Edge detection and segmentation of lesion in MR images

Andrea Scarpellini
Politecnico di Milano
Milan, Italy
andrea1.scarpellini@mail.polimi.it

Eleonora Sala
Politecnico di Milano
Milan, Italy
eleonora1.sala@mail.polimi.it

Federico Tognoni
Politecnico di Milano
Milan, Italy
federico.tognoni@mail.polimi.it

***Abstract*— The tumor segmentation process from an MRI image of brain is one of the highly focused areas in the community of medical science. This paper introduces the problem of lesion segmentation and implement a specific workflow over an MRI volume in Matlab. It includes a brief review of the topic of tissue and lesion segmentation over MRI images, and a sub-steps motivated workflow to pre-process an MRI image and segment a lesion based on methods we have seen during lessons. The performances of our implemented workflow were tested with different types and levels of noise.** **Keywords-MRI, lesion segmentation.**

I. Introduction

In the past years, a large improvement of non-invasive brain imaging technologies has introduced new possibilities in analyzing the brain anatomy and function. In particular, MRI provided a large amount of data with an increasingly high level of quality, but the analysis of these complex MRI datasets has become a difficult task for clinicians, who have to perform a manual extraction of important information, that is often time-consuming and prone to errors due to inter- or intra-operator variability. These difficulties in brain MRI data analysis could be improved by computerized methods to support disease diagnosis.

Brain MRI segmentation is an essential task in many clinical applications because it influences the outcome of the entire analysis, because different processing steps rely on accurate segmentation of anatomical regions. In fact, MRI segmentation has widespread applications in medical science, such as, tissue classification, localization of tumors, tumor volume estimation, delineation of blood cells, atlas matching, image registration, [1] visualizing different brain structures, analyzing brain development, and for image-guided interventions and surgical planning.

Although MRI can describe the structures of the brain accurately, medical image segmentation is a tough task because of poor spatial resolution, low contrast, ill-defined boundaries, inhomogeneity, partial volume effect, noise, variability of object shapes and some other acquisition artifacts in the retrieved data, that can require some further pre-processing steps. This diversity of image processing applications has led to development of various segmentation techniques of different accuracy and degree of complexity.

The segmentation methods, with application to brain MRI, may be grouped as follows [2]:

(i). manual segmentation;
(ii). intensity-based methods (including thresholding [3], region growing, classification, and clustering);
(iii). atlas-based methods;
(iv). surface-based methods (including active contours and surfaces, and multiphase active contours);
(v). hybrid segmentation methods.

In this project an intensity-based method, such as the thresholding, will be implemented in order to perform the lesion segmentation.

II. Materials and methods

A. Dataset description

The dataset is composed by a T1 contrast enhanced MRI volume of a affected tumor brain. The contrast material in T1 weighted images (T1c) helps to enhance tumor boundaries from the neighboring normal tissues[4], so that the lesion is far brighter than the surrounding regions.

The volume can be imported and visualized in Matlab, focusing on the axial and sagittal planes, in which the segmentation will be performed. Its dimensions are 256x256x112 and every slice is composed by voxels of sides 0.9375mm and thickness of 1.4mm.

B. Pre Processing

The pre-processing procedure has been computed on both axial and sagittal slices.

Procedure steps:

(i). Isolation of the Region Of Interest (ROI). In this case study the ROI was a tumor inside the brain volume.
In order to simplify the segmentation procedure, we used the Matlab *imcrop* function to set apart the ROI from the rest of the brain and non-brain tissues. In this way we obtained a parallelepiped volume which contains the tumor.

(ii). The second step of the procedure concerns the study of the image's histograms. Since some slices of the tumor's volume present artifacts, it is important to analyze the histogram of the image to understand how to improve the information. Eventually, we noticed that the artifacts could have been reduced by setting to 0 the level of the pixels bigger than a given threshold. This is because the artifacts were brighter that the ROI.
   a. $I > 240$ for axial slices
   b. $I > 230$ for sagittal slices.
(The gray scale range goes from 0 to 255)

(iii). At this point, an increase of the contrast with gamma=2 is computed to darken the image background and enhance the tumor body by increasing its pixel values. The results can be analyzed also from the histograms.

To reduce the presence of the bright non-tumor pixels in the background and to maintain the information about the edges of the lesion, we applied a median filter (6x6 neighborhood). Overall, this kind of filter helps to enhance the features of interest of the ROI.

C. *Segmentation and Volume Computation*

A necessary step to extract the contours of the lesion and calculate its volume is to binarize the image. We decided to do it with a global threshold of 0.8. The outcome of this process consists of an image representing the white tumor body over a black background. This image is used to extract the contours of the white figure for every slice of the volume.

By the command *imcontour* the edges are represented on the original images to give a visual result of tumor selection. Eventually, selecting only the white pixels for every slice it is possible to evaluate the volume of the lesion. The volume value has been calculated using both axial and longitudinal tumor cross-section areas, and, at the end, they have been compared to evaluate the process efficiency.

