Characterizing the brain arterial hemodynamics with subject-specific MRA-based computational fluid dynamics models

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Introduction

The mechanisms responsible for the initiation and progression of cerebrovascular diseases such as ischemic stroke and aneurysms are not completely understood [1]. Previous studies have identified the hemodynamics, wall biomechanics, wall mechano-biology, and peri-vascular environment as key factors. Although their relative importance and interactions are poorly understood, hemodynamics is thought to play an important role. Thus, it is important to characterize the healthy hemodynamic conditions and establish baseline values for the most relevant arterial blood flow variables in order to compare them to pathological conditions. This paper describes a methodology for constructing subject-specific image-based computational models of the brain arterial system from magnetic resonance data and its application to the characterization of the brain arterial hemodynamics.

Methods

Modeling Cerebral Arterial Networks

Subject-specific computational models of the brain arterial system were constructed from high resolution magnetic resonance angiography (MRA) data of normal subjects. These images covered the entire brain and were acquired on a 3T GE scanner using time of flight spoil gradient recalled echo pulse sequence with TR/TE=30/4.4. The arterial network was traced semi-manually using an in-house developed plug-in for the NIH ImageJ software called Neuron-Morpho. The result is a vector representation of the vascular structures, i.e. a set of points, radii and connections to previous or parent points along each arterial branch. A cubic spline was then fitted to each arterial branch and the coordinates and radii were smoothed using a non-shrinking algorithm [2]. Subsequently, a cylindrical surface triangulation was created along each branch. A check for possible intersections or overlaps of different branches was then performed in 3D space. Intersections were corrected automatically by displacing the intersecting arterial segments away from each other in the direction of their closest distance while preserving their local smoothness. Subsequently, all the arterial branches were fused together into a single watertight surface triangulation using an adaptive voxelization technique. The terminal branches of the resulting surface were then cut perpendicularly to their centerline (obtained from the vector representation). Finally, a 3D volumetric mesh composed of tetrahedral elements was generated using an advancing front method. The element size distribution was specified as a function of the distance to the centerline of each arterial branch (again obtained from the vector representation of the vasculature). This allows us to prescribe a fixed number of grid points (typically 10-20) in the cross section of all arterial branches, independently of its local diameter. The resulting grids contained between 20-40 million elements.

Modeling Cerebral Hemodynamics

Blood flows were modeled by the 3D unsteady incompressible Navier-Stokes equations, and numerical solutions were obtained using an implicit finite element formulation on unstructured grids [3]. Pulsatile physiologic flow conditions were prescribed as follows. A typical flow waveform obtained from phase-contrast magnetic resonance measurements in the cerebral arteries of normal subjects [4] was used. Flow rates were prescribed at all the model outlets (terminal branches) while equal pressure boundary conditions were applied at the inlets (both internal carotid and basilar arteries). At each outlet, the flow waveform was scaled with the vessel area in order to obtain a mean wall shear stress of 15 dyne/cm^2. This is consistent with the principle of minimum work (or Murray's law) that implies a constant wall shear stress distribution along the arterial arborization [5]. Time-dependent computational fluid dynamics (CFD) calculations were carried out for two cardiac cycles using 100 timesteps per cycle. Visualizations of the velocity, pressure and wall shear stress fields were created and are presented for the second cardiac cycle.

Results

A total of 34 vascular reconstructions and 3 CFD models have been constructed from MRA data. An example is shown in Fig. 1. This figure shows: a) the MRA dataset, b) the reconstructed vascular model, c) the pressure distribution, d) the wall shear stress distribution, and e-f) the flow velocity field at peak systole. It can be seen that in this subject there is an asymmetry in the pressure drop distribution between left and right hemispheres, which is confirmed by a statistical morphological analysis of the left and right arterial trees [6]. It can also be observed that the wall shear stress reaches its highest values at the level of the circle of Willis, i.e. the first few generations of the arterial trees. These are the locations where most vascular lesions such as aneurysms and stenoses tend to occur. Strong swirling flows in the internal carotid arteries and near bifurcations can be observed (Fig.1 e and f). The swirling seems to be stronger near the circle of Willis. It can be seen that the left middle cerebral artery of this subject is also fed from the posterior circulation through the left posterior communicating artery. This is consistent with both the left-right asymmetry in the vasculature and pressure distribution.

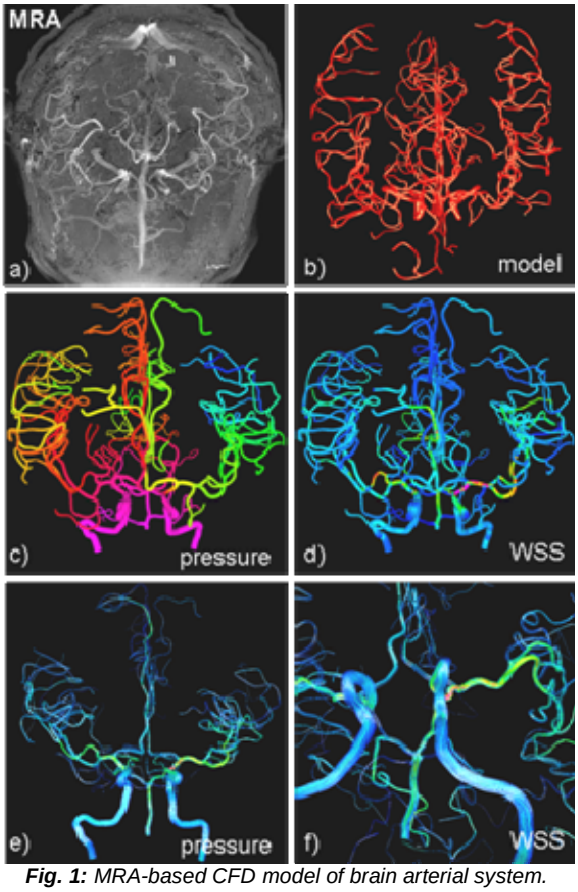

Fig. 1: *MRA-based CFD model of brain arterial system.*

Conclusions

Computational models of blood flows in cerebral arterial networks are important to characterize the normal hemodynamics in the cerebral arteries and compare them to pathological conditions such as aneurysms and stenoses. These subject-specific models can be constructed from non-invasive MRA images. The information provided by these models is useful for better understanding the initiation and progression of cerebrovascular diseases, which will help improve patient evaluation and management.

References

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