A morphological approach for infant brain segmentation in MRI data

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***Abstract*—This paper describes a skull stripping method for premature infant data. Skull stripping involves the extraction of brain tissue from medical brain images. Our algorithm initially addresses the reduction of the image artefacts and the generation of the binary mask that is used in the initialisation of a region growing brain segmentation process. After segmenting the brain tissue, we detail two novel post processing steps. First, we refine the edges using Kapur entropy, Low Pass Filter and gradient magnitude. Second, we remove the lacrimal glands by applying shape detection, morphological operators and Canny edge detection. The performance evaluation was conducted by comparing the segmented results with the ground truth data marked by our clinical partners.**

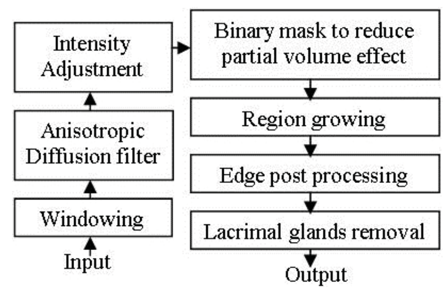

Fig. 1. Overview of the proposed skull stripping techniques

I. Introduction

The objective of this study is to deal with the challenges of segmenting the brain tissue from premature infants Magnetic Resonance Imaging (MRI) data. In this study we focus on a significant step of brain MRI segmentation called skull stripping. This procedure involves the removal of all non-brain tissue such as eyes, fat, fluid and skull. The remaining parts consists of the cortical grey matter, white matter, deep grey matter and the cerebellum. Several methods have been proposed to solve the task of skull stripping and representative algorithms can be found in: [1], [2]. The aim of this paper is to present a skull stripping approach with the focus on premature newborn brain MRI. We have improved on our previous approach in [3] while focusing on increasing the robustness of the skull stripping. Fig. 1 presents an overview of the proposed approach which focuses on removing the non brain-tissue by minimizing the influence of the partial volume effects. The algorithm in Fig. 1 begins with smoothing the image using an anisotropic diffusion filter [4] and adjusts the intensity throughout the volume in order to remove intensity shifts. To reduce the partial volume effects, a binary mask was generated using morphological operators and edge detection. The segmentation was achieved by applying a region growing algorithm. In this paper, we focused on addressing two aspects that influence the final segmentation results. The first aspect refers to the refinement of the outer and inner boundaries of the region of interest, whereas, the second aspect is related to the removal of the lacrimal glands. A quantitative evaluation was conducted by comparing the automatic segmented data against the manually annotated data.

II. Methods

A. *Refinement on the contours*

The first aspect we address refers to the processing of the edges from the brain. Fig. 2 illustrates an example of the refinement of the inner edges before (A) and after (B) applying the algorithm. To solve this task, we begin with stretching

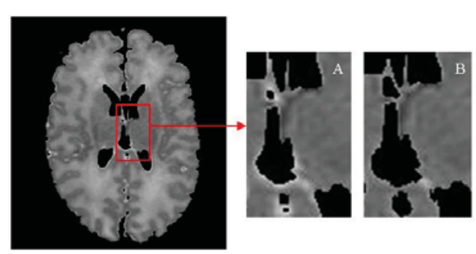

Fig. 2. An example of an image to demonstrate before (A) and after (B) processing the inner edge of the brain. It can be observed that the brighter contour pixels in (A) which represent fluid pixels, have been removed in (B).

the image intensity to enhance the contrast between the brain tissue and the fluid. The intensity expansion was achieved by using the following formula: $v(x, y) = u(x, y) - \|c - u_{LPF}(x, y)\|$ where u is the resulted image from the region growing step, *LFP* is the Low Pass Filter and c is a constant value which was calculated using the intensity values which distinguish the white matter from the cerebrospinal fluid.

