**Title**: Improved Vessel Visualization in MR Angiography by Nonlinear Anisotropic Filtering

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**Abstract**
This paper deals with a preprocessing technique of magnetic resonance angiography (MRA) images, applied before maximum-intensity-projection (MIP). The purpose was to recover small low-intensity vessels, visible in individual slices, but lost in MIP images that usually have higher background level than the individual slices. The authors have developed a nonlinear three-dimensional spatial filtering technique (called HD filter) based on anisotropic smoothing. The filter first searches for the local orientation of the vessel. It then performs a nonlinear smoothing in the vessel’s local direction so as to avoid blurring its boundaries. Noise level reduction, contrast enhancement, and improved small vessel visibility achieved by this filter are illustrated on dynamic contrast-enhanced subtraction MRA images of the lower limbs.

**Key words**: image processing, three-dimensional filtering, contrast enhancement, MR angiography.
INTRODUCTION
Dynamic contrast-enhanced subtraction magnetic resonance angiography (DCS MRA) is a new acquisition technique (1, 2) inspired by x-ray digital subtraction angiography. It combines an intravenous injection of a gadolinium bolus (3) and a digital subtraction of two data sets representing the same volume of interest, acquired before and after the injection of the contrast agent. The subtraction aims at eliminating all the anatomic structures except the vessels, assuming that the patient does not move in the meantime. The major advantage of this technique is its capability to explore a large field of view in a short time. However, subtraction amplifies noise.

Despite the emergence of new techniques, maximum-intensity-projection (MIP) is still the "golden standard" for the visualization of three-dimensional (3D) data. The MIP technique tends to increase the mean level of the background (4, 5), since it "gathers" the highest noise level along the projection ray path. Consequently, some vessels may be partially or completely lost, although they are visible in individual slices (6, 7). It is therefore necessary to reduce the noise level before projection, while preserving small low-intensity vessels as well as larger structures (e.g. large arteries, aneurisms) with their exact boundaries.

The aim of our work was to improve the quality of the MRA images obtained by MIP. We present a 3D anisotropic nonlinear filter that differentiates small vessels from noise spikes, using the following model: a vessel is assumed to be represented by a spatially structured, oriented set of voxels, while noise is assumed to be unstructured and isotropic. The first stage of the filter extracts the vessel’s most likely orientation at each location. The second stage locally performs a nonlinear smoothing in the selected direction. Our approach differs from the vessel enhancement techniques (8-10) that combine the outputs of directional operators, without an explicit extraction of the vessel local orientation. To evaluate its performance, our filter was applied to DCS MRA images of lower limb and abdominal arteries of 14 patients.

THEORY
In computer vision, the commonly used noise level reduction technique is smoothing. Isotropic smoothing is efficient within the homogenous regions (far from any boundary), but it tends to blur the boundaries and to wipe out thin, low contrast structures (small vessels in our case). Anisotropic smoothing can prevent these drawbacks. Indeed, to avoid blurring, all the voxels used to compute a "smoothed" intensity value assigned to the current voxel should belong to the same object as the current voxel. This requirement is approximately met, when using voxels located within a short straight line segment, called "stick", centered on the current voxel and parallel to the vessel’s local orientation. It is therefore necessary to extract this orientation.

The vessel’s most likely orientation is selected from a set of discrete orientations represented by the corresponding "sticks". A recently reported orientation extraction criterion, based on the fact that a vessel is locally brighter than the background, consists in searching for the stick having the maximum mean intensity (11, 12). However, for the background voxels close to a bright structure this criterion tends to select the sticks grossly perpendicular to the boundaries. Better results are obtained when searching for the stick with minimum intensity variance. This criterion, encouraging the sticks entirely included within one homogenous object (vessel or background), may also fail to find the vessel local orientation when, due to a negative noise spike, the intensity of a vessel voxel is closer to the background mean intensity than to the vessel mean intensity.
To prevent these drawbacks, we propose a criterion, that combines the above mentioned criteria and extends the homogeneity requirement onto a set of parallel neighboring sticks. Indeed, for the optimal orientation, the intensity should be homogenous within each stick separately. In the vicinity of a boundary however, the mean intensity may vary abruptly between neighboring parallel sticks (Fig. 1). As our criterion simultaneously exploits the intensity homogeneity along the sticks and the intensity difference between the central stick and its neighbors, we call our operator HD filter.

