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Threshold segmentation algorithm for automatic extraction of cerebral vessels from brain magnetic resonance angiography images

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HIGHLIGHTS

- A novel segmentation algorithm is proposed to extract cerebral vessels from brain magnetic resonance angiography (MRA) images.
- The vessel segmentation algorithm is fast and fully automatic.
- The performance of the threshold segmentation is acceptable.
- The segmentation method may be used for three-dimensional visualization and volumetric quantification of cerebral vessels.

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ABSTRACT

Background: Cerebrovascular segmentation plays an important role in medical diagnosis. This study was conducted to develop a threshold segmentation algorithm for automatic extraction and volumetric quantification of cerebral vessels on brain magnetic resonance angiography (MRA) images.
New methods: The MRA images of 10 individuals were acquired using a 3 Tesla MR scanner (Intera-achieva SMI-2.1, Philips Medical Systems). Otsu's method was used to divide the brain MRA images into two parts, namely, foreground and background regions. To extract the cerebral vessels, we performed the threshold segmentation algorithm on the foreground region by comparing two different statistical distributions. Automatically segmented vessels were compared with manually segmented vessels.
Results: Different similarity metrics were used to assess the changes in segmentation performance as a function of a weighted parameter w used in segmentation algorithm. Varying w from 2 to 100 resulted in a false positive rate ranging from 117% to 3.21%, and a false negative rate ranging from 8.23% to 28.97%. The Dice similarity coefficient (DSC), which reflected the segmentation accuracy, initially increased and then decreased as w increased. The suggested range of values for w is [10, 20] given that the maximum DSC (e.g., DSC = 0.84) was obtained within this range.
Comparison with existing method(s): The performance of our method was validated by comparing with manual segmentation.
Conclusion: The proposed threshold segmentation method can be used to accurately and efficiently extract cerebral vessels from brain MRA images. Threshold segmentation may be used for studies focusing on three-dimensional visualization and volumetric quantification of cerebral vessels.

1. Introduction

Cerebrovascular segmentation (Kirbas and Quek, 2004; Suri et al., 2002) plays an important role in medical diagnosis. This technique is necessary to perform a three-dimensional (3-D) visualization of cerebral vessels to diagnose, quantify, and grade vascular abnormalities, such as stenosis and aneurysm (Farag et al., 2004). Moreover, an accurate extraction of 3-D structures of cerebral vessels helps in planning and performing neurosurgical procedures (Frangi et al., 2001; Passat et al., 2005). 3-D time-of-flight (TOF) magnetic resonance angiography (MRA) is a noninvasive technique for vessel imaging. After cerebral vessels are segmented from 3-D TOF MRA images, maximum intensity projection (MIP) (Sun and Parker, 1999) method is generally utilized to construct a 3-D volumetric visualization of cerebral vessels and assess the size and location of vessels.

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Cerebral vessels are difficult to accurately segment because of complex geometric structures and limited spatial resolution and image contrast (Bogunović et al., 2011). Various segmentation methods have been developed to extract cerebral vessels from brain MRA images, and these methods can be divided into two main categories (Kirbas and Quek, 2004; Yan and Kassim, 2006): skeleton-based and non-skeleton-based. In skeleton-based methods (Kirbas and Quek, 2004; Sorantin et al., 2002), the centerlines of vessels are extracted and a vessel tree is generated by connecting these centerlines. A centerline structure is simulated explicitly or implicitly by using vessel modeling methods. However, the results of skeleton-based methods provide incomplete volumetric information of the vessels.

In non-skeleton-based methods, vessels are directly extracted from 3-D MRA images by using deformable models (Chen and Amini, 2004; Farag et al., 2004; Kozerke et al., 1999; Scherl et al., 2007; Yan and Kassim, 2006) or threshold techniques (Chung and Noble, 1999; Chung et al., 2004; Kim and Park, 2005; Wilson and Noble, 1999). For example, a level set method (Adalsteinsson and Sethian, 1995) is commonly used in deformable model approaches that track the interfaces and shapes of vessels. Level set segmentation is implemented by locally minimizing an energy function with a gradient descent algorithm (Cremers et al., 2007). Different forms of improved level set methods (Adalsteinsson and Sethian, 1995; Chen and Amini, 2004; Farag et al., 2004) have been designed for vessel surface segmentation, but the use of these methods is limited by common factors, such as sensitivity to initial value, speed, and algorithm convergence. Furthermore, threshold segmentation methods (Chung et al., 2004; Kim and Park, 2005) have been extensively investigated. In these methods, a threshold is chosen to distinguish vessels from brain tissues by combining reasonable statistical models and local voxel information. The selection of threshold value directly impacts the segmentation performance.