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These values were acquired from the intensity adjustment step as indicated in [3]. Out of all those local minimum values, we calculate the mean values to define the constant c. Then, the gradient magnitude of each contour pixel is calculated. To distinguish between fluid and non fluid pixels, a threshold is defined as follows: $threshold = min(gv(gv > k^*))$ where gv is the gradient magnitude of the edge values and k^* is the threshold value of the Kapur entropy [5]. In the above formula the threshold is calculated by using the minimum of the gradient magnitude values which are larger then the Kapur entropy threshold. The Kapur entropy threshold is calculated as follows: $k^* = Argmax_{k=1}^{N}\{\lg(\sum_{i=1}^{k} p_i) + \lg(\sum_{i=k+1}^{L} p_i) - \frac{\sum_{i=1}^{k} p_i \lg p_i}{\sum_{i=1}^{k} p_i} - \frac{\sum_{i=k+1}^{L} p_i \lg p_i}{\sum_{i=k+1}^{L} p_i}\}$ where p_i is the probability of grey level i and L is the total number of grey levels. k^* is the threshold that maximizes the total entropy.

B. Removal of the lacrimal glands

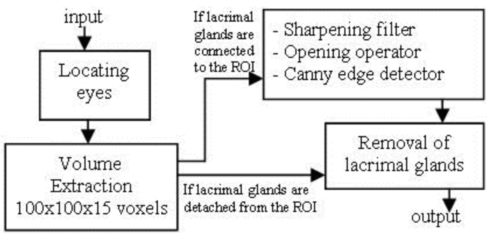

Fig. 3. Overview of the lacrimal glands removal algorithm

In infant brain MRIs, the boundaries between the brain tissue and lacrimal glands are unclear. As a consequence, the region growing algorithm will include these parts into the ROI during the brain tissue segmentation step as shown in Fig. 4A.

Fig. 3 presents an overview of the removal of the lacrimal glands. We first determine the position of the eyes by locating circular objects on the first mask images [3] using the formula $area/perimeter^2$. After locating the eyes, we focus on the region above them to identify the lacrimal glands. Therefore, we extract two volumes each having a size of $100\times100\times15$ voxels which was chosen experimentally. By analyzing the MRI data, we observed that the lacrimal glands are detached from the brain in the first few images until they connect. In order to detach the connected parts, we apply a sharpening filter and an opening operator with a kernel of 2×2 followed by a Canny edge detector where the scale parameter is set to 1.0. Finally, the voxels identified as lacrimal glands, are removed by marking them as background voxels.

III. Results

A. Data acquisition

For this study, eight T2 brain MR volumes of premature infants have been acquired by our colaborators from Children's University Hospital, Dublin, Ireland. Each image (TR: 2660; TE: 142,7; FOV: 16×16 cm) has a dimension of 512×512 voxels and a thickness of 1 mm. The entire database was manually marked in conjunction with a clinical expert from the Children's University Hospital, Dublin, Ireland for comparison purposes.

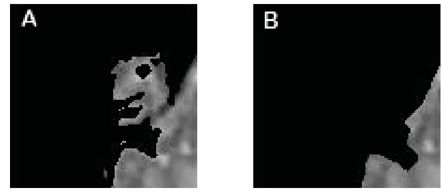

Fig. 4. An example from an image of the extracted volume before (A) and after (B) removing the lacrimal glands

B. Evaluation

We performed the quantitative evaluation using the Dice similarity (DSM), Jaccard similarity (JS), False Positive (FP) and the False Negative (FN) metrics. In Table I the average results of eight patient datasets with a total of 743 images are displayed. It can be observed in Table I that the evaluation results for DSM and JS are 0.961 and 0.925 which indicates a high agreement between the automatic segmentation and the ground truth.

TABLE I
AVERAGE RESULTS OF THE SKULL STRIPPING APPROACH

DSM	JS	FP	FN
0.961	0.925	2.66%	4.95%

IV. Conclusion

In this study, we have analysed two post processing steps of a skull stripping approach. In a first phase, we processed the edges of the brain by applying a Kapur entropy threshold, low pass filter and gradient magnitude. In the second phase, we remove the lacrimal glands by using shape information, morphological operators and Canny edge detector. The evaluation results demonstrate the accuracy of the proposed method.

Acknowledgment

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