Segmentation of Brain Images for Medical Diagnostic Assistance

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Abstract

Segmentation of brain images plays a crucial role in medical diagnostics, aiding clinicians in the accurate detection and analysis of various neurological conditions. This paper presents an overview of recent advancements and methodologies in brain image segmentation techniques, focusing on their application in medical diagnostic assistance. Various image-processing methods, such as region-based, boundary-based, and clustering-based approaches, are discussed, along with their advantages and limitations. We have developed an innovative algorithm based in particular on the segmentation by the region-growing method, are explored for their effectiveness in brain image segmentation tasks. The paper highlights the challenges and future directions in this field, including the need for robust algorithms capable of handling diverse image modalities and anatomical variations, as well as the integration of segmentation results into clinical workflows for improved diagnostic accuracy and patient care.

Keywords : Segmentation, neurological, brain image, region growing.

Introduction

Medical imaging technologies have revolutionized the field of diagnostic medicine, enabling non-invasive visualization of internal organs and tissues. Among these modalities, magnetic resonance imaging (MRI) is widely used for examining the brain, providing detailed information about its structure and function [1]. However, the interpretation of brain MRI scans often requires precise segmentation to delineate different anatomical regions and pathological abnormalities. Segmentation refers to the process of partitioning an image into multiple meaningful regions, facilitating quantitative analysis and aiding clinicians in disease diagnosis and treatment planning.

Medical Imaging encompasses the means of acquiring and rendering images of the human body through various physical phenomena. In recent years [2-4], this imaging domain has experienced a surge in motivation, leading to the development of new techniques for visualizing the human body or organs without the necessity of performing surgery on the patient. The primary objective is to establish a reliable diagnosis and ensure appropriate treatment monitoring. Despite these advancements, visualizing the brain remains challenging due to its complex and ambiguous anatomical structure.

Segmentation of brain images poses several challenges due to the complex and heterogeneous nature of brain anatomy, as well as variations in imaging protocols and acquisition parameters. Traditional segmentation techniques, such as thresholding, edge detection, and region growing, have been widely employed but often struggle with inaccuracies and lack of robustness, especially in the presence of noise and artifacts [5]. In recent years, there has been a growing interest in leveraging advanced computational methods, particularly machine learning and deep learning algorithms, to improve the accuracy and efficiency of brain image segmentation.

The nervous system is a intricate system consisting of structures, elements, and tissues that govern vital functions. Segmentation is a crucial step in the image analysis chain. In the context of this study, our focus is on proposing region-based segmentation for brain images. The aim is to establish methods that are sufficiently generalizable for diagnosing various diseases based on images [6]. We have developed an innovative algorithm primarily based on segmentation using the region-growing method. The implementation of the diagnostic support system will be utilized by specialized medical professionals through the development of various interfaces to facilitate the usage of the developed algorithm.

Methodology

The system proposed in this paper consists of two main steps to detect and segment our brain images. It starts by preprocessing; as well an extraction of the regions targeted and will eventually segmentation. The following figure shows the diagram of the proposed methodology:

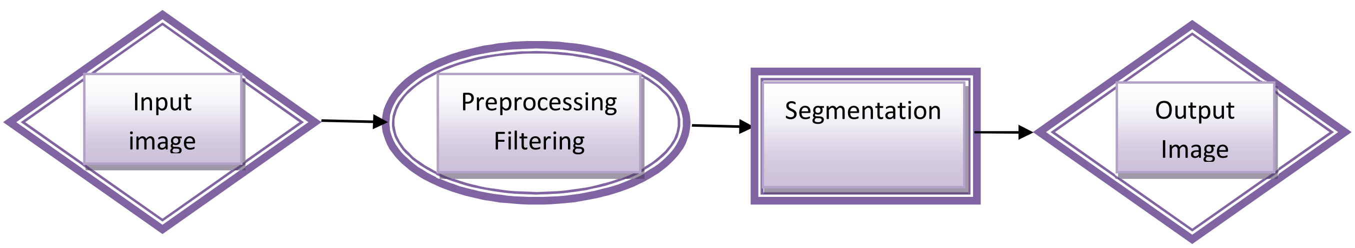

Figure 1. Block diagram of the proposed algorithm

In part this; it describes the details of the proposal more clearly.

A. Preprocessing

The objective of preprocessing is to improve the image and reduce the granularity without destroying the important characteristics of the cells used for the diagnosis.

1) Image resizing

The purpose of this step is to make all images to treat to a same size 256*256 for what is easy to manipulate by our segmentation method.

