A general paradigm for constructing adaptative and efficient multispectral imaging filters: Applications to NMR relaxometry in brain

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AgroResonance

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The standard NLM multispectral filter

Filters based on the nonlocal means (NLM) principle provide a high degree of overall image denoising while, to a certain extent, preserving edges and small structures as compared to other advanced filters. The restored intensity of the index voxel i, belonging to the frame k, is a weighted average of all voxel intensities within the image, given by (1):

$$F(v_k)(i) = \frac{\sum_{j\in I} w(i,j) v_k(j)}{\sum_{j\in I} w(i,j)} \quad [1]$$

Restoration

$w(i,j)$ is a weight that quantifies the similarity between voxels *i* and *j*. A large $w(i,j)$ value indicates that the signal intensities of voxels *i* and *j* are similar suggesting that their respective observations come from the same true signal intensity. In a multispectral configuration, the weight is calculated from the L_2-norm using the multispectral information through (2):

$$w(i,j) = \exp\left(-\frac{1}{h^2}\|\boldsymbol{v}(i) - \boldsymbol{v}(j)\|_2^2\right) \quad [2]$$

where $\boldsymbol{v}(i) = [v_1(i) \cdots v_K(i)]^T$ is the multispectral intensity vectors of voxel i. However, this formulation considers similar contribution from all multispectral weights which may preclude detection of non-similar voxels.

Novelties

The new construction paradigm is based on the following:

(1) Using the Bayes theorem, the similarity weight between two measured signal intensities can be derived from the probability of having the same true value, i.e.

$$\mu_k(i,j) = \frac{\int_{-\infty}^{+\infty} p(v_k(i)|a) p(v_k(j)|a) da}{\int_{-\infty}^{+\infty} p(v_k(i)|a) da \int_{-\infty}^{+\infty} p(v_k(j)|a) da} \quad [3]$$

Similarity computation

(2) $\mu_k(i,j)$ is calculated in each frame *k* which leads to a vector $\boldsymbol{\mu}(i,j)$ carrying the information regarding the similarity between voxels *i* and *j*. An appropriate fusion operator g is required to combine this in a scalar weight such as:

$$w_g(i,j) = g(\boldsymbol{\mu}(i,j)) \quad [4]$$

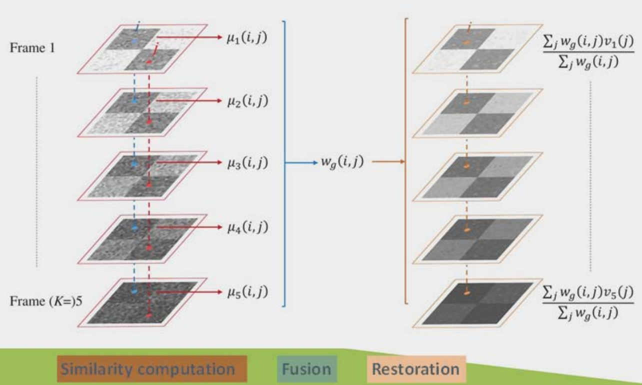
Fusion

(3) A new operator, named *f*-min, is introduced based on the product of the f lowest values of all μ_k

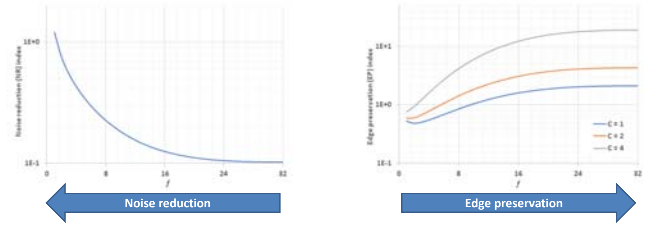
$$w_{f-min}(i,j) = \prod_{k=1}^{f} \vec{\mu}_k(i,j) \quad [5]$$

This combination is a compromise between the f frames exhibiting the lowest similarities. For f = K, $w_{f-min}(i,j)$ is equivalent to $w(i,j)$ introduced in Eq.[2], which corresponds to the case of the conventional multispectral NLM filter.

General paradigm



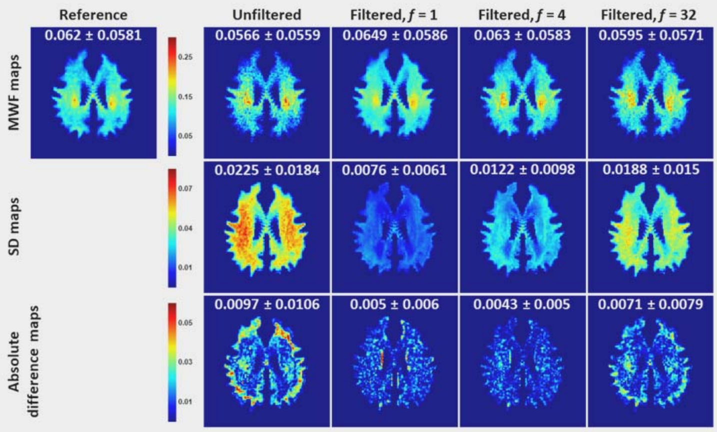
Choice of *f*



Noise reduction and edge preservation indices were calculated as a function of *f* by simulations. A small value of *f* leads to a higher noise reduction. In contrast, a large value of *f* leads to a lower partial volume effect, that is, a higher preservation of edges and small structures. Indeed, when the contrast between frames is higher (i.e. when C increases from 1 to 4 in the figure above), the edge preservation index also improves. A compromise is required to define an optimal value of *f* to ensures a sufficient denoising level with an acceptable preservation of edges and small details.

Brain relaxometry

GRASE T2-weighted images at different echo times were acquired from the brains of 28 healthy male and female participants spanning an age range comprised between 28 and 49 years. the GRASE images of all participants were spatially normalized and then averaged to create a reference image template exhibiting a high SNR. Myelin water fraction (MWF) was calculated by multiexponential inversion of this template (3), without and with incorporation of noise to achieve a clinically representative SNR of 200.



A low value of *f* ensures a greater reduction in noise in several cerebral regions, but leads to an over-smoothing, especially close to edges and small structures. In contrast, a large value of *f*, while ensures a good preservation of the edges, provides a sub-optimal noise reduction. The MWF maps derived from the filtered images at *f* = 4, exhibit regional values that are virtually identical to those of the reference maps.

CONCLUSIONS

In this proof-of-concept, we introduced a new general paradigm for the design of advanced NLM multispectral filters. Using numerical simulations and experimental imaging data, we demonstrated the flexibility of this framework, and illustrated the performance of this novel formalism to design advanced filters to greatly improve image denoising and subsequent parameters determination by quantitative imaging.

References

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