evidently confirmed by the results presented in Table 5 in terms of the maximum, mean and minimum values of volume difference $V_{dult}$. The method (Geremia et al., 2010) performs better than other existing methods, but its results are far from the results of the proposed technique that are the best.

Additionally, it is worth mentioning that the methods considered for the comparison work on 3D data, and some of them employ additional data as different MRI weighting. Contrarily, the proposed method works on 2D axial cut images. The possibility of processing only one 2D axial cut image instead of 3D processing may be considered as a possible paper contribution.

4. Conclusions

A methodology for automatic white matter hyper-intensities identification and segmentation using 2D axial cut magnetic resonance images has been proposed. The obtained final results of automatic WMH identification and segmentation approach the results obtained from manual WMH segmentation supervised by an expert.

The proposed methodology automatically eliminates the cranial cavity presented in MRI images performing image pre-processing for the posterior skull stripping using the proposed method, which is based on choosing the large image volumes that correspond to brain tissues and eliminating the remaining volumes. The obtained results show strong correlation between the images obtained from the automatic skull stripping and those obtained manually performed under expert supervision.

In the paper, a method for automatic elimination of the grey matter part that affects WMH identification has been proposed. The method uses two algorithms: the hole filling algorithm, and the algorithm of volume percentage proposed in this paper. Using this method, 92.2% of grey matter hyper-intensities are correctly eliminated in all processed MRI images, thus reducing the false positives rate.

The WMH identification was performed first processing the images to enhance the image contrast using our proposed method for the identification of the region of interest and their corresponding WMH centroids determination. The achieved accuracy of WMH identification was 87.8%. The obtained rate of true positives and the similarity index were as high as 90% of the segmented white matter hyper-intensities.

Future research may deal with the application of the proposed methodology to process MRI brain cuts of different types: coronal, axial and transversal. To process the images of wide spectra, i.e. of different weighting and sequence types, the proposed methodology can be improved with the use of different artificial intelligence techniques. In particular, to reduce the false positives rate, an additional processing stage might be added to the developed methodology; to this end, different techniques described in literature such as fuzzy clustering or hidden Markov chain segmentation can be applied to identify WMH more correctly. Other possible future work can be oriented to recognize the type of white matter hyper-intensities (lesions, inflammations and brain folds) employing neural networks or support vector machines.

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