

An Analysis of Vessel Enhancement Filters Based on the Hessian Matrix for Intracranial MRA

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Introduction

Vessel enhancement filters applied to 3D MRA data sets prior to rendering as a 2D image may improve visualization of vessel detail. We previously compared several line enhancement filters for intracranial 3D MR angiography images[1]. We examined filters based on discrete lines (e.g., Du and Parker's filter [2]) and on the Hessian matrix (Frangi [3]). We found the Du and Parker filter to provide the best discrimination between vessel and background tissue. However, the continuous directional properties available from using the Hessian matrix are important features not available from discrete kernels. As such we have made further investigations into the Hessian matrix as a basis for vessel enhancement filtering. In this abstract we describe a detailed analysis of Frangi's filter applied to intracranial TOF MRA images. We propose an alternative filter, based on differences in the eigenvalues of the Hessian matrix (HessDiff).

Methods

The Frangi filter provides a measure of "vesselness" (V) based on the eigenvalues of the Hessian matrix. Let l_1, l_2 and l_3 be the eigenvalues of the Hessian matrix sorted by increasing magnitude ($|l_1|, |l_2|$ and $|l_3|$). For l_2 or l_3 greater than zero V is set to zero otherwise $V = (1 - \exp(-R_a^2/2a^2)) \exp(-R_b^2/2b^2) (1 - \exp(-S^2/2c^2))$, where R_a is the ratio $|l_2| / |l_3|$, R_b is the ratio of $|l_1|$ to the geometric mean of $|l_2|$ and $|l_3|$, S is the summation of $|l_1|, |l_2|$ and $|l_3|$, and a, b , and c are normalizing constants taken to be 0.5, 0.5 and $0.5 \max(S)$ respectively. The HessDiff filter is a generalization of Du and Parker's filter that uses the continuous directionality properties of the Hessian matrix. As with Frangi's filter, we solve for the eigenvalues of the Hessian matrix and sort them according to magnitude. For the filter response to be nonzero we again require that both l_2 and l_3 be less than zero (for bright blood) otherwise we take the filter response (V) to be simply $V = |l_3| - |l_1|$. This is a natural extension to Du and Parker's filter. For both Frangi's filter and the HessDiff filter an identical multiscale implementation was used. Successfully larger Gaussian functions for the filter kernels were used. Scales were grown linearly. The maximum response over all the scales was selected at each voxel.

The filters were tested using three images acquired on volunteers participating in a familial aneurysm study. Each patient provided informed consent. A single slab 3D TOF pulse sequence on a 1.5 T Signa scanner was used for each acquisition. Images were acquired on a 512x192x64 grid and reconstructed on a 1024x768x128 grid. Magnetization transfer was used to suppress background signal. The filters were applied to a 512x512x120 subregion centered on the circle of Willis. We sampled voxels from randomly selected slices within the images and classified them as vessel (large, medium, small and very small) or background. A total of 15648 points were sampled and classified as follows: large vessel (2701), small vessel (635) and background (12312). The filter performance was analyzed in terms of how well the vessel voxels were separated from the background voxels. Separation was measured with the trapezoidal ROC curve (AUC). The mean and 10% confidence intervals (two tailed) for these curves were calculated by performing 2000 bootstraps. The ROC areas were calculated for the HessDiff filter, Frangi's filter and its three components, R_a, R_b , and S . A digital phantom was also used to test the relationship between the filters and the MIP algorithm.

Results

Example axial MIP images are shown in Fig. 1. The mean AUC and 90% confidence intervals for the filter performances are shown in Tables 1a and 1b. Overall the Frangi filter performed worse than S for small vessels and worse than R_a for large vessels. R_b is seen to be a poor discriminator for both vessel sizes. By contrast the HessDiff is a good discriminator having the highest mean AUC except for R_a for large vessels. Fig. 2 shows the standard deviation of the projection images as a function of the number of slices included in the MIP. The standard deviation of the HessDiff MIP projections resembles that of the MIP projections of the original image. However, the Frangi MIP

projections retain a significantly higher variance, making the MIP a suboptimal projection for this filter. The high variance of the Frangi projection is due to the exponential functions - the same variance characteristics can be found for the HessDiff response if its response is transformed as $V = (1 - \exp(-V^2/\max(V)^2/2))$ as in S in the Frangi filter.

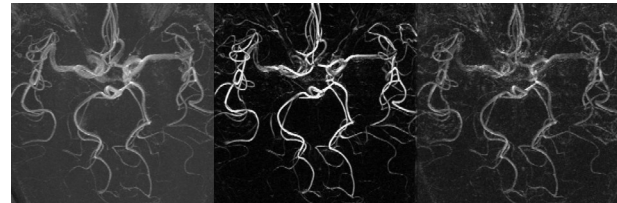


Fig. 1. Axial MIP Images for (left) original image, (center) Frangi filter, (right) HessDiff filter

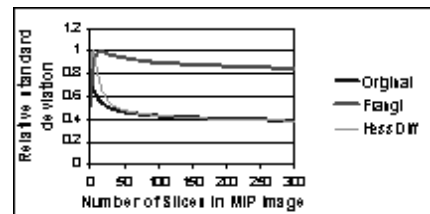


Fig. 2. MIP Behavior for Filter Responses and Original Image

Discussion

The Hessian matrix provides an effective means for detecting vessel structures in MRA volumes. This detection can be used for modest enhancement of vessels, as in this abstract, or for extracting vessel information such as scale and orientation for the construction of models. The Frangi model would perhaps be improved by dropping R_b . The contrast provided by the Frangi filter is exquisite. The relatively poor performance, however, is likely due to thinning of the vessels. The contrast provided by the HessDiff filter is less than that provided by Frangi, however, the vessel size appears more appropriate. Both filters reduce the AUC for large vessels, but increase the AUC for small vessels. The HessDiff filter provides good vessel discrimination based on a very simple function of the eigenvalues. The use of the exponential function in the Frangi model may lead to suboptimal performance with the MIP algorithm.

References

1. BE Chapman, DL Parker pro. ISMRM 2000
2. YP Du, DL Parker, JMRI 1995 5(3):353-9.
3. AF Frangi, et al., MICCAI -98, LNCS 1496.

Table 1a. Volume Response AUC Values for Small Vessels

	Frangi	Ra	Rb	S	HessD.	Orig.
Mean	0.922	0.880	0.752	0.929	0.942	0.919
90% CI	(0.910-0.934)	(0.847-0.912)	(0.723-0.779)	(0.898-0.956)	(0.931-0.952)	(0.908-0.930)

Table 1b. Volume Response AUC Values for Large Vessels

	Frangi	Ra	Rb	S	HessD.	Orig.
Mean	0.918	0.989	0.670	0.907	0.945	0.987
90% CI	(0.912-0.924)	(0.985-0.993)	(0.684-0.716)	(0.895-0.918)	(0.939-0.951)	(0.984-0.989)