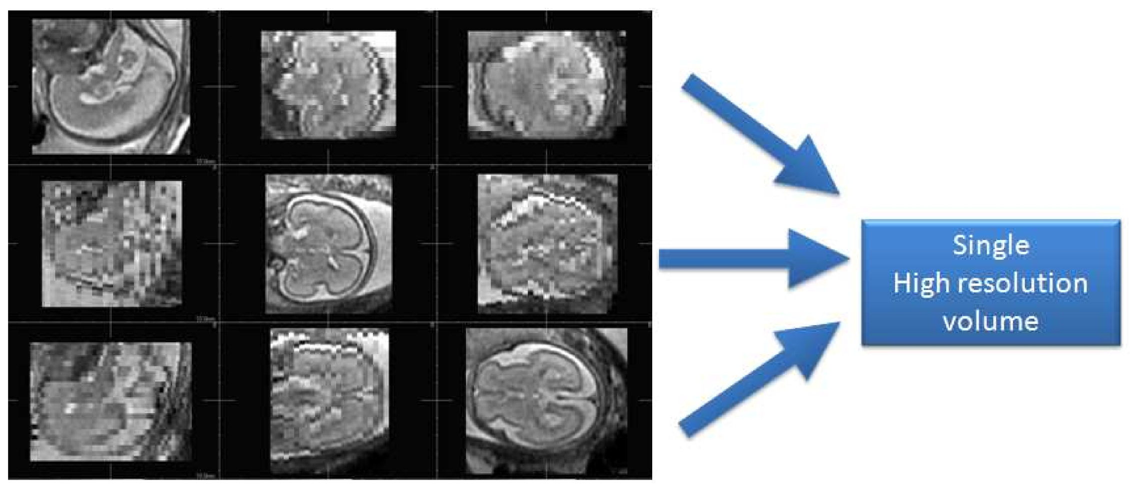
# An Example-based Approach for High-Resolution Reconstruction of Developing Brain MRI

F. Rousseau[1], K. Kim[2], C. Studholme[2]

[1]LSIIT (UMR 7005 CNRS-ULP), Strasbourg, FRANCE, [2]Biomedical Image Computing Group, UCSF, San Francisco, USA.

## High-Resolution Reconstruction




Imaging moving subjects remains an open issue for Magnetic Resonance Imaging (MRI). Several clinical imaging protocols make use of multiple orthogonal 2D multi-planar acquisitions with non-isotropic voxel size for brain studies. A registration-based method to compound multiple orthogonal sets of 2D fetal MRI slices into a single isotropic high resolution volume have been proposed in [2]. It is composed of the following steps:

- rigid registration of 2D slices,
- relative image contrast correction,
- local approach for image reconstruction.

In this work, we focus on the final image reconstruction step and we propose a new example-based super resolution approach based on the non-local means (NLM) framework [1] in order to improve reconstructed image quality.

## Super-Resolution

### SR modeling

The most common SR approaches consist in modeling the physical problem and to invert it. These approaches use a generic observation model such as:

