BRAIN SEGMENTATION IN HEAD CT IMAGES

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Abstract: Brain segmentation in head computed tomography scans is essential for the development of computer-aided diagnostic methods for identifying the brain diseases. In this paper we present a hybrid framework to brain segmentation which joints region-based information based on watershed transform with clustering techniques. A pre-processing step is used to reduce the spatial resolution without losing important image information. An initial partitioning of the image into primitive regions is set by applying a rainfalling watershed algorithm on the image gradient magnitude. This initial partition is the input to a computationally efficient region segmentation process which produces the final segmentation. We have applied our approach on several head CT images and the results reveal the robustness and accuracy of this method.

1 INTRODUCTION

Image segmentation is one of the largest domains in image analysis, and aims at identifying regions that have a specific meaning within images. The role of imaging as complementary mean of diagnosis has been expanding beyond the techniques of visualization and checkups in anatomical structures. This area has become a very useful tool in planning of surgical simulations and location of pathologies.

The Computed Tomography (CT) is an imaging modality that allows the imaging of sections of the human body, with almost no overlap of organs or anatomical structures. Thus allowing us to actually doing tests with a large number of sections quickly and with high spatial resolution. The need for quantitative analysis in tests with many sections has served as a stimulus for the development of computational methods for the detection, identification and delineation of anatomical structures. The segmentation of the brain from CT scans is an important step before the analysis of the brain. This analysis can be performed by a specialist, which manually surrounds the area of interest on each slice of the examination. This requires very careful and attentive work and practical exams with a high number of slices, the identification of regions becomes a tedious and time consuming task, subject to variability depending on the analyzer, which makes it desirable to have automated methods. However, if on one hand, manual segmentation has the problems mentioned above, the automatic identification of structures from CT images becomes a tricky task not only because of the volume of data associated with the imaging study, but also the complexity and variability in the anatomical study, and that noisy images can provide. So developing new accurate algorithms with no human interaction to segment the brain precisely is important.

The watershed algorithm is an example of a hybrid method, combining information about the intensity and the image gradient. This algorithm is a powerful edge-based method of segmentation, developed within the framework of mathematical morphology (Vincent and Soille, 1991; Grau et al., 2004). Sometimes, the use of the watershed over-segmentation results in unwanted regions. To circumvent this problem markers are applied to the image gradient in order to avoid over-segmentation, thus abandoning the conventional watershed algorithm (Shojaii et al., 2005). This operation allows the reduction of regional minima, grouping them in the region of interest.

The proposed methodology in this paper has three major stages. First, from the gradient image we create, based on the watershed transform, an over-segmented image. The regions formed are atomic regions. In the next step, the region similarity graph (RSG) will be created (Monteiro and Campilho, 2008), from the over-segmented image, for apply a graph clustering approach in the last station. This framework integrates edges and region-based segmentation with spectral based clustering through the watershed transform. Figure 1 presents the stages of

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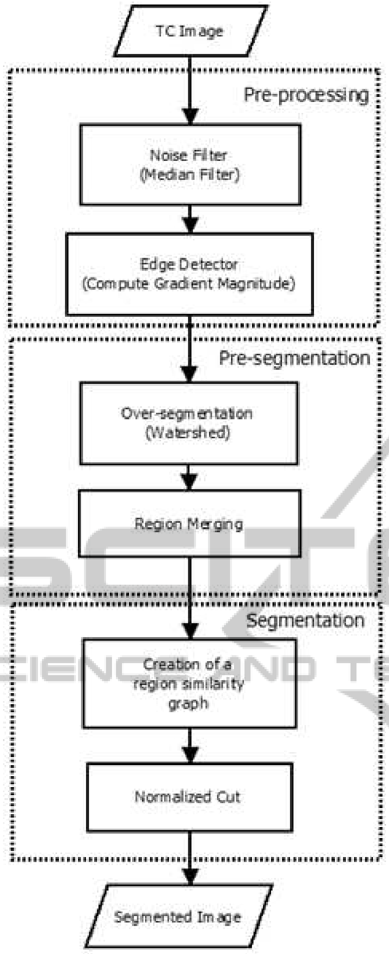


Figure 1: Phases of the proposed method.

the entire process.

