Assisted Lesion Segmentation in MRI Scans of the Brain using MATLAB

Chiara Boscarino
Department of Electronics, Information and Bioengineering
Politecnico di Milano, Milan, Italy
chiara.boscarino@mail.polimi.it

Alberto Borroni
Department of Electronics, Information and Bioengineering
Politecnico di Milano, Milan, Italy
alberto3.borroni@mail.polimi.it

Andrea Cantore
Department of Electronics, Information and Bioengineering
Politecnico di Milano, Milan, Italy
andrea1.cantore@mail.polimi.it

Abstract – The goal of this project is to design an image processing workflow to segment brain lesions from contrast enhanced MRI images and calculate their volume. This result was achieved by experimenting with a variety of approaches and workflows requiring multiple levels of interaction between algorithm and user. After identifying the most effective image processing method to highlight the lesion, it has been used to segment the lesion and calculate its volume. Lastly, the workflow's robustness and coherence have been assessed by introducing different types of noise to the input volume and repeating the entire process.

Keywords - *MRI, segmentation, brain images, brain lesions, lesion enhancement, ROI identification, salt & pepper noise, uniform noise, volume quantification, automated algorithms, image processing.*

I. Introduction

Lesion segmentation in MRI images of the brain is a crucial step in the diagnosis and treatment of various neurological conditions. Manual segmentation of these lesions can be time-consuming and prone to human error, making it an ideal candidate for automation.

In this paper, we present an efficient, accurate, and semi-automatic approach to lesion segmentation using MATLAB. The procedure presented in this study, indeed, does not intend to propose a fully automated segmentation, but rather an assisted process that calls for practitioner interaction to verify that the algorithm is performing segmentation correctly. We made this choice based on the assumption that automating the segmentation process greatly reduces the risks of human error in such repetitive work of precision. Nonetheless, when it comes to a person's health, it is good practice to have an expert oversee the algorithm. This is to ensure the correctness of the final assessment.

In the following sections, we first describe the approach used to define the MRI image pre-processing workflow, for image enhancement and lesion detection. Then, we present the effectiveness of the identified process on the available MRI scans to perform the segmentation and quantify the lesion volume.

II. Materials and Methods

1) Data Description

To work on this project, out team was provided with a T1 contrast enhanced MRI volume. This kind of images provides information about current disease activity and highlights the areas of active inflammation, which can be caused by the lesion. The volume dimensions are 256x256x112 and the dimensions of each voxel are 0.9375x0.9375x1.4 mm. The values stored in the voxels range from 0 to 255, so we can visualize greyscale 8-bit images.

2) Study Design and Image Processing

The study focused on the image processing techniques able to enhance the MRI scans to improve the automatic segmentation process. The processing workflow on each slice has been structured in 3 macro phases: the image enhancement, the ROI identification, and the area computation. The rationale behind this approach consists in finding the optimal processing, to be applied to each MRI scan, so that the lesion area is enhanced, and the semi-automated ROI identification step is simplified as much as possible. To identify the optimal approach to implement the workflow, we iteratively evaluated the results attempting multiple methods at each step and proceeding by trial and error.

At first, we established the optimal ROI identification approach and the area quantification method. The basic idea consisted in (i) binarize the processed image using a threshold obtained with the Otsu's method, (ii) ask the expert to check the area selection, (iii) isolate the selected area, (iv) fill the selected area to obtain a homogeneous lesion profile, (v) calculate the area of the lesion on the given slice starting from the number of pixels covered by the lesion profile. The main issue we focused on here, beside the processing technique that will be addressed in detail below, was the identification of the filling technique. In addition to the traditional hole filling method, a median filter-based technique was also considered. Since the median filter algorithm, especially when applied to a binary image, produces homogenization of the areas as an intrinsic result, the latter option was considered valuable, and indeed it was. Our final workflow, however, included the other filling algorithm because the median in some cases resulted in too much smoothing of the shape of the lesion area, thereby reducing the accurate volume estimate.