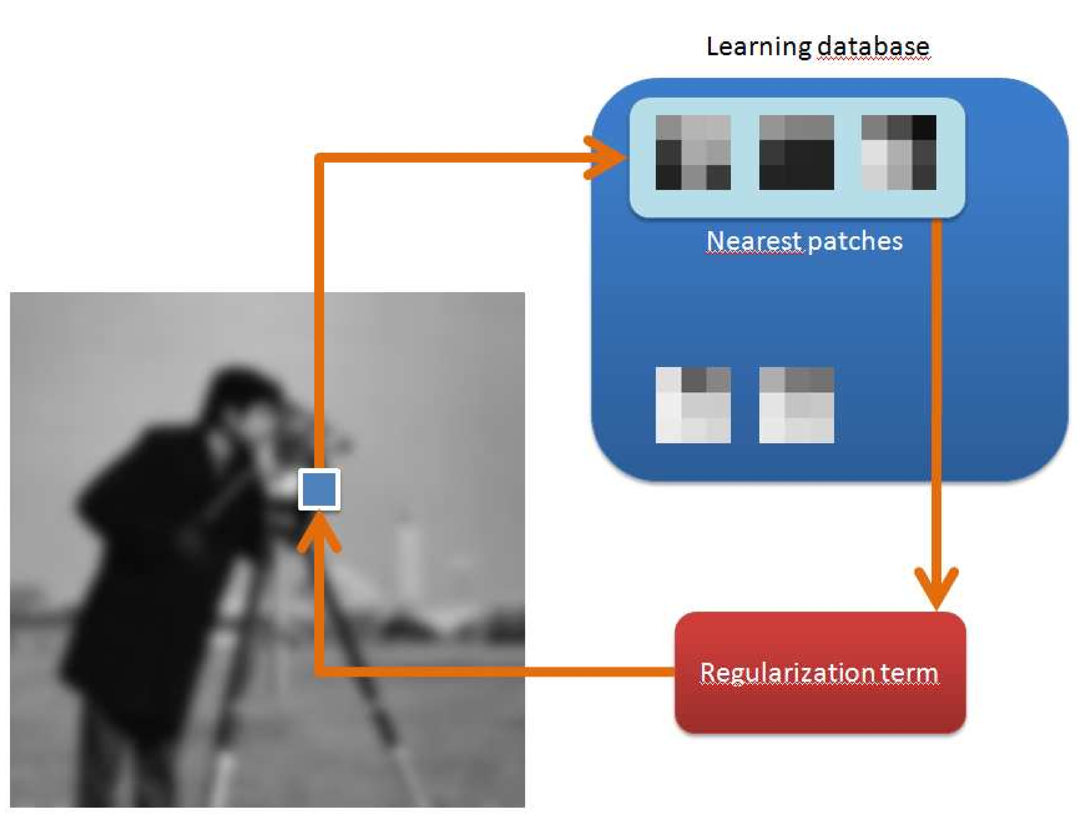
$$\mathbf{y_r} = DBW_r\mathbf{x} + \mathbf{n_r} \quad for \quad 1 \le r \le n \tag{1}$$

where $\mathbf{y_r}$, $r \in \{1...n\}$ denotes the low resolution (LR) images, $\mathbf{x}$ is the high resolution (HR) image, $\mathbf{n_r}$ represents observation noise, $D$ is the subsampling matrix, $B$ a blur matrix, $W_r$ is the geometric transformation of $r$th low resolution image.
The HR image is computed by considering the following equation:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \mathcal{L}(\mathbf{x}, \mathbf{y}, H) + \lambda\mathcal{R}(\mathbf{x}). \tag{2}$$

$\mathcal{L}(\mathbf{x}, \mathbf{y}, H) = \sum_r \|\mathbf{y_r} - H_r\mathbf{x}\|^2$ is a data term related to the physical model and $\mathcal{R}(\mathbf{x})$ is a regularization term.

### Example-based SR methods




$$\mathcal{R}(\mathbf{x}, \mathcal{E}) = \sum_{\mathbf{v},k \in \Omega(\mathbf{v})} w_{\mathbf{v},k} \|f(\mathbf{x}(\mathbf{v})) - \mathcal{E}_{\mathbf{v},k}\|^2 \tag{3}$$

where $f(\mathbf{x}(\mathbf{v}))$ is an operator on the HR image $\mathbf{x}$ at the voxel $\mathbf{v}$, $\Omega(\mathbf{v})$ is a neighborhood of $\mathbf{v}$, $\mathcal{E}$ is the learning database, $\mathcal{E}_{\mathbf{v},k}$ is a element of $\mathcal{E}$ related to $\mathbf{v}$ and $w_{\mathbf{v},k}$ is a local weight. It is important to note that in example-based methods the regularization term $\mathcal{R}$ depends on the learning database $\mathcal{E}$.

