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Vascular segmentation of head phase-contrast magnetic resonance angiograms using grayscale and shape features

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ABSTRACT

Background and objective: In neurosurgery planning, vascular structures must be predetermined, which can guarantee the security of the operation carried out in the case of avoiding blood vessels. In this paper, an automatic algorithm of vascular segmentation, which combined the grayscale and shape features of the blood vessels, is proposed to extract 3D vascular structures from head phase-contrast magnetic resonance angiography dataset.

Methods: First, a cost function of mis-segmentation is introduced on the basis of traditional Bayesian statistical classification, and the blood vessel of weak grayscale that tended to be misclassified into background will be preserved. Second, enhanced vesselness image is obtained according to the shape-based multiscale vascular enhancement filter. Third, a new reconstructed vascular image is established according to the fusion of vascular grayscale and shape features using Dempster–Shafer evidence theory; subsequently, the corresponding segmentation structures are obtained. Finally, according to the noise distribution characteristic of the data, segmentation ratio coefficient, which increased linearly from top to bottom, is proposed to control the segmentation result, thereby preventing over-segmentation.

Results: Experiment results show that, through the proposed method, vascular structures can be detected not only when both grayscale and shape features are strong, but also when either of them is strong. Compared with traditional grayscale feature- and shape feature-based methods, it is better in the evaluation of testing in segmentation accuracy, and over-segmentation and under-segmentation ratios.

Conclusions: The proposed grayscale and shape features combined vascular segmentation is not only effective but also accurate. It may be used for diagnosis of vascular diseases and planning of neurosurgery.

1. Introduction

In the process of clinical diagnosis, the maximum intensity projection (MIP) [1] of computed tomography angiography (CTA) or magnetic resonance angiography (MRA) is often utilized for the diagnosis and treatment of vascular diseases. However, this technique cannot truly reflect the vascular structure in 3D space. Given that blood vessels and non-vascular tissues are present in angiograms, the segmentation of blood vessels from the dataset is the basis of quantitative diagnosis and treatment of vascular diseases [2,3]. Additionally, in the application of neurosurgery [4], specifically for the development of minimally invasive neurosurgery, such as electrode insertion for deep brain stimulation or locating the epileptogenic zone [5,6], how to guide surgical instruments to reach the planned area safely based on the preoperative imaging of blood vessels will also depend on the accurate segmentation of head vascular structures.

Currently, MRA is a commonly used vascular imaging modality in clinical settings. In addition to its high imaging resolution, patients do not need to receive radiation during angiography. According to whether contrast agent is injected or not, MRA can be divided into two kinds, namely contrast-enhanced MRA and noncontrast-enhanced MRA. In the former, contrast agent is injected into the patient's blood to obtain an enhanced angiographic image, and it is generally recognized as contrast-enhanced imaging. Certain studies have shown that some patients are prone to nephrogenic systemic fibrosis in the process of contrast agent injection; therefore, contrast enhancement MRA should be carefully conducted for clinical application. Noncontrast-enhanced MRA comprises time-of–flight (TOF), susceptibility-weighted imaging (SWI), and phase-contrast (PC) MRA. According to the angiography principle of TOF and SWI, these techniques mainly contain only a single imaging information of an artery or vein. Compared with TOF and SWI, PC-MRA is obtained according to the interaction

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between blood flow and its gradient field; thus, non-vascular tissues will be suppressed, and both artery and vein structures are retained. Both structures of artery and vein should be considered in the procedures of clinical neurosurgery, so the extraction of vascular structure from the PC-MRA dataset is studied in this paper.

For the shape of blood vessels of head PC-MRA, the complexity of vascular network structures; variation in vascular direction, size, and curvature; and appearance of diseased vessels, specifically the geometry characterized caused by vasodilation, calcification, aneurysms, stenosis, and other diseases, are all factors that lead to the difficulty of vascular segmentation. For the grayscale of blood vessels of head PC-MRA, the intensity of small blood vessels appears low in images because of their slow flow rate, thereby making them difficult to be detected. Some noise is often detected in PC-MRA data, which is similar to the vessels in grayscale. Therefore, accurate and complete segmentation of the entire vascular network from the head PC-MRA data is a difficult task [7].