The establishment of the final workflow for image processing was, somewhat more challenging. Initially, starting with the pre-implemented functions and trying to work on the 135 sagittal slice, even a local contrast enhancement (properly designed to leave strong edges unchanged) seemed to be sufficient to correctly identify the lesion area with binarization. Nevertheless, as soon as we reviewed the workflow with the remaining scans, it became obvious that a more complex method would be required to differentiate some white areas surrounding the lesion in some parts of the volume. As a result, we developed our own algorithms, and we evaluated them both on the original and negative versions of images. At first, we attempted to differentiate the areas on the image by implementing a custom multi-thresholding algorithm to quantize the grayscale and we tried to fine-tune the number of quantization intervals. The results were still unsatisfactory despite this. Therefore, we decided to change the approach and apply smoother transformations. Hence, we moved to point processing operator in the form $s(x,y) = C * r(x,y)^{\gamma}$, and several γ values were used to determine which gray levels should be expanded to better identify the ROI. In the end, we realized that the most effective thing to do was to enhance the contrast around the average grey level characterizing the lesion area. To do so, in a smooth manner, we attempted using a general logistic function, with parameters set to properly locate the raise. It provided positive results, but we weren't satisfied yet with the area estimation obtained with such preprocessing. Thus, we chose a different approach based on highlighting only the gray level of the lesion. To implement such a technique, we implemented an intensity transformation using a smoothed rectangle-like function, whose raises have a logistic shape located at the extremes of the gray range characterizing the lesion area. It provided satisfactory results, especially when applied on the negative version of the original image. In the end, we included this processing approach in the final workflow since it proved to be most the effective one.

Having established the processing workflow, we explored the entire volume applying it slice by slice from the perspective of the 3 planes (sagittal, coronal, and axial) to provide an estimation of the lesion volume.

3) Volume quantification

Using the method based on the smoothed rectangle-like function, which resulted the most accurate one, we iterated on each slice for every plane. We started from a pre-determined slice and iterated over the entire plane analyzing the previous and the next slices. For every slice the preprocessing workflow described in the previous section was applied. After this, the region of interest was obtained with an initial binarization of the slice and a subsequent hole filling.

So, after this procedure we obtained an array for every plane filled with the values of the area of the region of interest in each slice in pixels. Every value of the area was then multiplied by the voxel volume and the sum of the array computed. In doing so, we were able to collect 3 different values of the volume of the lesion calculated iterating over the 3 different planes. Finally, an average of the 3 values was computed to get a realistic estimation of the volume. Measurements conducted on different planes tend to overestimate or underestimate the volume depending on the image processing and the elements resulting in the MRI scans, so we considered the average a valid estimator.

4) Robustness assessment with noise

At this point, we wanted to assess the robustness of the workflow we developed by adding different types of noise to the volume in input and then repeat the entire process on noisy volumes. More precisely, we tested our workflow at first with 3 different uniform noises: all 0-mean and variances of 0.01, 0.04, and 0.09. Then, we added salt & pepper noise to the original volume with different densities: 5, 7, and 10 %. Our workflow resulted consistent and robust with all types of uniform noise and even better with salt & pepper noises.

III. RESULTS

The 3 volumes obtained are:

- iteration on the axial plane: 16.09 cm3
- iteration on the sagittal plane: 15.27 cm3
- iteration on the coronal plane: 18.37 cm3

So, the average volume is 16.57 cm^3, which is a reasonably accurate estimation consistent with what can be deduced from the volume visualization.

Furthermore, our main goal was to implement a semi-automatic segmentation process that reduces the risks of human error. We accomplished this purpose and we have been able to implement a workflow that with some improvement could be used on a regular basis to assist experts in their segmentation work.

IV. DISCUSSION

1) Limitations

a. The workflow we implemented needs little work from the operator, but it remains cause of inter-operator variability. This interaction also introduces longer and uncompressible timing in completing the process, with respect to a fully automated algorithm to produce results.
b. The filter implemented is still affected by artefacts present in the original volume, especially if the values of the artifact match the values of the voxels we want to segment.

2) Further developments

a. Some AI frameworks could be included in the process in the future to let the model learn a more precise workflow, increasing diagnostic capabilities while operator interaction.

V. REFERENCES

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