Patch-based super-resolution for arterial spin labeling MRI
Cédric Meurée, Pierre Maurel, Elise Bannier, Christian Barillot

To cite this version:

HAL Id: inserm-01558183
https://www.hal.inserm.fr/inserm-01558183
Submitted on 7 Jul 2017

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In clinical conditions, ASL images are often acquired at low resolutions (LR). This implies partial volume effects (PVE), limiting the validity of cerebral blood flow (CBF) quantifications.

We propose an adaptation of a super-resolution algorithm, taking advantage of a high resolution (HR) structural image to reconstruct CBF maps at a higher resolution, without increasing the acquisition time.

The purpose of the super-resolution algorithm is to retrieve a HR CBF map $x$ from a LR one $y$ provided by the scanner, subject to a decimation operator $D$, a degradation model $H$ and noise $\eta$:

$$y = DX + \eta$$

$X$, the estimation of $x$ obtained by reconstruction from $y$, is the result of the minimization of the optimization function:

$$\hat{x} = \arg \min_{x} ||y - DX||_{2}^{2} + \gamma \Phi_{S}(x)$$

with $\gamma$ a scalar and $\Phi_{S}$ a non-local patch-based regularization term, including information from the structural image $S$.

The proposed algorithm therefore consists in:

- a 3rd order spline interpolation to increase the image dimensions
- iterations between the non-local patch-based regularization and an original data fidelity term until convergence

$$X_{t+1}^{*} = \frac{1}{Z_{t}} \sum_{j \in V_{i}} X_{j}^{*} \exp\left(-\frac{||N(S_{i}) - N(S_{j})||_{2}^{2}}{2\sigma_{i}^{2}} + \frac{||N(X_{i}) - N(X_{j})||_{2}^{2}}{2\sigma_{j}^{2}}\right)$$

$$X^{t+1} = X^{t+1} - (DHX^{t+1} - y)$$

with $N(X_{i})$ a 3x3x3 neighborhood, $V_{i}$ a 7x7x7 search volume around voxel $i$, $\sigma_{i}$ the empirical variance and $Z_{t}$ a scaling parameter.

In order to validate the ability of the algorithm to retrieve a HR image, we applied it to an original HR CBF map downsampled by a factor of 2 in each direction.

The dimensions of the CBF maps were also increased using nearest neighbor, trilinear and 3rd order spline interpolation as a matter of comparison.

The following images present the CBF maps obtained with the different methods:

From left to right: HR CBF image, nearest neighbor, trilinear, 3rd order spline and super-resolution reconstructions

The original HR CBF map being considered as the reference image, the quality of the reconstructions was evaluated by calculating the PSNR between this reference and the generated images.

PSNR between the reference HR CBF map and the maps reconstructed using nearest neighbor, trilinear, 3rd order spline and the proposed super-resolution algorithm.