**Orientation Extraction**

We have implemented both 2D and 3D versions of the HD filter. The stick’s length results from a compromise between the spatial resolution and the computational cost on the one hand and the smoothing efficiency of the filter on the other hand. It has experimentally been fixed to five voxels. For this length, the number \( L \) of possible discrete orientations is 8 in 2D and 49 in 3D. In 2D, each orientation corresponds to a distinct pair of symmetric pixels (ends of the corresponding stick) on the perimeter of a \( 5 \times 5 \) square (Fig. 2). The 3D orientations are more difficult to represent. They are defined by the distinct pairs of symmetric voxels on the surface of a \( 5 \times 5 \times 5 \) cube.

**Homogeneity Measure**

For each voxel \( p \) and for each orientation \( i \), a set \( S_{pi} = \{ S^j_{pi}: j = 0,\ldots,n \} \) of parallel neighboring sticks is considered, where \( S^0_{pi} \) is the central stick and \( n \) is the number of its neighbors : \( n = 2 \) in 2D (Fig. 3) and \( n = 8 \) in 3D. An individual homogeneity measure is computed for each stick of the set. This measure is the intensity standard deviation \( \sigma^j_{pi} \) within the stick: \( j \in \{0,\ldots,n\} \). The global homogeneity measure \( \overline{\sigma}_{pi} \), for a given voxel \( p \) and for a given discrete orientation \( i \), is the mean value of the individual homogeneity measures of all the sticks belonging to \( S_{pi} \):

\[
\overline{\sigma}_{pi} = \frac{1}{n+1} \sum_{S_{pi}} \sigma^j_{pi} .
\]  

**Difference Measure**

The difference measure between the central stick and its \( j \)th neighbor is an oriented intensity gradient orthogonal to the stick orientation, averaged along the stick:

\[
g^j_{pi} = \frac{1}{5} \sum_{k=1}^{5} (I^0_k - I^j_k) \quad j \in \{1,\ldots,n\}
\]

where \( I^0_k \) is the intensity of the \( k \)th voxel of the central stick, while \( I^j_k \) is the intensity of the \( k \)-th voxel of the neighboring stick. This gradient is equal to the difference of mean intensities between the central stick and its \( j \)th neighbor. The global difference measure is the mean of the absolute values of the \( n \) oriented gradients:

\[
\overline{g}_{pi} = \frac{1}{n} \sum_{j=1}^{n} |g^j_{pi}| .
\]

The optimal stick should take small values of \( \overline{\sigma}_{pi} \) and, close to the boundaries, large values of \( \overline{g}_{pi} \). It should therefore maximize the following criterion:

\[
HD_{pi} = \overline{g}_{pi} - \alpha \overline{\sigma}_{pi}
\]
\[ i_{\text{opt}} = \arg \max_{i=1,\ldots,L} (HD_p) \]  

The weighting coefficient was fixed as follows: \( \alpha = \frac{5}{3} \) in 2D and \( \alpha = \frac{23}{4} \) in 3D. These values were calculated so as to take into account the strongly curvilinear vessels and boundaries.

**Anisotropic Smoothing**

Once the optimal orientation is selected, the current voxel \( p \) is assigned the median value of the voxel intensities of the corresponding stick. In this way, very short discontinuities due to noise spikes are removed, while longer discontinuities due to stenosis are preserved.

**MATERIALS AND METHODS**

**Image Acquisition**

The images were obtained using a 1.5-T whole-body Magnetom SP system with a circular polarized body coil for excitation and signal detection. Two identical sets of 19 contiguous coronal sections were consecutively acquired in 45 s. The first one was acquired without contrast medium. The second data set was collected after an intra-venous bolus injection of 0.1 mmol/kg of gadoterate meglumine with a power injector (5 ml/s) placed outside the magnet room. The best compromise (available on Magnetom SP) between the slice thickness (5 mm) and the acquisition time, was obtained using a 2D gradient echo sequence with the following parameters: flip angle of 90°, repetition time (TR) of 90 ms and echo time (TE) of 5 ms. A large field of view of 50 cm \( \times \) 50 cm resulted in a pixel size of 2.6 mm \( \times \) 1.9 mm using a 192 \( \times \) 256 pixel matrix. The study was performed under a protocol approved by our institutional review board and informed consent was obtained from all patients according to the guidelines of this review board.

