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Segmentation of arteries in MPRAGE images of the ventral medial prefrontal cortex

N. Penumetcha [a], B. Jedynak [a,b,c], M. Hosakere [a], E. Ceyhan [d], K.N. Botteron [e,f], J.T. Ratnanather [a,g,*]

[a] *Center for Imaging Science, The Johns Hopkins University, Baltimore, MD 21218, United States*
[b] *Department of Applied Mathematics and Statistics, The Johns Hopkins University, Baltimore, MD 21218, United States*
[c] *Université des Sciences et Techologies de Lille, 59655 Villeneuve d'Ascq Cédex, France*
[d] *Department of Mathematics, Koç University, 34450 Sarıyer, Istanbul, Turkey*
[e] *Department of Psychiatry, Washington University School of Medicine, St. Louis, MO 63110, United States*
[f] *Department of Radiology, Washington University School of Medicine, St. Louis, MO 63110, United States*
[g] *Institute for Computational Medicine, The Johns Hopkins University, Baltimore, MD 21218, United States*

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Abstract

A method for removing arteries that appear bright with intensities similar to white matter in Magnetized Prepared Rapid Gradient Echo images of the ventral medial prefrontal cortex is described. The Fast Marching method is used to generate a curve within the artery. Then, the largest connected component is selected to segment the artery which is used to mask the image. The surface reconstructed from the masked image yielded cortical thickness maps similar to those generated by manually pruning the arteries from surfaces reconstructed from the original image. The method may be useful in masking vasculature in other cortical regions.

Keywords: Fast Marching method; Blood vessels; Segmentation; Callosomarginal artery; Pericallosal artery

1. Introduction

Accurate cortical analysis of gray matter (GM), white matter (WM) volumes and gray/white surfaces can be impeded by the presence of blood vessels. These appear as high intensity structures in gradient echo magnetic resonance (MR) images due to flow related enhancement. As tissues in the desired volume are scanned, their magnetizations become partially saturated, causing longitudinal magnetizations in this region to not recover fully between pulses. Blood outside this region, and therefore not saturated in this manner, then flows into the region. It is imaged and produces a very high signal intensity, causing blood vessels to appear bright in these images (e.g. [1]). A simple thresholding to isolate white matter would result in blood vessels being reconstructed as well (and vice versa). While manual segmentation of the vessels is possible, it is time-consuming and tedious.

Cortical characteristics including cortical thickness metrics, are derived with reference to gray matter/white matter (GM/WM) surfaces, therefore if vessels are not removed from a region of interest they can be misidentified as a GM/WM surface and may artificially influence derived cortical metrics. There is variability in the extent of overlying vasculature in different cortical regions. Certain cortical regions have a significant number of overlying large vessels, which have the potential to induce errors or bias in the neighboring cortical metrics. In the ventral medial prefrontal cortex (VMPFC) there are several major vessels that transverse the region and can cause issues related to cortical characterization. The two main arteries in the region are the callosomarginal and pericallosal arteries [2]. Fig. 1 shows the location of the VMPFC relative to the whole brain and these arteries in a sagittal slice of an MR subvolume of the VMPFC. The VMPFC is the lower, central portion of the prefrontal cortex, which is anterior to the precentral sulcus. Studies have found that in clinically depressed subjects there is a significant reduction of gray matter volume in the subgenual prefrontal cortex,

* Corresponding author at: Center for Imaging Science and Institute for Computational Medicine, Whitaker Biomedical Engineering Institute, The Johns Hopkins University, Clark 301, 3400 N Charles St, Baltimore, MD 21218, United States. Tel.: +1 410 516 2926; fax: +1 410 516 4557.
E-mail address: tilak@cis.jhu.edu (J.T. Ratnanather).

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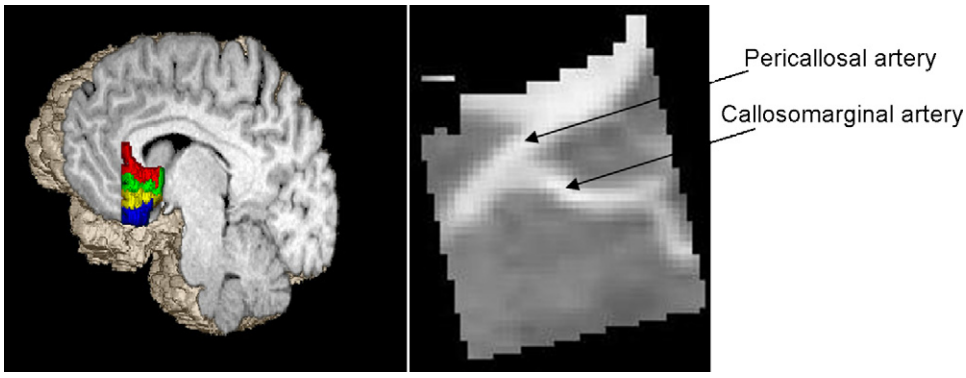

Fig. 1. (Left) Location of the ventral medial prefrontal cortex with colored gyri. (Right) Sagittal MR slice of the VMPFC with callosomarginal and pericallosal arteries.

