An Algorithm for Automatic Segmentation of Spontaneous Cerebral Hemorrhages

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Abstract— **Computerized tomography images (CTI) are widely used in the diagnosis of stroke. In this paper, an algorithm for automatic segmentation of human spontaneous intra-cerebral brain hemorrhages (ICH) from computerized tomography images is proposed. The proposed strategy consists of five main steps: elimination of white matter, image enhancement, detection of region-of-interest via a reconstruction, and automatic segmentation. The method combines, essentially, a set of tools of mathematical morphology. To evaluate the proposed algorithm was implemented a graphical interface, in MATLAB and a dataset of 30 patients studies (360 image slices) was used. Obtained results were compared with the ground truth (a manual segmentation carried out by specialized medical personnel). The method provides 98% accuracy in detecting the ICH; and achieves an average precision of 96% at the slice level. The goal of this algorithm is later carry out automatic morphometrical analysis for helping the diagnostic and prognostic of specialists**

Key words: White matter, enhancement, markers, image segmentation, reconstruction, mathematical morphology, cerebral hemorrhage.

I. Introduction

Spontaneous intra-cerebral hemorrhage (ICH) is one of the most devastating forms of stroke. It accounts for approximately 7-15% of all strokes and carries the highest mortality rate of 40% compared to other kinds of strokes [1, 2]. Strokes are mainly classified in two categories: 1) Ischemic stroke or infarct (due to lack of blood supply) and 2) Hemorrhagic stroke. In this last case, a stroke occurs when a blood vessel either bursts or there is a blockage of the blood vessel. Due to lack of oxygen, nerve cells in the affected brain area are not able to perform basic functions and cause sudden death. Stroke results in serious long term disability or death [3].

Computerized tomography images (CTI) and magnetic resonance imaging (MRI) are two modalities that are regularly used form brain imaging. However, in many practical cases, CTI is preferred over MRI due to wider availability, lower cost and sensitiveness to early stroke. In most instances, CTI provides information required to make decisions during emergency [4]. From point of view of contrast, a difference there is between hemorrhage and ischemic strokes. In CTI, a hemorrhage appears as a bright region (hyper dense) well contrasted against its surrounds, and an ischemic stroke appears as a dark region (hypo dense), with the contrast relative to its surround depending on the time elapsed since the stroke occurred. Therefore, automatic detection of stroke is thus challenging as the structures vary in contrast with time and shape.

Segmentation and contour extraction (tracking) are important steps towards image analysis. Segmented images are now used routinely in a multitude of different applications, such as, diagnosis, treatment planning, localization of pathology, study of anatomical structure, computer-integrated surgery, among others. However, image segmentation and tracking remain difficult tasks due to both the variability of object shapes and the variation in image quality. Particularly, medical images are often corrupted by noise and sampling artifacts, which can cause considerable difficulties when applying rigid methods.

Many segmentation methods have been proposed for medical-image data [5-10]. Unfortunately, segmentation using traditional low-level image processing techniques, such as thresholding, histogram, and other classical operations, requires a considerable amount of interactive guidance in order to get satisfactory results. Automating these model-free approaches is difficult because of shape complexity, shadows, and variability within and across individual objects. Furthermore, noise and other image artifacts can cause incorrect regions or boundary discontinuities in objects recovered from these methods.

In mathematical morphology (MM) important methods have been developed for image segmentation [11, 12]. One of the most powerful tools developed in MM is the reconstruction, which has been used in many problems of image segmentation [13, 14]. This technique is very effective to extract regional maxima in an image without taking in consideration the size and form of these maxima. For this reason, the method can be very useful to isolate cerebral hemorrhages, due to that, as was pointed out, a hemorrhage appears as a bright region. The design of a good strategy involves the use of specific knowledge of the series of images under study. As was pointed out, the goal of this strategy is later carry out automatic morphometrical analysis for helping the diagnostic of specialist.