To date, most of the developed vascular segmentation algorithms can be divided into two types, namely grayscale- and shape-based methods. For grayscale-based methods, vascular structures are segmented from the dataset according to their grayscale distribution in angiograms; these methods include statistical model- [8–10], region growing- [11,12], active contour- [13], and level set-based [14] methods. Among them, statistical model-based methods are commonly utilized in the segmentation of blood vessels. These methods employ the Bayesian classification method, in which two or three grayscale functions are constructed to fit the image intensity distribution, and the vascular structures are subsequently extracted by optimizing the probability density function. For example, Wilson and Noble [15] introduced the Gaussian mixture model to describe the grayscale distributions of blood vessels and background; they used the expectation maximization (EM) algorithm to solve for the mixed probability density function and finally detected the vascular grayscale distribution area in angiograms. On this basis, Cauchy [16], Rician [17], double Sigmoid [18], Rayleigh [9], Gumbel [19], and many other distribution functions are also introduced to improve the statistical distribution function or optimization method [8]. However, the signal of small blood vessels is very weak, so they are inevitably lost because of truncation error in segmentation via the statistical model. Therefore, many researchers have considered adding other constraints based on the statistical model to complete the missing information. For example, Chung et al. [10,20] proposed a cerebral vascular segmentation method based on the statistical model and local phase coherence, which does not only extract normal large blood vessels but also recognizes the low grayscale area of aneurysm and vein. Hassouna et al. [9] introduced the Markov random field (MRF) in the application of a statistical model, and they also used the maximum pseudo likelihood estimation to optimize the parameters of 3D MRF; thus, the small size of the vascular structures is not destroyed. However, the above models are established in the situation that only a small amount of low-contrast vessels is present. If an image contains a considerable amount of noise, which is similar to the blood vessel in grayscale distribution, then vascular structures will be difficult to obtain by only using grayscale features.

The shape-based methods extract vascular structures in images through preconstructed models, which are achieved according to the tubular geometry of the vascular shape. Among them, tracking- and Hessian matrix-based methods are commonly studied. In tracking-based methods, some tubular structures are utilized as templates, and the important parameters of vascular centerline, diameter, and bifurcation are fit in the tracking procedure. For example, Friman et al. [21] modeled the centerline, direction, and sectional grayscale distribution in the tracking of local 3D vascular segment, and they fit the best matching degree of vascular segments to obtain the global vascular structures. Zhou et al. [22] used a Gabor filter to track the vascular segment of target structures, and the phase and amplitude of the Gabor filter were adjusted to fit the orientation and size of the local vascular segment. The tracking-based vascular segmentation methods are dependent on the setting of initial tracking points and end points; therefore, they are highly suitable for handling a small amount of vascular branches but not for the extraction of the entire 3D vascular network in head. The vascular grayscale turns from bright to dark when moving from the center to the edge because of the specific tubular structure of blood vessels, that is, the grayscale distribution of blood vessels exhibit a ridge characteristic. When reflected to the differential information of image, grayscale can be expressed by the Hessian matrix's eigenvalues, that is, the absolute of the Hessian matrix's eigenvalue is nearly equal to 0 in the direction of vascular centerline, but it is far larger than 0 in the directions perpendicular to the vascular centerline. According to this specific distribution of Hessian matrix's eigenvalues, the amount of vascular enhancement filters has been constructed through the combination of Hessian matrix's eigenvalues. To enhance all scales of vessels and protect the small blood vessels, a multiscale space is often constructed, and the vascular enhancement filters are performed by finding the optimized response in the multiscale space. Commonly used multiscale vascular enhancement filters have been proposed by Lorenz et al. [23], Sato et al. [24], and Frangi et al. [25]. In our previous work [26], we segmented the vascular structures of the brain region based on the multiscale vascular enhancement filter proposed by Frangi et al. Nevertheless, to construct a multiscale space, Gaussian functions of different standard deviations should be convoluted with angiograms. This measure causes the expansion of the vascular area in the image and results in over-segmentation.

In this paper, we propose an automatic vascular segmentation method via a combination of vascular grayscale and shape features; this method can accurately extract 3D vascular structures from the head PC-MRA dataset. First, according to the vascular grayscale distribution, the initial vascular segmentation is achieved through the improved Bayesian statistical model. Subsequently, the corresponding vesselness image of the original PC-MRA dataset is produced by applying a Hessian matrix-based multiscale enhancement filter. Based on the obtained initial vascular segmentation and enhanced vascular response image, the reconstructed vascular image is designed by combining with vascular grayscale and shape features, and a new vascular profile is segmented from it. To remove the interference of noise in the head PC-MRA dataset, we propose the segmentation ratio coefficient (SRC). According to the distribution of noise in angiograms, the SRC varies linearly from the top to bottom of the head PC-MRA dataset. The SRC can quantitatively control the final segmentation by removing noise in each slice.

2. Methods

To segment the entire vascular network from the head PC-MRA, we obtain the initial vascular contour according to the vascular grayscale feature. The vesselness image according to the vascular shape feature is then captured. The contour and vesselness image are combined according to the Dempster–Shafer evidence theory to construct the vascular reconstruction image, from which we extract the final vascular structure.

2.1. Initial segmentation based on grayscale feature

As illustrated in Fig. 1, PC-MRA image contains the background and vascular areas of low and high intensities, respectively; thus, the background and blood vessels can be distinguished based on