

Tumor Detection in MRI Brain Images Based on Saliency Computational Modeling

Muwei Jian*, Xianxin Zhang**, Lifu Ma***, Hui Yu****

* School of Computer Science and Technology,

Shandong University of Finance and Economics, Jinan, 250014, China

(e-mail: jianmuwei@163.com).

** Shandong Chest Hospital, Jinan, 250013, China

(e-mail: 2195750064@qq.com).

*** Linyi Central Hospital, Yishui, 276400, China,

(e-mail: malifu@163.com)

**** School of Creative Technologies, University of Portsmouth, Portsmouth, UK,

(e-mail: hui.yu@port.ac.uk)

Abstract: In recent years, the issue of tumor detection for Magnetic Resonance Imaging (MRI) brain images has become a research hotspot in the field of medical imaging, multimedia and pattern recognition. In this paper, we propose a tumor detection method based on saliency modeling for MRI brain images. Firstly, in order to overcome the influence of the skull, we utilize the morphological method to strip the skull of the MRI brain images. Then, we introduce a principal local contrast based saliency-detection method to enhance the foreground regions which facilitates to get the lesion region. Finally, the results are further improved by denoising, segmentation and morphological operations. Experiments performed on MRI brain images show that the proposed method is useful and effective.

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Keywords: Brain image; lesion region; saliency detection; morphology; saliency modeling.

1. INTRODUCTION

Medical images play an increasingly important role in medical diagnosis and disease treatment. Magnetic resonance imaging (MRI) is used as an advanced medical imaging technique to generate high-quality images of the parts of the human body, while without side effects of ionizing radiation on the patients. MRI is very effective for detecting cerebral hematoma, brain tumor, intracranial aneurysm and other common intracranial diseases. It is of great significance to assist the doctor to perform clinical diagnosis and treatment of brain tumors by automatically extracting tumors in MRI brain images.

Brain tissue can be divided into white matter (White Matter, WM), gray matter (Gray Matter, GM) and cerebrospinal fluid (Cerebro-Spinal Fluid (CSF)). These tissues are segmented from MRI brain images and are beneficial to brain diseases' diagnosis and treatment [1, 20, 21].

Pre-processing of MRI images is a primary step in image analysis, which performs image enhancement and noise-reduction techniques to enhance the MRI image quality, then some morphological operations can be applied to detect the tumor in the image. The morphological operations are basically applied based on some assumptions that the size

and shape of the tumor is visible. In the end, the tumour is mapped onto the original gray scale image with 0-255 intensities, in order to make the tumors in the image to be notable. The above popular algorithm has been widely applied on patients MRI data of brain tumor images in practice.

In this paper, we propose an effective tumor detection method based on saliency computational modeling for MRI brain images. Based on a robust principal local contrast saliency-detection framework, foreground-salient regions of MRI brain images can be enhanced, which will be helpful for the diagnosis and treatment of brain diseases. To evaluate and test the proposed saliency-detection model, we carried out extensive experiments on MRI brain images and the experimental results show that our method is robust.

The rest of this paper is organized as follows. In Section 2, we describe the proposed framework in detail. Section 3 shows the experimental results. Finally, conclusion and discussion are presented in Section 4.

2. THE PROPOSED FRAMEWORK

2.1 Skull Peeling

The specific steps of the morphological-based skull stripping algorithm are described as follows:

- (1) Converting the original image into a grayscale image for mean filtering processing and smoothing;
- (2) Applying threshold processing. The optimal threshold of the original image is obtained as 0.34, and the image is binarized according to the optimal threshold;
- (3) Performing void filling on the binary image;
- (4) Open the binary image, in which the structural elements are disc-shaped, the radius is taken as 8 pixels, the skull is peeled off, and the brain tissue template is obtained;
- (5) Multiplying the template with the original image to obtain a brain tissue image.

An illustration of the Skull Peeling step is shown in Figure 1.