The remainder of the paper is structured in the following way: in section 2, we present some features of the studied images. In Section 3, the details of the most significant theoretical aspects of the morphological reconstruction are given. In section 4, we introduce the proposed algorithm. In Section 5, the experimental results and discussion are presented. Finally, in Section 6, the most important conclusions are given.

II. FEATURES OF THE STUDIED IMAGES

A representative dataset of ICH images were obtained from the Radiology Department of Morón Hospital, formed by 30 patients (360 image slices). In Figure 1, it can be seen a panoramic view of a typical ICH study case. In Figure 2, a horizontal profile can be observed through the centre of the lesion (hemorrhage); that is, a plot of the pixel intensities along a single row.

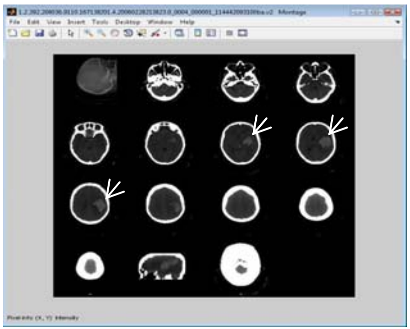


Fig. 1. Panoramic view of a study case. The regions of hemorrhages can be observed. Some of them are marked with arrows.

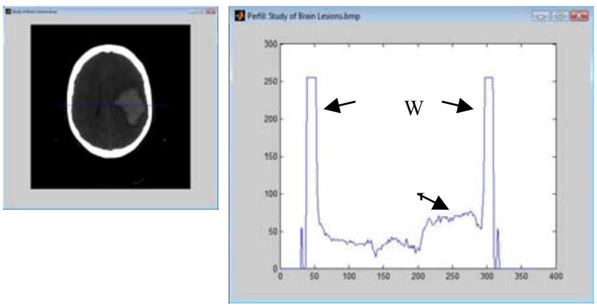


Fig. 2. (a) An intensity profile through the centre of the lesion. Profile is indicated by a line. (b) Coordinate "***y***" indicates intensity values.

There are several remarkable characteristics of these images, which are common to typical images that we encounter in the cerebral hemorrhage images:

1. Slight local variation of intensity is observed both, within the lesions and the background. However, the local variation of intensities is higher within the background than in the ICH regions.
2. The histogram of images (see Fig. 2(b)), without considering the whiter matter, in general, it is bimodal (lesion and background).
3. The cerebral lesions have better contrast than the background (see Figs. 1 and 2). For this reason, the cerebral lesions (haemorrhages) in a region of the image may appear lighter than the background in a distant region.
4. It is common of these images the diversity in shape and size of the cerebral lesions.

While the characteristics presented above testify the difficulty in identifying ICH in global way, a close examination reveals information that can be used. We observed that two features of the image, local variation of intensity and image intensity level, can be used to identify regions of the image, of automatic way, that describe lesions. High local variation of intensity is exhibited by regions within and near the boundaries of cerebral lesions. Thus, local variation of intensity can roughly identify regions of the image that contain lesions. Across the entire image, changes in intensity level can not reliably distinguish lesions, due to possible non-uniformity of the average background intensity and low contrast between lesions and background, principally, in the very small cerebral lesions. However, within a region of interest, changes in intensity level can effectively distinguish a lesion, since locally a lesion has major contrast of intensities than its surrounding background. It is here, the importance of locally working and segmenting without considering the size and form of cerebral lesions.

III. THEORETICAL ASPECTS

This section briefly presents the most important theoretical aspects.

Definition 1 *(Regional maximum):* A regional maximum at altitude h of greyscale image I is a connected component C of $T_h(I)$ such that $C \cap T_{h+1}(f) = \phi$.