2) Filtering

In order to improve the visual effects of the image test filtering is necessary, which mainly includes eliminate the noise and improve the quality of the image.

B. Segmentation region growing

In this section, we present the segmentation method based on the algorithm region growing. The region growing technique consists of gradually growing the regions around their starting point.

1) General principle:

We initialize the region R at a pixel a group of pixels (seed). The region R has certain mean μ_R and standard deviation σ_R.

We add to R all the neighboring pixels of R which are sufficiently similar to R, for example [7]:

$$|I(x) - \mu_R| < seuil \qquad (1)$$

Or:

$$\begin{cases} min\ \{|I(x) - I(y)|; y \in R \cap V(x)\} < seuil \\ |I(x) - \mu_R| < 2\sigma_R \end{cases} \qquad (2)$$

We can also add geometric regularity criteria [8], such as:

R∩V(x) has cardinality at least 3 and has a single connected component.

The general principle [9] of the region growing method is essentially based on the following steps:

- Bottom-up approach.
- Departure from a seed pixel (or group of pixels).
- Analysis of its neighboring pixels and analysis of the homogeneity criterion P.

- Growth of the region up to the stopping criterion (no more pixels satisfy the criterion).

2) Region growing algorithm

The algorithm consists of two steps [10]:

Find the starting points of the regions.

Enlarge the regions by agglomerations of neighboring pixels.

Starting points (seeds):

The choice of starting points is the step is the critical part of the algorithm. Indeed, the growth step will use a similarity measure to choose the pixels to agglomerate. If the starting point is located in a non-homogeneous area, the similarity measure will produce strong variations and growth will stop very early. Therefore, starting points should be chosen in the most homogeneous areas possible.

Growing:

This step aims to enlarge a region by agglomeration of neighboring pixels. The pixels are chosen to maintain the homogeneity of the region. For this, we must define a homogeneity indicator. Neighboring pixels are added to the region if the homogeneity flag remains true. Growth stops when we can no longer add pixels without breaking the homogeneity.

C. Dataset

As part of our work, a simulated image base was used, it is entitled “The whole brain atlas” [11]. This database contains the brain atlas intended for research with the aim of gathering, presenting and discovering knowledge about the human brain.

We downloaded images from this database with their information to distinguish the types of strokes that exist.

Results and discussion

Our experimental section is dedicated to the processing of brain images affected by Cerebral Vascular Accident (CVA), with the aim of identifying abnormal areas.

