Vessel Adapted Regularization for Iterative Reconstruction in MR Angiography

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Purpose/Introduction: Recently proposed iterative methods such as Compressed Sensing [1,2] involve regularization terms to stabilize and accelerate the optimization. Prior knowledge such as smoothness and sparsity assumptions have been widely used as regularization, but the special structure of angiographic data concerning the spatial continuity of vessels is not yet part of the regularization.

From one slice to the next (in the 2D case) or following a single dimension (in the 3D case) the localization and the size of the vessels will be subject to smaller changes but not to big displacements. We propose a new method that takes into account the localization and brightness of vessels, adapted to each individual vessel. Beneficial for the optimal fit of this regularization even to difficult situations is furthermore a developed ellipsoid-based segmentation method. The advantage of this method is twofold. First, including this information into the reconstruction leads to a faster reconstruction, as the optimal data fit is reached earlier. Second, the general image quality is better as less iterations have to be done, which limits the amplification of noise.

Subjects and Methods: The regularization consists of 3 steps. In the first step, the initial slice (which may as well correspond to a different dimension in the 3D case) is segmented automatically and the information is extracted with an ellipsoid-based method in order to take vessels non-orthogonal to the slice optimally into account.

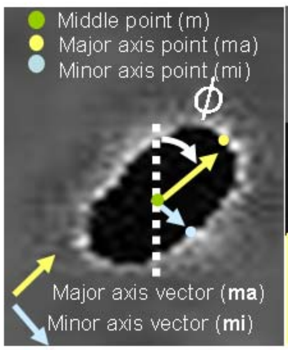

Figure 1: *Ellipsoid based information extraction*

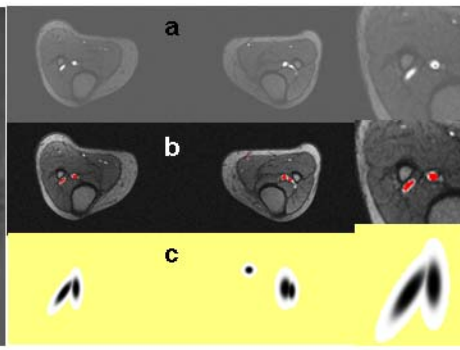

Figure 2: *Illustration of the segmentation b) and the penalty map c)*

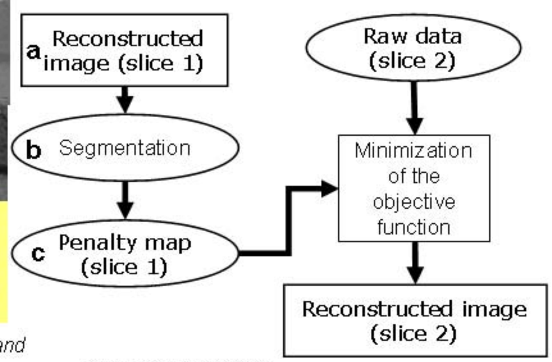

Figure 3: *Workflow*

The second step includes the calculation of a penalty map by a modified Gaussian distribution, used in the regularization term in the iterative reconstruction of the objective slice. In order to adapt to vessel segments that are aligned non-orthogonal to the slice as well, the positions are rotated

$$\textbf{(1)} \begin{pmatrix} i' \\ j' \end{pmatrix} = R \begin{pmatrix} i \\ j \end{pmatrix} = \begin{pmatrix} \cos\Phi & \sin\Phi \\ -\sin\Phi & \cos\Phi \end{pmatrix} \begin{pmatrix} i \\ j \end{pmatrix} \quad \textbf{(2)}\ N(\mathbf{m}_v, \mathbf{mi}_v, \mathbf{ma}_v, i', j') = \sigma_0 exp\left(- \left[\left(\frac{i' - \mathbf{m}_{v,1}}{\sigma_{ma}|\mathbf{ma}_v - \mathbf{m}_v|^2} \right)^2 + \left(\frac{j' - \mathbf{m}_{v,2}}{\sigma_{mi}|\mathbf{mi}_v - \mathbf{m}_v|^2} \right)^2 \right]^b \right)$$

relative to the vessel center and the major axis (equation (1)) before they are included in the Gaussian function. The lengths of the axis are entered as a factor of the standard deviation in the rotation corrected formula (2).

In-vivo experiments were performed on a 3T MR scanner (MAGNETOM Trio A Tim System, Siemens AG, Healthcare Sector, Erlangen) from the peripheral vasculature of healthy volunteers using an ECG-triggered 2D scan with matrix 768 x 782 and field-of-view of 384 x 384 mm. Fig. 2 and 3 illustrate the workflow. 2a) shows the reconstructed slice 1, 2b) the segmentation and 2c) the calculated penalty map which is used for the reconstruction of slice 2.

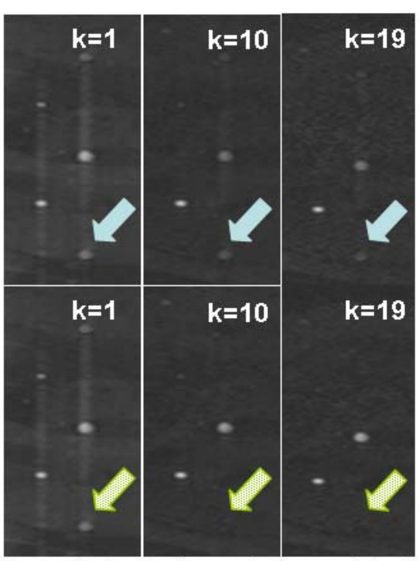

Figure 4: *a) without vessel prior regularization b) with vessel prior regularization*

The regularization term is then included in the minimization problem with the factor λ (equation (3)), regulating its influence relative to the data fidelity term.

$$\textbf{(3)} \min_x \underbrace{||y - Ax||_2^2}_{\text{data fidelity term}} + \underbrace{\lambda \mathrm{VP}(x)}_{\text{regularization}}$$

Results: The upper row of fig. 4 shows the reconstruction with λ=0 (corresponding to the standard iterative reconstruction), the lower row illustrates reconstruction results with vessel prior knowledge regularization (λ=0.5). A better data fit can be observed in that the aliasing artifact visible at the arrow disappears in the lower row before iteration step 10, while it is still visible without the regularization for step 20. The reconstruction thus reached an optimal result in less than half of the iterations. Due to this, the final image is less corrupted by amplified noise and therefore provides a better signal-to-noise ratio.

Discussion/Conclusion: The proposed regularization takes special properties of angiographic data into account during the reconstruction procedure and proved to offer better image quality as well as a faster reconstruction. Further investigation will include the choice of an optimal sampling pattern, adapted both to the needs of iterative reconstruction and the vessel prior regularization.

References: [1] Pruessmann et al., MRM 2001; 46:638 [2] Donoho, IEEE Trans. 2006; 52:1289

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