The combination of watershed and clustering methods solves the weaknesses of each method. Rather than clustering single feature points we will cluster small regions, confident that the underlying primitive regions are reliable. Our approach actually prefers the objects to be over-segmented into a number of smaller regions to ensure that a minimal amount of background is connected to any of the brain regions.

The algorithm described in this paper can be well classified into the category of hybrid techniques, since it combines the edge-based, region-based and the morphological techniques together through the spectral based clustering approach. We propose that our method can be considered as an image segmentation framework within which existing image segmentation algorithms that produce over-segmentation may be used in the preliminary segmentation step.

The remainder of this paper is organized as follows. Section 2 gives a description of the methods used in this paper. Followed by the experimental results and discussion in Section 3. The concluding remarks are given in the last section.

2 BRAIN SEGMENTATION

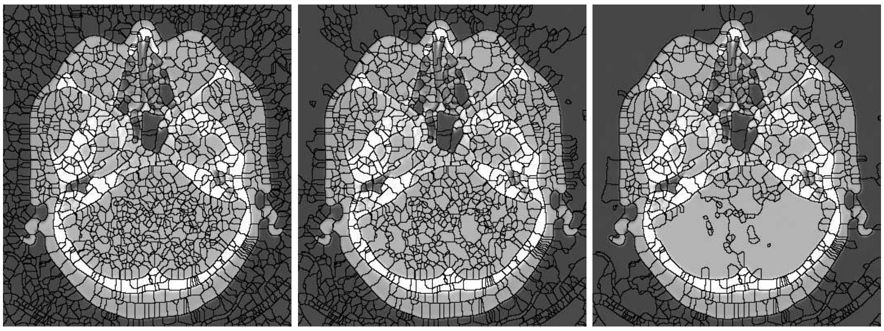
The segmentation of an image is one of the most important factors in the analysis and identification of the brain on CT images. One of the objectives of developing new algorithms for image segmentation is to increase the accuracy by reducing the computational cost (Pham et al., 2000).

The watershed transform partitions the image in to numerous regions depending on the number of local minima of the gradient, usually the watershed tends to produce an over-segmentation (Callaghan and Bull, 2005). In order to facilitate the calculations are over-segmentation can be eliminated by incorporating a pre-processing of the image. Many methods have been proposed in order to reduce unwanted regions and produce a meaningful segmentation.

In this work are provide some methods to overcome this problem. For example, if the images containing noise the first step is to use non-linear filters such as the bilateral anisotropic filter, which smooths images while preserving its contours and structure, since it only acts on neighbours who are part of the same core region. The next step is to eliminate the weaker contours through gradient minima suppression, the process known *pre-flooding* (See Fig. 2). This methodology uses a constant depth of certain basin. Before to the transform each catchment basin is flooded up to a certain height above its bottom, this is, the lowest gradient magnitude and it can be thought as a flooding of the topographic image at a certain level (flooding level). In the latest step, is made by a segmentation fusion, merging atomic regions with a graph-based clustering approach.

Segmentation result directly using watershed algorithm is shown in Fig. 2.(a) and from it we can find that serious over-segmentation (1587 atomic regions) makes the result meaningless even when we use pre-flooding as showed in Fig. 2.(b) and (c), with 1281 regions and 814 regions, respectively.

Spectral-based methods use the eigenvectors and eigenvalues of a matrix derived from the pairwise similarities of features (pixels or regions). This effect is achieved by constructing a fully connected graph. Considering all pairwise pixel relations in an image may be too computational expensive. Unlike other well known clustering methods (Shi and Malik, 2000) which use down-sampling pixel-based to construct the graph, our method is based on selecting links from



(a) (b) (c)

Figure 2: Atomic regions from watershed. (a) No pre-flooding. (b) Low level of pre-flooding. (c) Medium level of pre-flooding.

a weighted undirected graph $G = (V, E, W)$ based on a region similarity graph where each node corresponds to an atomic region (Monteiro and Campilho, 2008).

The proposed region similarity graph structure takes advantage on region-based representation. The set of nodes V are represented by the centroid of each atomic region. The sets of links E and link weights W represent, respectively, relationships and similarity measures between pair of regions. Each region r_i represents a small group of pixels where the centroid $\overline{x}_i$ is utilized as a node of the graph.