- **Test 1 :**

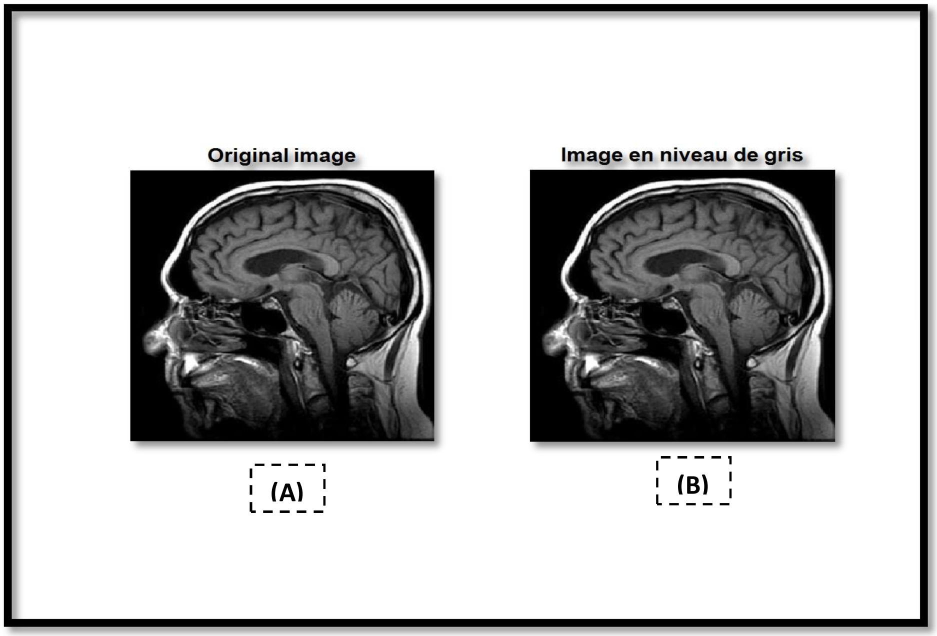

Figure 2: (A) Original Image (B) Image converted to gray level

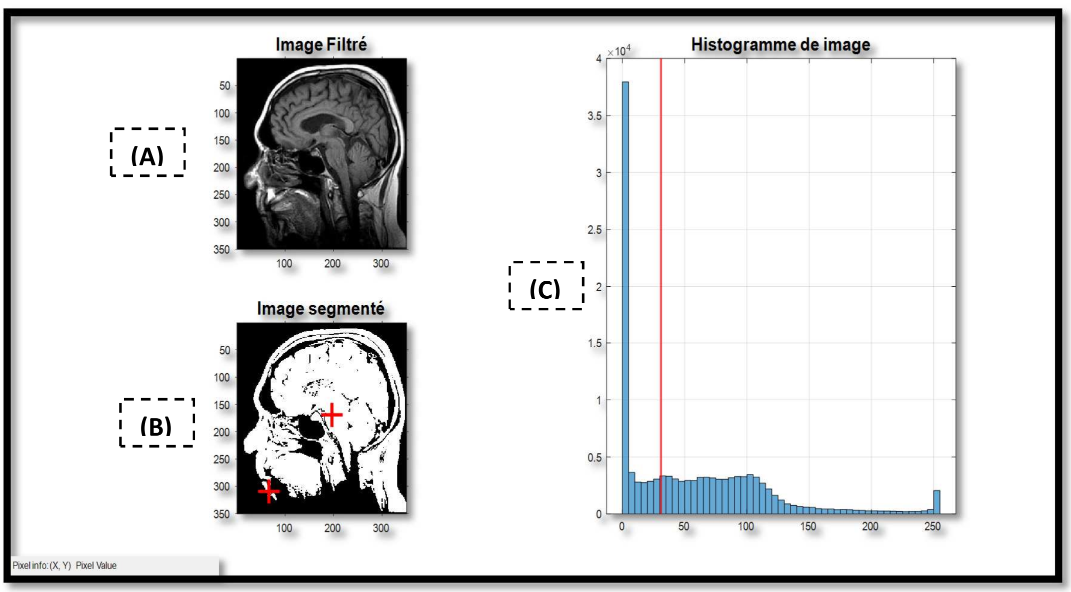

Figure 3 : (A) Filtered Image (B) Segmented Image (C) Image Histogram

- **Test 2 :**

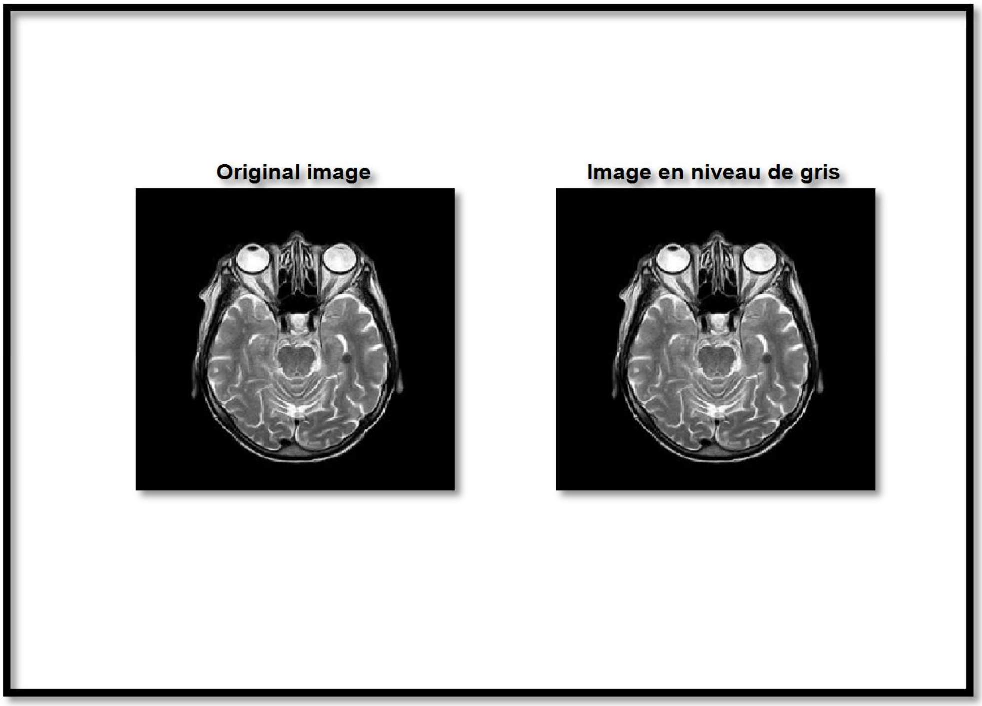

Figure 4 : (A) Original Image (B) Image converted to gray level

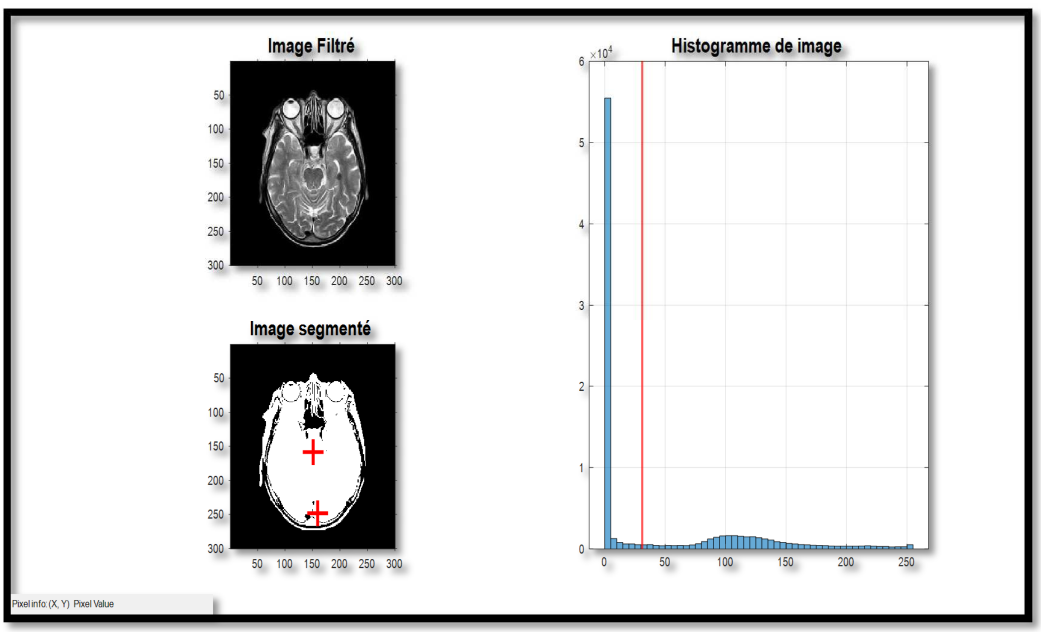

Figure 5 : (A) Filtered Image (B) Segmented Image (C) Image Histogram

- **Test 3 :**

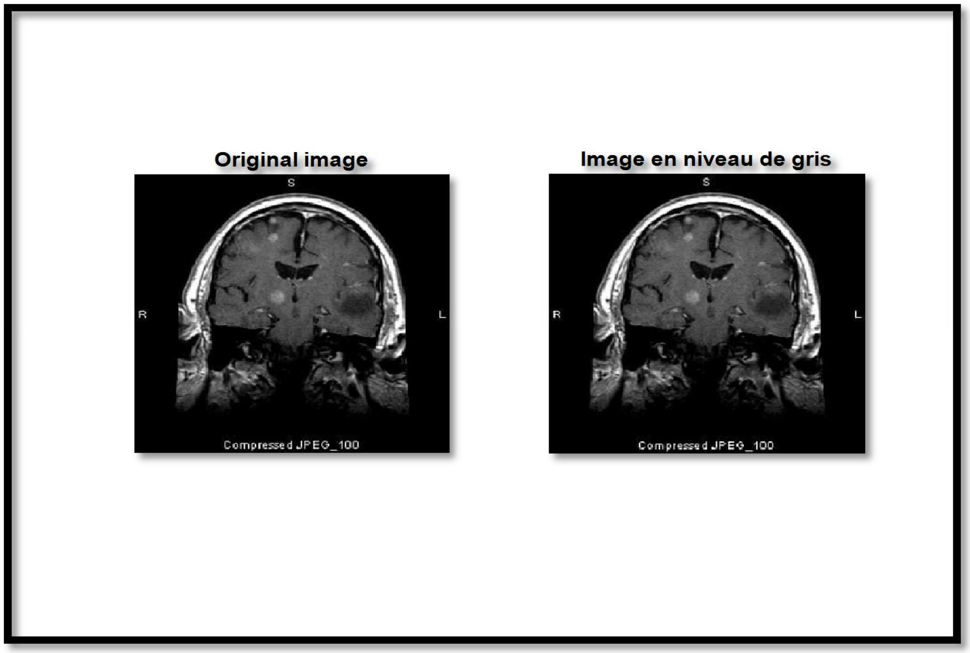

Figure 6 : (A) Original Image (B) Image converted to gray level

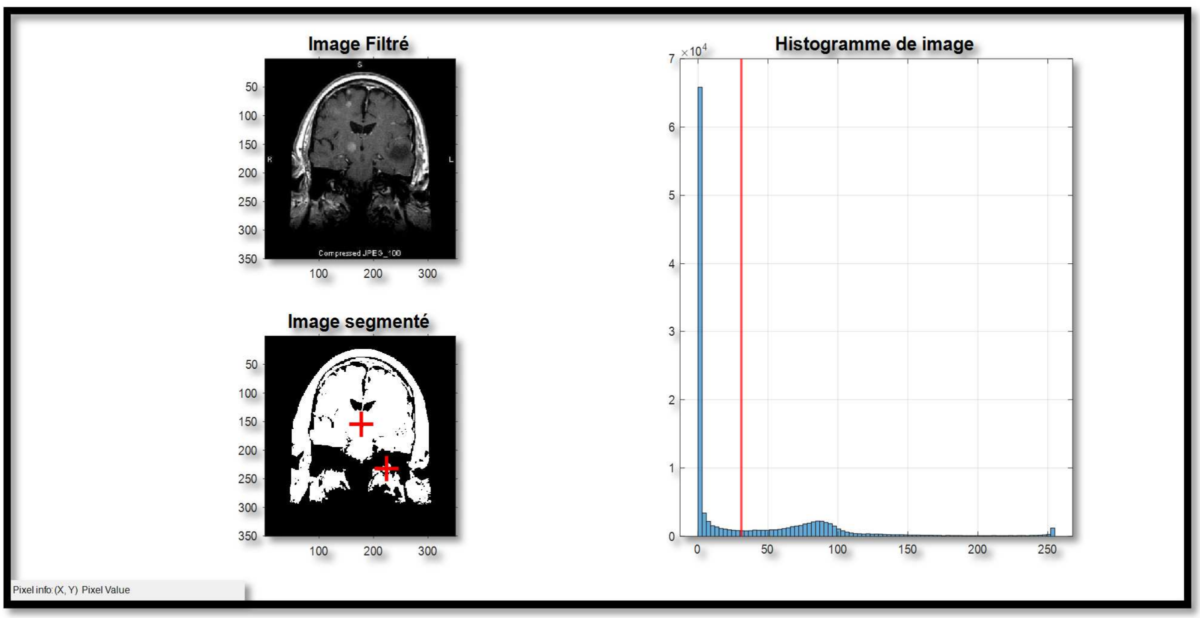