In this paper, a threshold segmentation method was developed to extract cerebral vessels from 3-D TOF MRA images. In general, extreme value theory (De Haan and Ferreira, 2007) can be used to detect outliers of abnormally low or high values, which occur at the tails of specific probability distributions, such as normal distribution. In MRA images, cerebral vessels present signals higher than surrounding brain tissues with intermediate signals. Homogeneous brain tissues excluding the vessels can be represented by normal distribution, and cerebral vessels can be detected using a specific extreme value distribution, namely, the Gumbel distribution (Kotz and Nadarajah, 2000; Roberts, 2000; Wang et al., 2014). To extract the cerebral vessels from brain MRA images, we determine a threshold by comparing the probability density function (PDF) of the two statistical distributions.

This study aimed to design a threshold segmentation algorithm that can be used to extract cerebral vessels from 3-D TOF MRA images. Two statistical distributions were applied to determine a threshold that could be used to distinguish vessels from brain tissues. To evaluate the performance of the proposed threshold segmentation, we investigated the MRA images of 10 individuals and compared automatically segmented vessels with manually segmented vessels.

2. Materials and methods

2.1. Subjects and image acquisition

This study was approved by our institutional review board, and a written informed consent was obtained from each patient. Ten individuals (four males and six females) were enrolled in this study and subjected to cerebrovascular segmentation. These individuals aged between 29 and 85 years (mean age = 59.7 years). 3-D TOF MRA images were acquired using a 3 Tesla MR scanner (Intera-achieva SMI-2.1, Philips Medical Systems). The main imaging parameters were listed as follows: repetition time/echo time = 30/3.4 ms; flip angle = 20°; rows × cols = 960 × 960; pixel spacing = 0.24 × 0.24 mm^2; FOV = 230 mm; slice thickness = 1.2 mm; spacing between slices = 0.6 mm; and an axial 3-D slab with 180 slices. All of the raw MRA images were loaded by MIPAV software (http://mipav.cit.nih.gov/) and transformed into new bitmap images with intensities between 0 and 255 by using a robust scaling method in MIPAV software.

2.2. Segmentation method

The gray histogram plot of a TOF MRA dataset is shown in Fig. 1A. Two distinct peaks are found on the histogram. The leftmost peak represents the background region (namely the whole brain) and the rightmost peak indicates the foreground region, which presents a dark signal on the MRA images. In particular, the intensity distribution of the foreground was investigated in this study using the logarithmic histogram (Fig. 1B). In fact, the rightmost peak indicates homogeneous brain tissues excluding the vessels; by contrast, the long tail (Fig. 1B) on the right side of the peak represents the cerebral vessels. The homogeneous brain tissues excluding the vessels can be efficiently modeled by normal distribution. Nevertheless, the intensity distribution of the cerebral vessels located at the tail in the histogram is not well explained by the normal distribution. Thus, a generalized extreme value distribution, namely, the Gumbel distribution, was used in this study to extract the cerebral vessels from the MRA images.

2.3. Normal and Gumbel distributions

Normal distribution is commonly applied to model a homogeneous tissue in brain image segmentation. The contrast between the white matter (WM) and the gray matter (GM) is relatively low in MRA images, thereby producing a homogeneous background region with an intermediate signal. Thus, the intensity distribution of homogeneous brain tissues excluding the cerebral vessels could be effectively represented by normal distribution. For instance, let x_i denote the intensity of the ith voxel in a TOF MRA dataset. The PDF of the normal distribution (Bishop, 2006) is expressed as follows:

$$p_{\text{Normal}}(x_i;\mu,\sigma)=\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{1}$$

where μ and σ stand for the mean and variance of the homogeneous foreground region. However, the intensity distribution of the cerebral vessels did not conform to their corresponding normal distribution. Thus, the extreme value theory was used to solve this problem. Gumbel distribution is a kind of generalized extreme value distribution and can be potentially applied to represent maxima or minima in the data of the generated distributions, such as normal or exponential distributions (Roberts, 2000). Thus, Gumbel distribution is used in some outlier detection methods to find samples with abnormally high or low values, which are far from the expected statistical results of a normal data set. The PDF of the Gumbel distribution is defined as (Roberts, 2000) follows:

$$p_{\text{Gumbel}}(x_i;\mu,\sigma)=\frac{1}{\sigma}\exp\left(-\frac{x-\mu}{\sigma}-\exp\left(-\frac{x-\mu}{\sigma}\right)\right) \tag{2}$$

The intensities of the cerebral vessels extremely deviated from the median intensity of the whole brain (including the vessels). Thus, Gumbel distribution was used to detect cerebral vessels as outliers to the rest of the brain tissues. PDFs were compared between the normal distribution and Gumbel distribution (Fig. 2).