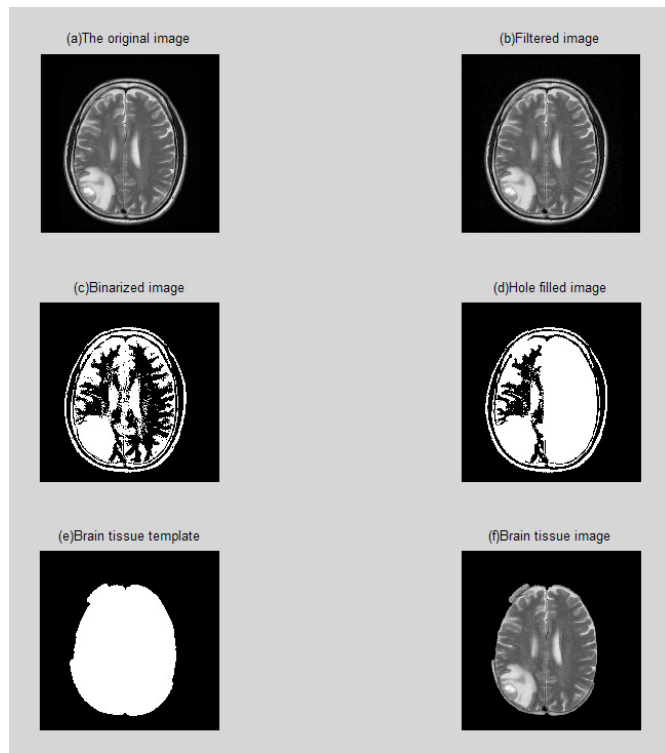


Fig. 1. Examples of skull stripping process.

2.2 Principal Local Contrast based Saliency Detection

Image saliency is an important visual feature in an image, reflecting the degree to which the human eye paying attention to certain areas of the image. Since the work of Itti [2] in 1998, a large number of significant mapping methods have been proposed. Image saliency detection has also been widely used in image compression, coding, image edge and region enhancement as well as significant target segmentation and extraction.

Recent years have witnessed rapidly increasing interests in salient object detection [3]. It is motivated by the importance

of saliency detection in applications such as object aware image retargeting [4], [5], image cropping [6] and object segmentation [7, 22]. Due to the absence of high level knowledge, all bottom up methods rely on assumptions on the properties of objects and backgrounds. The most widely utilized assumption is that appearance contrasts between objects and their surrounding regions are high. This is called contrast prior and is used in almost all saliency methods [8–18].

From human perception, in MRI images, the lesion is clearly a salient object in the complex background of brain tissue. Based on this observation, in this paper, we employ a principal local contrast based saliency-detection method to further process the MRI brain images. In most of the existing saliency-detection modeling approaches based on the bottom-up computational strategy, local contrast is widely used as a low-level visual feature in images for salient object detection, which has achieved satisfactory results in highlighting the foreground objects. In this designed framework, we propose an efficient and effective local contrast method called principal local intensity contrast (PLIC) for saliency detection. The main idea is that we utilize the square region S_q inside the salient object to estimate the principal local intensity contrast between the salient object and the image background region. Specifically, we can determine the center based on the spatial distribution of the extracted directional patches [19]. Then, instead of calculating local contrast or blindly comparing similarity over each pixel in the entire image one by one resulting in vast computational cost, the designed PLIC method not only is sufficient to highlight semantic objects from complicated scenarios, but also can significantly reduce the computing complexity during segmenting and scratching salient objects from the image background.