In almost all the graph-based approaches proposed in the literature the spatial distance cue is also used to compute the similarity between graph nodes. However, during our experiments, we noted that such cue is responsible for the partition of homogeneous areas in the image - an issue commonly associated to normalized cut algorithm. Instead, we use intervening contours (Leung and Malik, 2000) which are equivalent to spatial distance without suffering from the same problems. For each pair of nodes, node similarity is inversely correlated with the maximum contour energy encountered along the line connecting the centroids of the regions. If there are strong contours along a line connecting two centroids, these atomic regions probably belong to different segments and should be labeled as dissimilar.

Let i and j be two atomic regions and the orientation energy OE^* between them, then the intervening contours contribution to the link weight is given by:

$$w_{ic}(i,j) = \exp\left[-\frac{\max_{t \in line(i,j)} \left\| OE^*(\overline{x}_i, \overline{x}_j) \right\|^2}{\sigma_{ic}^2}\right] , \tag{1}$$

where $line(i,j)$ is the line between centroids $\overline{x}_i$ and $\overline{x}_j$ formed by t pixels.

The mean intensity of each node contributes for the link weight according to the following function:

$$w_I(i,j) = \exp\left(-\frac{\left(I_{\overline{x}_i} - I_{\overline{x}_j}\right)^2}{\sigma_I^2}\right) . \tag{2}$$

These cues are combined in a final link weight similarity function, with the values σ_{ic} and σ_I selected in order to maximize the dynamic range of $\mathbf{W}$:

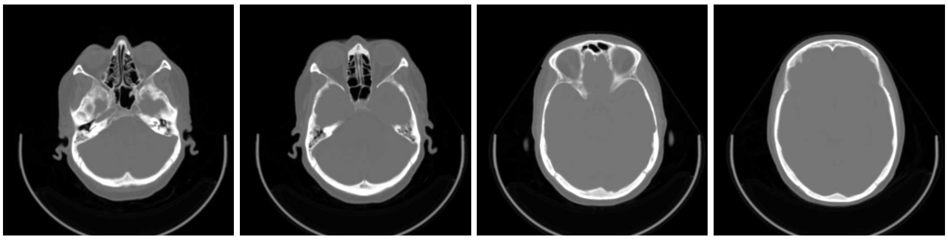
$$\mathbf{W}(i,j) = w_{ic}(i,j) \cdot w_I(i,j) . \tag{3}$$

To compute the similarity matrix the current approach uses only image brightness and magnitude gradient. Additional features such as texture, could be added to the similarity criterion. This may slow the construction of the RSG but the rest of the algorithm will proceed with no change.

3 EXPERIMENTAL RESULTS

The brain CT images used in this paper were providing by the database of IPB. The number of slices varies from exam to exam, but not all slices of the exam contain information regarding the brain, and for that reason we used only a few images of a single scan to his head. The images obtained in this condition are stored with size of 512512 pixels. Each pixel is 16 bits in size and 0.85 mm resolution. The images are in greyscale mode, stored in DICOM format. This group of images selected includes the entire anatomy of the brain from the top, the middle and the bottom. Figure 3 shows four slices selected from different parts of the head to show the accuracy of this technique.

The brain segmentation results for the slices in Fig. 3 are shown in Fig. 4. Comparing the segmented brain regions with the original image confirms that our approach separates accurately the brain regions.



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

Figure 3: Original CT head images.

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

Figure 4: Brain segmented images corresponding to the slices in Fig. 3, respectively.

4 CONCLUSIONS

In this paper we have proposed an image segmentation methodwhich combines edge- and region-based information with spectral techniques through the morphological algorithm of watersheds. An initial partitioning of the image into primitive regions is set by applying a watershed simulation on the image gradient magnitude. This initial partition is the input to a computationally efficient graph partition process that produces the final segmentation. The latter process uses a region similarity graph representation of the image regions.

Using small atomic regions instead of pixels leads to a more natural image representation - the pixels are merely the result of the digital image discretization process and they do not occur in the real world. Besides producing smoother segmentations than pixel based partitioning methods, it also reduces the computational cost in several orders of magnitude.

As future work it would be interesting to obtain brain contours in the region carried out by experts, to be subsequently developed a methodology for evaluating the accuracy of brain contours resulting from the segmentation algorithms. This assessment methodology can understand some criteria to overcome the subjectivity barrier between the silhouette of the brain performed by different specialists.

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