**Image Processing**

From a group of 100 patients explored by DCS MRA, 14 patients with aorto-iliac or lower limb arterial disease were randomly selected for the purpose of testing the HD filter. In the available data, each slice was twice as thick as the \( x \) and \( y \) dimensions of the voxel. Since such anisotropic data are not well suited to 3D processing, we applied the 2D version of the filter, separately within each slice after subtraction. The set of the filtered slices was then projected onto the frontal plane, using the MIP technique. The algorithms were implemented in C-language on a Sun Sparc-10 workstation. Processing time was 18 s per slice, i.e., about 6 min for a 192\( \times \)256\( \times \)19 data volume.

**Data Analysis**

The performance of the HD filter has been evaluated using the MIP images of the initial and filtered data. The vessel visibility and continuity, as well as the alignment of the sticks on the vessels, have been assessed qualitatively. The quantitative evaluation was based on two complementary criteria: contrast improvement and noise standard deviation reduction. The contrast \( C \) locally measures how high a vessel intensity is above the background mean intensity (i.e., above noise mean level), while the noise standard deviation \( \sigma_N \) measures the noise intensity variation around this mean value. Both measures are combined within a single criterion, contrast-to-noise ratio (13), defined as:

\[ \text{CNR} = \frac{C}{\sigma_N} \]  

\[ C = \overline{I}_V - \overline{I}_B \]

where \( \overline{I}_V \) is the local mean intensity of a short vessel segment, while \( \overline{I}_B \) is the local mean intensity of the background pixels contiguous to the vessel. Computed in this way, \( C \) also
measures the sharpness of the vessel boundaries. The HD filter is supposed to preserve the useful signal $I_v$, while reducing the background level $I_b$. If the filter blurred the boundaries, the vessel signal (close to a boundary) would be reduced, thus reducing $\overline{I_v}$, while the background level $\overline{I_b}$ would be increased.

We deliberately chose to measure the noise standard deviation $\sigma_N$ within background regions corresponding to tissues eliminated by subtraction, containing nor vessels neither acquisition artifacts. The results are expected to be worse than outside the patient’s body, but it seems to be more interesting from the clinical point of view. Indeed, the visibility of the vessels mostly depends on what happens directly around them. The noise level (mean as well as standard deviation) after subtraction, is higher in the regions corresponding to tissues than in the air. Furthermore, it is much easier to eliminate noise far from the vessels.

Measuring both $\sigma_N$ and contrast requires separating the pixels belonging to the vessels from the pixels belonging to the background. An experienced radiologist manually selected the vessel pixels in zoomed MIP images. Since such a manual selection of all the vessels in all patients would be an extremely tedious task, two complementary evaluation protocols are proposed to provide a significant set of results in a reasonable time.

**Protocol 1: Intra-patient**
The first evaluation protocol consists in collecting a set of 28 contrast and $\sigma_N$ measures along two vessels (14 measures for the tibial posterior artery and 14 measures for the peroneal artery) visible in one leg of one arbitrarily chosen patient (Fig. 4).

**Protocol 2: Inter-patients**
The second protocol is designed to rapidly collect a set of measures for all the considered patients. This set also consists of 28 measures: two measures for each of the 14 patients (one measure per leg). These measures are all performed at one arbitrarily fixed level below the popliteal trifurcation. Only one artery is selected in each leg so as to guarantee the same number of measures for all patients suffering from different arterial obstructions.

**RESULTS**

**Qualitative Results**
The background in the filtered images is visually smoother than in the initial images. As expected, the vessels appear sharper and more continuous. Their extremities, invisible in the noisy original images, become visible in the filtered images (Fig. 5). It can also be noticed that the diameter of the initially visible vessels is preserved. The boundaries and the intensities of the larger structures are also preserved (Fig. 6). The sticks are well aligned on the vessels, boundaries and all locally oriented structures (Fig. 7). These qualitative remarks are corroborated by the quantitative measures.

**Quantitative Results**
Table 1 summarizes the contrast ($C$) and the noise standard deviation ($\sigma_N$) mean values obtained with both evaluation protocols. In the case of protocol 1, $\sigma_N$ is reduced by 2.93 (47%), while the contrast is improved by 6.0 (23%). The absolute improvement measured using protocol 2 is consistent with these results: $\sigma_N$ is reduced by 1.92 (33%), while the contrast is improved by 7.1 (108%). The latter large percent change is due to the initial contrast mean value, which is much lower than that of protocol 1. Indeed, the filtering effect
can best be seen for low-contrast vessels. Figure 8 shows the CNR improvement. All the points are located above the continuous line which represents the "no improvement" case (CNR$\text{filtered} = \text{CNR}_{\text{initial}}$). The dashed line is a first order polynomial approximation of the measured data. It shows that the CNR in the filtered images, on average, is almost twice as good as in the initial images. We note three cases of vessels initially having negative CNR values, i.e., intensities lower than the surrounding background mean value (Fig. 8b). These vessels become visible in the filtered images. Figure 9 illustrates one of these cases. It shows an intensity profile crossing two vessels. After filtering, both vessels are enhanced, while the noise level (initially higher than the vessels’ signal amplitude) is significantly reduced.