Regional maxima should not be mistaken with *local* maxima. A pixel p of I is a local maximum for grid H if and only if its value $I(p)$ is greater or equal to that of any of its neighbours. All the pixels belonging to a regional maximum are local maxima, but the converse is not true. For example, a pixel p belonging to the inside of a plateau is a local maximum, but the plateau may have neighbouring pixels of higher altitude and thus not be a regional maximum.

3.1. Morphological grayscale reconstruction

Let $\boldsymbol{J}$ and $\boldsymbol{I}$ be two grayscale images defined on the same domain $\boldsymbol{D_I}$, taking their values in the discrete set $\{0, 1, \ldots\ldots, L\text{-}1\}$ and such that $J \leq I$ (i.e., for each pixel $p \in \boldsymbol{D_I}$, $J(p) \leq I(p)$). L being an arbitrary positive integer. In this way, it is useful to introduce the geodesic dilations according to the following definition [12]:

Definition 3.1.1 (Geodesic dilation). The elementary geodesic dilation of $\delta_I^{(1)}(J)$ of grayscale image $J \leq I$ "under" I (J is called the *marker* image and I is the *mask*) is defined as,

$$\delta_I^{(1)}(J) = (J \oplus B) \wedge I \tag{1}$$

where the symbol Λ stands for the pointwise minimum and $J \oplus \boldsymbol{B}$ is the dilation of J by flat structuring element $\boldsymbol{B}$. The grayscale geodesic dilation of size $n \geq 0$ is obtained by,

$$\delta_I^{(n)}(J) = \delta_I^{(1)} \circ \delta_I^{(1)} \circ \cdots\cdots \circ \delta_I^{(1)}(J),\ n \text{ times} \tag{2}$$

Definition 3.1.2 (Grayscale reconstruction)**.** The grayscale reconstruction $\rho_I(J)$ of I from J is obtained by iterating grayscale dilations of J "under" I until stability is reached [12], that is,

$$\rho_I(J) = \bigcup_{n \geq 1} \delta_I^{(n)}(J) \tag{3}$$

Definition 3.1.3 (Geodesic erosion). Similarly, the elementary geodesic erosion $\varepsilon_I^{(1)}(J)$ of grayscale image $J \geq I$ "above" I is given by,

$$\varepsilon_I^{(1)}(J) = (J \,\theta\, B) \vee I \tag{4}$$

where $\vee$ stands for the pointwise maximum and $J \,\theta\, B$ is the erosion of J by flat structuring element $\boldsymbol{B}$. The grayscale geodesic erosion of size $n \geq 0$ is then given by,

$$\varepsilon_I^{(n)}(J) = \varepsilon_I^{(1)} \circ \varepsilon_I^{(1)} \circ \cdots\cdots\cdots \circ \varepsilon_I^{(1)}(J), n \text{ times} \tag{5}$$

Definition 3.1.4 (Dual reconstruction)**.** The dual greyscale reconstruction $\rho_f^*(J)$ of mask I from marker J is obtained by iterating grayscale geodesic erosions of J "above" I until stability is reached [12]; that is,

$$\rho_I^*(J) = \bigwedge_{n \geq 1} \varepsilon_I^{(n)}(J) \tag{6}$$

Reconstruction turns out to provide a very efficient method to extract regional maxima and minima from grayscale images. Furthermore, the technique extends to the determination of maximal structures, which will be call *h-domes* and *h-basins*. The h-dome transformation extracts light structure without involving any size or shape criteria. The only parameter *(h)* is related to the height of these structures. The mathematical background and other definitions can be found in [12].