[3–8]. There is also data suggesting disruption of the adjacent cortex, the VMPFC (Botteron et al., in preparation and [9]).

We have previously developed a procedure for cortical thickness analysis of the VMPFC that required manual removal of the arteries by pruning the blood vessels from the reconstructed gray/white surfaces of the VMPFC [10] but this method is tedious and time-consuming especially in current longitudinal and large-scale neuroimaging studies. Thus a simple, automated method to remove these blood vessels would make cortical analyses of the VMPFC more efficient.

The problem of vessel segmentation in general has been addressed before and multiple methods for solving it exist [11]. Many of these solutions are single scale [12–18]. Several multiscale methods exist as well [19–22]. Many vessel segmentation algorithms involve finding centerlines, or skeletons, of the vessels [23–26]. These algorithms are faster than nonskeleton algorithms, which work without finding a centerline [27–29]. None of these methods have been applied and rigorously tested for specific cortical regions, such as the VMPFC. Thus, we develop a skeleton-type method based on a novel application of the Fast Marching method which is commonly used in level set methods in image analysis [30,31] and apply it to remove arteries from MR subvolumes of the VMPFC.

2. Methods

2.1. Algorithm

The proposed approach finds a path completely contained by the artery and segments it from that path. The problem of finding the skeleton itself was modeled as a minimum path estimation problem.

The method to solve the minimal path problem was proposed for 2D problems by Cohen and Kimmel [32] and later extended to 3D by Deschamps and Cohen [33]. A cost function is defined inside the image such that the desired path is the minimum of the integral of the cost between the two end points. This minimal path problem has been very well studied and a number of solutions exist, such as the Dijkstra method or the Bellman–Ford method [34]. Dijkstra [35] solved the problem using dynamic programming and graph theory. Cohen and Kimmel [32] solved the problem by propagating a front between the two end points. This method has the advantage of being geometric, unlike the Dijkstra method, which is purely topologic. As a consequence, it is more precise. The disadvantage of this method is that the cost function used must meet the requirements of the Eikonal equation.

The Eikonal equation can be solved using the level set method [36] which considers the problem of an evolving interface by increasing the dimensionality of the problem. The initial front is considered the zero level set, and the front at each subsequent time is a higher level set. Thus, a point growing into a circle at uniform speed would be portrayed as a cone with the tip being the zero level set. In the case of monotonically advancing fronts, the surface satisfies the Eikonal equation.

In the blood vessel segmentation method, first a curve is traced inside the blood vessel and is verified by the user. Then the vessel is segmented. Tracing the curve occurs in two steps: calculating a distance map (the front propagation) using a distance function and extracting a minimal path based on this map.

We define the distance in the image between two voxels u and v in two steps. First, for any regular parameterized curve $\gamma(s) : [0, 1] \to \mathbb{R}^3$, such that $\gamma(0) = u$ and $\gamma(1) = v$, define the functional

$$C(\gamma, u, v) = \int_{s=0}^{1} (|x(\gamma(s)) - \mu|^{\alpha} + \omega)\, |\dot{\gamma}(s)|\ \mathrm{d}s$$

where $x(w)$ is the image value at location (voxel) w, $\dot{\gamma}$ is the gradient of the curve γ, α and ω are positive constants. Then, the distance between u and v is defined as the minimum value of the functional C over all regular curves $\gamma(s) : [0, 1] \to \mathbb{R}^3$, such that $\gamma(0) = u$ and $\gamma(1) = v$. In the above integrand, $|x(\gamma(s)) - \mu|^{\alpha}$ and ω, are described as data term and regularization term respectively. If there were no data term, $C(\gamma, u, v)$ would be ω times the length of the curve γ which is minimal when γ is a straight line joining u and v. The data term is small when the image intensity values along γ are close to a constant μ. Deviations from μ are penalized more with large positive α. We experimented with several values of μ, α and ω. Since voxels u and v are selected manually and both $x(u)$ and $x(v)$ are known, we use $(x(u) + x(v))/2$ for μ which crudely estimates the average intensity along the blood vessel. $\omega = 1$ is chosen and being relatively small means that there is essentially no regularization used. Finally, $\alpha = 1$ was found to give better results than $\alpha = 2$.