Figure 7 : (A) Filtered Image (B) Segmented Image (C) Image Histogram

- **Test 4 :**

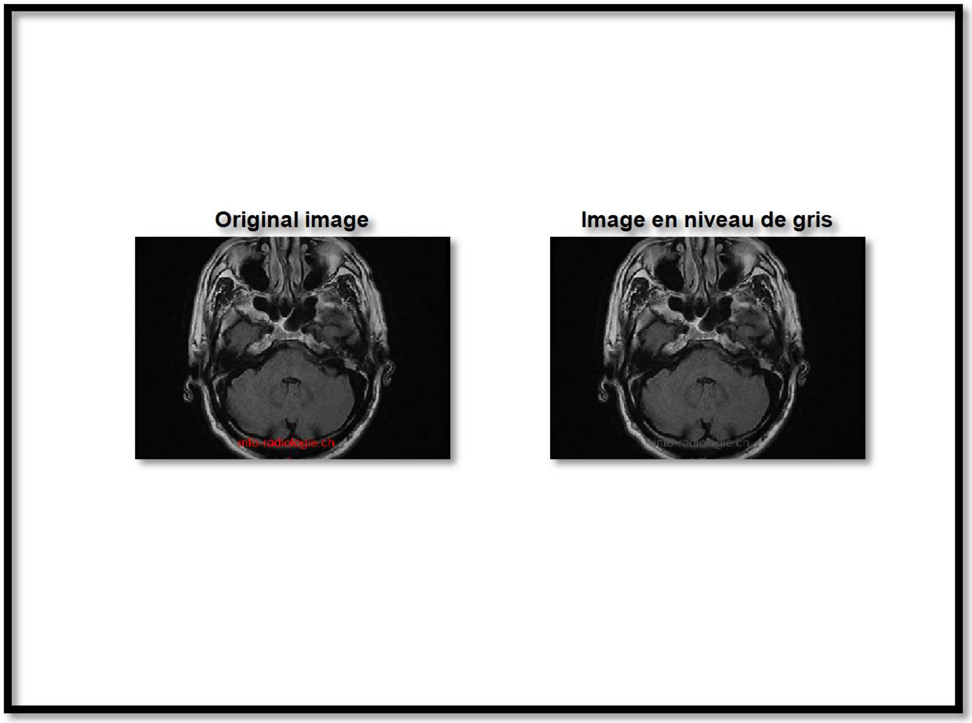

Figure 8 : (A) Original Image (B) Image converted to gray level

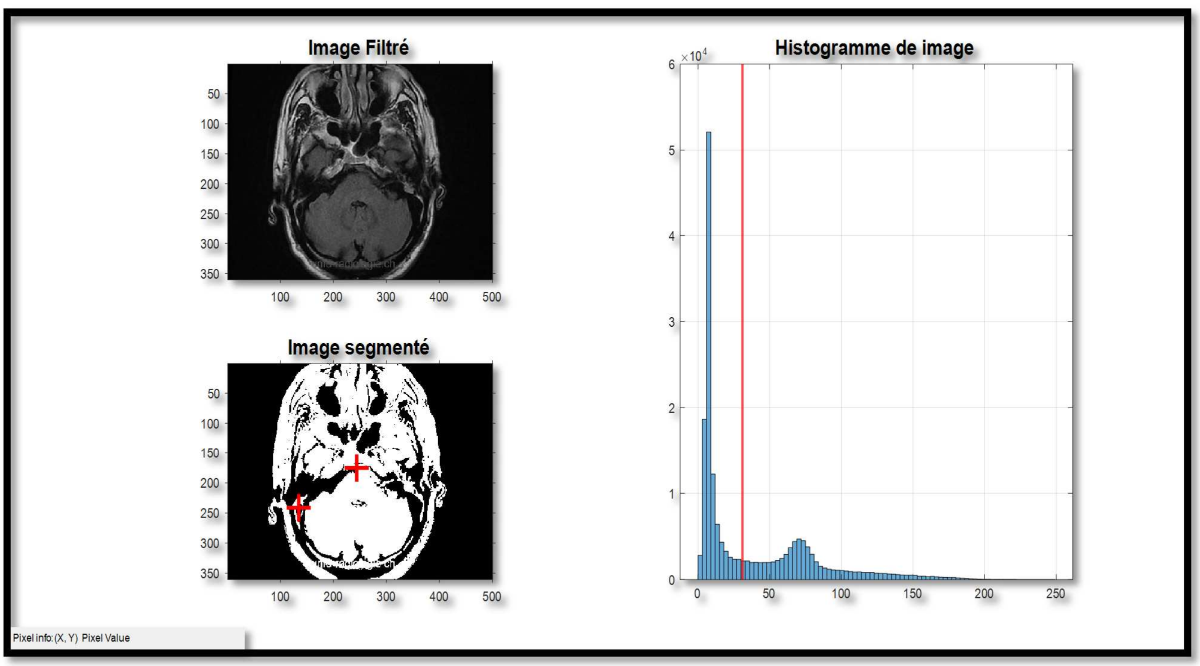

Figure 9 : (A) Filtered Image (B) Segmented Image (C) Image Histogram

The results of our work clearly demonstrate the identification of the anomaly zone (Figure 3,5,7 and 9 (B)), indicating that our method assists specialized medical professionals in monitoring tumors and diagnosing patients in an easy and straightforward manner. We were able to detect even the coordinates of existing abnormal pixels.

Conclusion

The segmentation of brain images is a crucial step in any image analysis process. It involves preparing the image to make it more accessible for an automated process such as interpretation. There are two major purely local approaches [12]. The approach employed in our work demonstrates the effectiveness of the obtained results, providing a clear insight and effective monitoring of our treated condition (Cerebral Vascular Accident - CVA). Segmentation of brain images plays a vital role in medical diagnostic assistance, enabling accurate detection and analysis of various neurological conditions. While the region growing technique of image processing has been widely used, have shown promise in overcoming many of the limitations associated with traditional methods. However, several challenges remain to be addressed, including the availability of annotated data, robustness to imaging variations [13], and integration into clinical workflows. Addressing these challenges will require interdisciplinary collaborations between computer scientists, radiologists, and clinicians, ultimately leading to improved diagnostic accuracy and patient care in neuroimaging.

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