**DISCUSSION**

As expected, the HD filter improves the image quality. It removes noise while preserving vessels and thus allows a better vessel delineation in the resulting MIP images. The filter’s first stage, integrating the directional homogeneity information over a voxel’s neighborhood, guarantees a robust orientation selection. This allows the anisotropic smoothing to be really done along the vessels. Moreover, the robust orientation extraction is expected to be the first step towards an orientation-based segmentation algorithm. Although the computational cost of our method is obviously higher than in the case of the filters using single sticks, this increase is not dramatic since most of the intermediate results obtained for the neighboring voxels can be re-used. An evaluation of diagnostic utility of the filter was performed as part of the medical thesis of O. Champin (14). He concluded that the filter does not affect the experts’ appreciation in the case of large vessels (e.g., femoral arteries), but it significantly improves the visualization of small peripheral vessels below the popliteal trifurcation: the number and the length of visible vessels are increased.

Nevertheless, the proposed filter shows some limitations. Designed to remove noise while preserving vessels and larger structures, it cannot remove the acquisition artifacts such as background elements not completely removed by subtraction in the DCS MRA images. Furthermore, straight vessel segments are better enhanced than the strongly curvilinear ones.

**CONCLUSION**

In conclusion, the HD filter improves the vessel depiction in noisy MRA images. Further improvement is expected when using the 3D version of the filter applied to isotropic data, provided that such DCS MRA data will soon be available. The clinical interest of the filter needs to be validated on a larger group of patients. The ongoing research aims at exploiting the extracted orientations within a segmentation process.

**REFERENCES**


Figure 1. Optimal orientation (arrow) in 2D, for different locations of the current voxel p: a) p is within a thin vessel (almost all the voxels of the central stick belong to the vessel, while the neighboring parallel sticks are almost entirely included within the background), b) p is within a large bright structure, close to its boundary (one of the neighboring sticks belongs to the same structure as the central stick, while the other one belongs to the background), c) p is within the background, close to a boundary.
Figure 2. Discrete orientations in 2D.

Figure 3. Examples of 2D neighborhoods $S_{pi}$ used to compute the criterion $HD_{pi}$: a) $S_{p5}$ (orientation 5), b) $S_{p4}$ (orientation 4). Bold characters correspond to the point $p$. 
Figure 4. MIP images of the lower limb arteries before (a) and after filtering (b), patient 1. The horizontal line shows the parameter extraction level fixed in the protocol 2.

Figure 5. MIP images of the lower limb arteries before (a) and after filtering (b), patient 4.
Figure 6. MIP images of the abdominal arteries before (a) and after filtering (b). The background is smoothed, while the intensity and the boundaries of both large and small vessels are preserved, leading to an enhanced contrast.

Figure 7. Orientation extraction, zoom of a region of interest representing a vessel bifurcation in a single slice: a) before filtering, b) after filtering with the extracted local orientations superimposed.
Figure 8. Contrast-to-noise ratio in the filtered versus initial image. The dashed line representing a first order polynomial \( p(x) \) fitted to the data is significantly above the continuous line corresponding to the "no improvement" case (\( \text{CNR}_{\text{filtered}} = \text{CNR}_{\text{initial}} \)): a) protocol 1, \( p(x) = 1.96x + 1.71 \), b) protocol 2, \( p(x) = 1.82x + 1.92 \).

Figure 9. Intensity profiles of a selected line (cf fig.7) before (dashed line) and after (continuous line) filtering, patient 4.
Table 1. Results Obtained Using Two Evaluation Protocols.

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<th>Protocol 1 : Intra-patient</th>
<th>Protocol 2 : Inter-patients</th>
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<tr>
<td></td>
<td>Initial</td>
<td>Filtered</td>
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<tr>
<td>Contrast $C$</td>
<td>25.8</td>
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<td>$\sigma_N$</td>
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