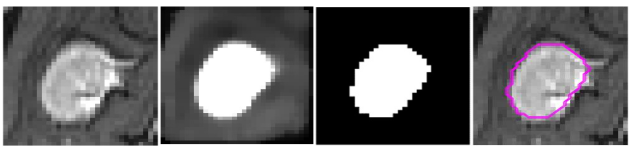
D. *Adding different types of noise*

In order to test the robustness of the workflow we tried to add different types of noise to our original images with the command *imnoise*. We decided to apply this procedure only in the axial plane because, as we will see in the next section, the sagittal plane presents some artifacts, so it was very difficult to perform segmentation even on the non-noised preprocessed image.

First of all, we tested the algorithm with a *salt & pepper* noise with a noise density of 0.05 superimposed to the image, then with a *Gaussian noise* with mean 0 and variance 0.01 (low-level noise), and at last with a Gaussian noise with mean 0 and variance 0.1 (high-level noise). In the last case we also applied an averaging spatial filter using a 3x3 matrix kernel with all values set as 1/9 before testing again the workflow to try to increase its performance.

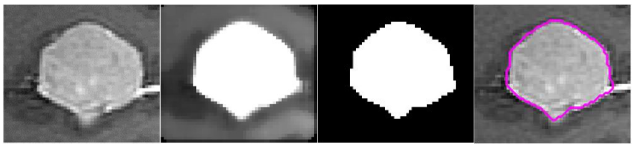
III. Results and Discussion

Introducing our results, it is important to say that the original MRI images given to us were very optimal in terms of quality and resolution, reason why there has been no difficulty to individuate the slices containing the tumorous lesion. Without adding any noise, the isolation and the segmentation of the lesion have been done quite successfully in the axial plane; on the other hand, in the sagittal one artifacts prevented us from detecting the correct edges of the lesion, and therefore we didn't find the same measure of volume of that in axial plane.



(a) (b) (c) (d)

Figure 1: implementation of the workflow on the sagittal plane, example on slice 135: (a)identification of the ROI, (b)ROI after applying manual reduction of artifacts, increase of contrast and median filter, (c)binarization if the ROI, (d)selection of lesion's contours.



(a) (b) (c) (d)

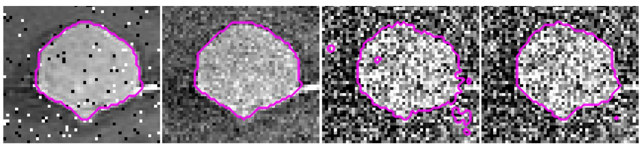
Figure 2: implementation of the workflow on the axial plane, example on slice 75: (a) identification of the ROI, (b) ROI after applying manual reduction of artifacts, increase of contrast and median filter, (c) binarization if the ROI, (d) selection of lesion's contours.

Fig. 1 and 2 displays the outcomes of the four steps of the implemented workflow respectively for sagittal and axial plane. As we can see, the edges lesion are well identified.

The total volume calculated over the two planes should be theoretically equal, but the actual comparison shows us that the two volumes differ by 14,68%. The volume calculated over the axial plane is bigger than the other one.

Regarding the second phase of the analysis, we proceeded to evaluate the workflow in the added noise images cases (Fig. 3). In particular with a superimposed salt&pepper noise (case a), the performance of our algorithm remains quite the same because of the median filter included in the main steps of our workflow. The volume calculated with this kind of noise is around 0.15% smaller than the non-noise case. Also in the low level Gaussian noise case (b) the volume results slightly smaller than the non-noise case by a value around 0.2%, which is an acceptable difference. Conversely by applying a high level Gaussian noise (c) the results obtained are not as good as the previous ones and the edges of the lesion are not well captured, so when calculating the entire volume, we obtained a difference of a range between 1% to 10%. (The range is due to the randomness of the generation of the added Gaussian noise).

Hence, we decided to apply an Averaging filter before re-applying the procedure and the edges resulted more smothered. The volume obtained was from 0.5% to 4% bigger than the original one, so the performance of the workflow increased with the further implementation of this filtering phase.



(a) (b) (c) (d)

Figure 3: test of the robustness of the workflow on images with (a)salt & pepper noise, (b)low-level Gaussian noise, (c)high-level Gaussian noise, (d)high-level Gaussian noise + Averaging filter.

References

[1] Ben Rabeh A, Benzarti F, Amiri H. Segmentation of brain MRI using active contour model. Int J Imaging Syst Technol 2017;27(1):3–11.

[2] Despotović I, Goossens B, Philips W. MRI segmentation of the human brain: challenges, methods, and applications. Comput Math Methods Med. 2015;2015:450341. doi: 10.1155/2015/450341. Epub 2015 Mar 1. PMID: 25945121; PMCID: PMC4402572.

[3] Otsu N. A threshold selection method from gray-level histograms. IEEE Trans Syst Man Cybern 1979;9(1):62–6.

[4] Hasan A, Meziane F, Aspin R, Jalab H. Segmentation of brain tumors in MRI images using three-dimensional active contour without edge. Symmetry 2016;8(11):1