With the aid of the square region S_q determined using the spatial distribution of the extracted patches [19], for an input image we first set pli as the principal local intensity vector by taking the mean value of the pixels inner the square region S_q in the intensity image, and Cen is the spatial position center of the square region S_q . Let $pos(x, y)$ denote the spatial position with pixel coordinates (x, y) in the input intensity image, the Gaussian distance from the spatial position center Cen of the square region S_q , which can be expressed as:

$$Dis(x, y) = \exp\left(\frac{-\|pos(x, y) - Cen\|}{2\sigma^2}\right). \quad (1)$$

Suppose $pi(x, y)$ is used to represent its intensity vector of the pixel in an input image. Then, the computational scheme of the principal local intensity contrast (PLIC) can be defined as follows:

$$\begin{aligned} PLIC(x, y) &= \frac{1}{\|pi(x, y) - pli\| \bullet Dis(x, y)} \\ &= \frac{1}{\|pi(x, y) - pli\| \bullet \exp\left(\frac{-\|pos(x, y) - Cen\|}{2\sigma^2}\right)}, \quad (2) \end{aligned}$$

where σ^2 controls the strength of spatial weighting.

2.3 Threshold Segmentation and Morphological Operation

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection).

Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s) [1]. When applied to a stack of images, typical in Medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes. Then, we apply median filter to enhance the quality of image and perform morphological operation to refine tumour regions.

3. EXPERIMENTAL RESULTS AND ANALYSIS

Tumor extraction experiments in MRI brain images were performed on the Intel Core 3.7 GHz, Windows 7 PC, and Matlab platforms. When extracting tumor sites in MRI brain images, all images were converted to the size of 512×512. We have conducted experiment on the MRI brain image dataset containing 100 MRI brain images of various brain tumors. To highlight the tumor, image pixels other than the tumor are set to black.

Fig. 2 gives an example of tumor detection for a typical MRI brain image, which shows the effectiveness of the proposed method.

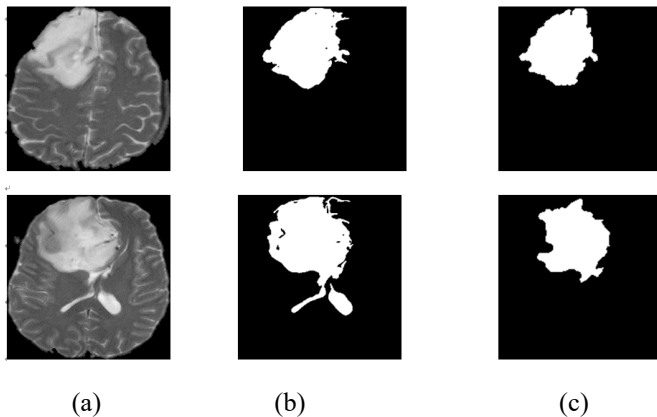


Fig. 2. Tumor detection on MRI brain images. (a) Input images, (b) The texture insensitive method in [22], and (c) the proposed method.

In order to objectively assess the performance of the designed method and other representative approaches, the Precision, Recall, and F -measure are used for comprehensive comparison. F -measure is an overall evaluation index in theory that can be defined as follows [19-22]:

$$F_{\beta} = \frac{(1 + \beta) \times \text{Precision} \times \text{Recall}}{\beta \times \text{Precision} + \text{Recall}}, \quad (3)$$

where β denotes a real positive number with equal to 0.3.

Table 1. Performance of the designed method compared with the different representative approaches.

Approaches	Precision	Recall	F -measure
The method in [20]	0.7904	0.8027	0.7932
The method in [21]	0.7822	0.8168	0.7899
The method in [22]	0.7965	0.8016	0.7977
The designed method	0.8255	0.8206	0.8244

Table 2 tabulates the statistical indicators of the proposed algorithm with the other representative approaches. It can be seen that the designed method is able to generate more reliable results over the typical approaches according to precision, recall and F -measure.

4. CONCLUSIONS

In the process of clinical imaging diagnosis, extracting the tumor profile from the medical image can provide reference for the doctor to judge the benign degree of the tumor, the degree of calcification in the tumor area, the confirmation of the condition of the tumor and the effect of the treatment. In this paper, we propose a simple tumor detection method based on saliency modeling for MRI brain image via a robust principal local contrast saliency-detection scheme, which is beneficial to the diagnosis and treatment of brain diseases. Meanwhile, the MRI brain image tumor extraction method based on graph cut can overcome the problems of the extraction method based on local features. Experiments on MRI brain images and the experimental results show that our method is useful and effective.

