Patch-based super-resolution for arterial spin labeling MRI
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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.

The CBF maps were estimated using the red on the perfusion maps. The M0 and structural images were registered to the first volume. The ASL series were realigned on the first volume. Images were processed using an inhouse processing pipeline based on Nipype\textsuperscript{2}, SPM8 and Python functions. The ASL series were realigned on the first volume. The M0 and structural images were regristered on the perfusion maps. The CBF maps were estimated using the general kinetic model\textsuperscript{3}.

**Method**

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 \(\eta\):

\[
y = DHx + \eta
\]

\(X_i\), the estimation of \(x\) obtained by reconstruction from \(y\), is the result of the minimization of the optimization function:

\[
\hat{x} = \arg\min_x \|y - DHx\|^2 + \gamma \Phi_S(x)
\]

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

\[
X_i^{t+1} = \frac{1}{Z} \sum_{j \in V_i} X_j^t \exp\left(-\frac{\|N(S_i) - N(S_j)\|^2}{2\sigma_{i,j}^2} + \frac{\|N(X_j^t) - N(X_j^t)\|^2}{2\sigma_i^2}\right)
\]

\[
X_i^{t+1} = X_i^{t+1} - (DHX_i^{t+1} - y)
\]

with \(N(X_i)\) a 3x3x3 neighborhood, \(V_i\) a 7x7x7 search volume around voxel \(i\), \(\sigma_i\) the empirical variance and \(Z\), 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 3\textsuperscript{rd} order spline interpolation as a matter of comparison.

**Results**

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

From left to right: HR CBF image, nearest neighbor, trilinear, 3\textsuperscript{rd} 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, 3\textsuperscript{rd} order spline and the proposed super-resolution algorithm.