Definition 3.1.5 The *h-dome* image $D_h(I)$ of the *h-domes* of a greyscale image I is given by

$$D_h(I) = I - \rho_I(I - h)$$

IV. PROPOSED ALGORITHM

The segmentation algorithm for automatic detection of cerebral hemorrhage comprises the following steps:

1. Elimination of white matter. This is eliminated with simple threshold. Its graylevel are superior to 175. See Fig. 3(b). Let ***I3*** be the resulting image.
2. Erode the resulting image of step 1. This step is as follows: The ***I3*** image is eroded three times and later a filter is passed for filling holes. In this step is obtained only the gray matter. Let ***Igray*** be this image.
3. To the ***Igray*** image, the background is obtained via an opening filter with structuring element type disk. The diameter of this structuring element should be large, superior to 50. Of this way is guaranteed to obtain completely the background around lesion. Let ***Iback*** be the resulting image.
4. To the ***Igray*** image is subtracted the ***Iback*** image. In this step the lesion is accentuated. Let ***Ilesion*** be this image.
5. Carry out a reconstruction by dilatation to the ***Ilesion*** image. Let ***Irecons*** be the resulting image.
6. To the resulting image of step 5 a value h is subtracted. Let $h = 40$ be the subtracted value. See *definition 3.1.5*
7. To the resulting image of before step, to carry out an opening filter with a linear structuring element. This line is varied with an angle from 80 to 100, where this specifies the angle (in degrees) of the line, as measured in a counterclockwise direction from the horizontal axis. In this step the middle line of brain is eliminated. Let ***Iopenl*** be this image.

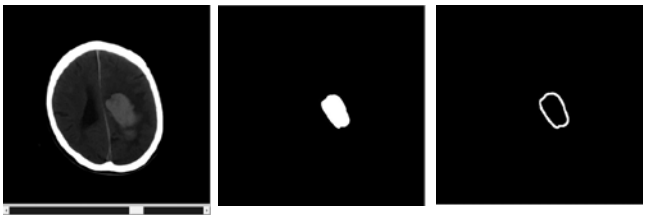
8. To the ***Iopenl*** image, to carry out a closing filter. This step guarantees to eliminate possible holes that might arise.
9. Label the resulting image of the previous step. Let ***Iseg*** be this image. In this step, the cerebral hemorrhage is only obtained.

V. EXPERIMENTAL RESULTS AND DISCUSSION

Examples of segmentation and outline can be seen in Figures 5, 6, and 7

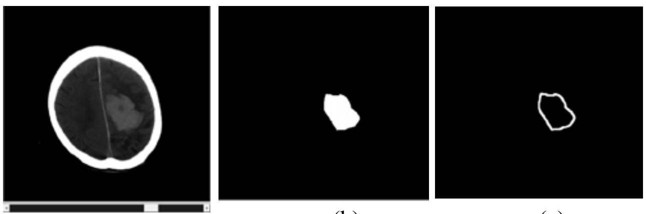
(a) (b) (c)

Fig. 5. (a) Original image, (b) Segmented lesion, (c) Outlined lesion



(a) (b) (c)

Fig. 6. (a) Original image, (b) Segmented lesion, (c) Outlined lesion



(a) (b) (c)

Fig. 17. (a) Original image, (b) Segmented lesion, (c) Outlined lesion

Note that in all the cases, the proposed algorithm suitably detected lesions. However, in some cases the detection is not completely exact This happens in regions where diffuse areas of ICH exit. In practice, the issue is very difficult of avoiding and until now, a perfect automatic segmentation algorithm does not exist. For this reason, for analysing the performance of our algorithm, we carry out a comparison with manual segmentation (ground truth) carried out by specialized medical personnel

VI. CONCLUSIONS

In this work, we proposed a strategy in order to isolate, of automatic way, spontaneous intra-cerebral hemorrhages (ICH). In such sense, we introduced a new algorithm, which identified correctly the ICH and all undesirable information is considerably eliminated. With our strategy the application of the morphological transformation provided good results, and we obtained the close contours of the cerebral lesions. We showed by extensive experimentation by using real image data, that the proposed strategy was robust for the type of considered images. This strategy was tested, according to the criteria of specialists via manual segmentation, obtaining a per cent of relative error minor than 2 %. Our algorithm archived 98% accuracy in detecting the ICH; and had an average precision of 96% at the slice level.

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