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REFERENCES

- [1] Fu J C, Chen C C, Chai J W, et al. Image segmentation by EM-based adaptive pulse coupled neural networks in brain magnetic resonance imaging[J]. Computerized Medical Imaging and Graphics, 2010, 34(4): 308-320.
- [2] L. Itti, C. Koch, & E. Niebur. A model of saliency based visual attention for rapid scene analysis. IEEE Transactions on Pattern Analysis and Machine Intelligence, 20(11):1254-1259, 1998.

- [3] A. Borji, D.N. Sihite, and L. Itti. Salient object detection: A benchmark. In ECCV, 2012.
- [4] Y. Ding, J. Xiao, and J. Yu. Importance filtering for image retargeting. In CVPR, 2011.
- [5] J. Sun and H. Ling. Scale and object aware image retargeting for thumbnail browsing. In ICCV, 2011.
- [6] T. Liu, J. Sun, N. Zheng, X. Tang, and H. Shum. Learning to detect a salient object. In CVPR, 2007.
- [7] R. Achanta, S. Hemami, F. Estrada, and S. Susstrunk. Frequency-tuned salient region detection. In CVPR, 2009.
- [8] S. Goferman, L. Manor, and A. Tal. Context-aware saliency detection. In CVPR, 2010.
- [9] D. Klein and S. Frintrop. Center-surround divergence of feature statistics for salient object detection. In ICCV, 2011.
- [10] M. Cheng, G. Zhang, N. Mitra, X. Huang, and S. Hu. Global contrast based salient region detection. In CVPR, 2011.
- [11] L. Wang, J. Xue, N. Zheng, and G. Hua. Automatic salient object extraction with contextual cue. In ICCV, 2011.
- [12] F. Perazzi, P. Krahenbuhl, Y. Pritch, and A. Hornung. Saliency filters: Contrast based filtering for salient region detection. In CVPR, 2012.
- [13] Y. Wei, F. Wen, W. Zhu, and J. Sun. Geodesic saliency using background priors. In ECCV, 2012.
- [14] Q. Yan, L. Xu, J. Shi, and J. Jia. Hierarchical saliency detection. In CVPR, 2013.
- [15] H. Jiang, J. Wang, Z. Yuan, Y. Wu, N. Zheng, and S. Li. Salient object detection: A discriminative regional feature integration approach. In CVPR, 2013.
- [16] Z. Jiang and L. S. Davis. Submodular salient region detection. In CVPR, 2013.
- [17] C. Yang, L. Zhang, H. Lu, X. Ruan, and M.-H. Yang. Saliency detection via graph-based manifold ranking. In CVPR, 2013.
- [18] M.-M. Cheng, J. Warrell, W.-Y. Lin, S. Zheng, V. Vineet, and N. Crook. Efficient salient region detection with soft image abstraction. In ICCV, 2013.
- [19] Muwei Jian, Wenyin Zhang, Hui Yu, et al., Saliency detection based on directional patches extraction and principal local color contrast, *Journal of Visual Communication and Image Representation*, 57, 1-11, 2018.
- [20] N. Sandeep, DR. B. R. Vikram. Brain Tumour Extraction Functioning from MRI Images using MATLAB. *International Journal of Innovative Technologies*, Vol. 04, Issue No.02, pp. 0329-0332, 2016.
- [21] Y. Zhang and L. Wu. An MR brain images classifier via principal component analysis and kernel support vector machine. *Progress in Electromagnetics Research*, Vol. 130, 369–388, 2012.
- [22] A. Hati, S. Chaudhuri, R. Velmurugan, An Image Texture Insensitive Method for Saliency Detection, *Journal of Visual Communication and Image Representation*, Vol. 43, pp. 212–226, 2017.