## Proposed Reconstruction Approach

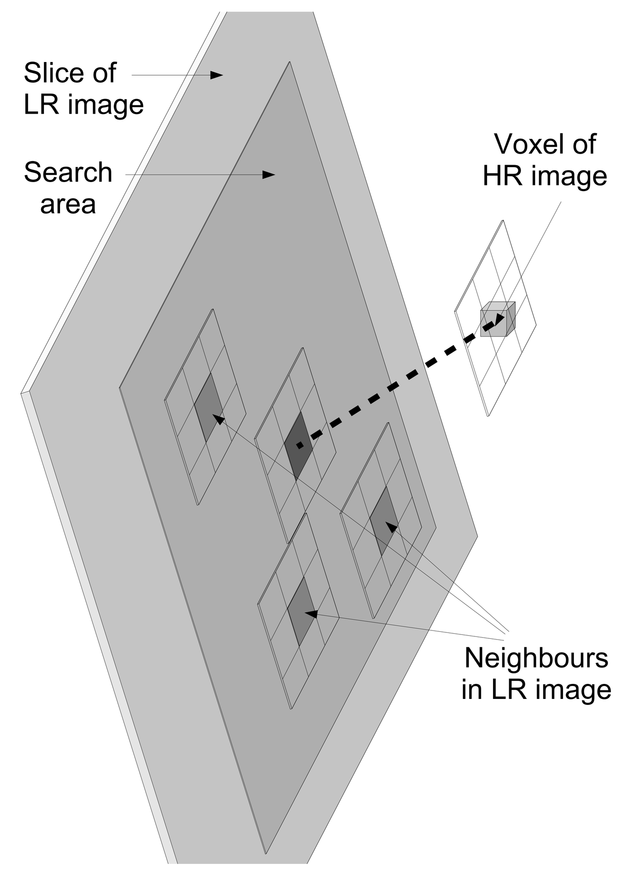



FIGURE 1: Link between example patterns in LR images and voxel in HR image.

### A new regularization term

- We assume that 2D slices of LR images contain relevant examples of the HR image reconstruction.
- The set of LR images is then considered as a relevant candidate to be the learning database $\mathcal{E}$.
- The regularization term can be seen as a similarity constraint between the voxels of HR image and closest examples in the LR images:

$$\mathcal{R}(\mathbf{x}, \mathcal{E}) = \sum_{\mathbf{v}} w_{\mathcal{R}}(\mathbf{v}) \|\mathbf{x}(\mathbf{v}) - d_{NLM}(\mathbf{x}(\mathbf{v}), \mathcal{E})\|^2$$

- $$d_{NLM}(\mathbf{x}(\mathbf{v})) = \sum_{k \in \Omega(\mathbf{v})} w_{NLM}(\mathbf{v}, k)\mathbf{y}(k)$$

where $\Omega(\mathbf{v})$ corresponds to the neighborhood of the voxel $\mathbf{v}$ in the LR images $\mathbf{y}$.

## Results

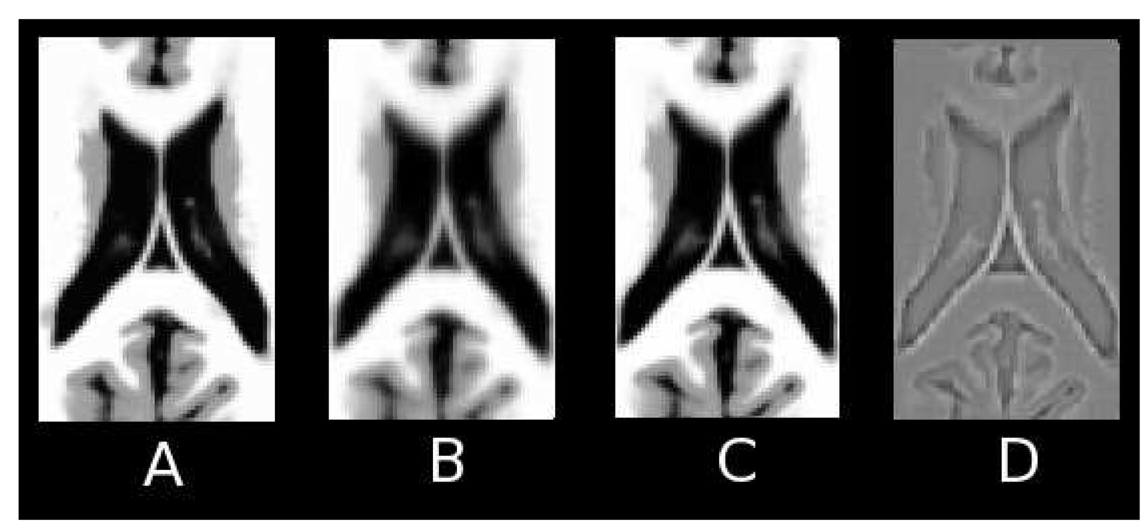



FIGURE 2: Details of reconstructed images (simulation on Brainweb images). From left to right: A) ground truth, B) reconstructed image using local interpolation [2], C) proposed approach, D) difference between C and B.

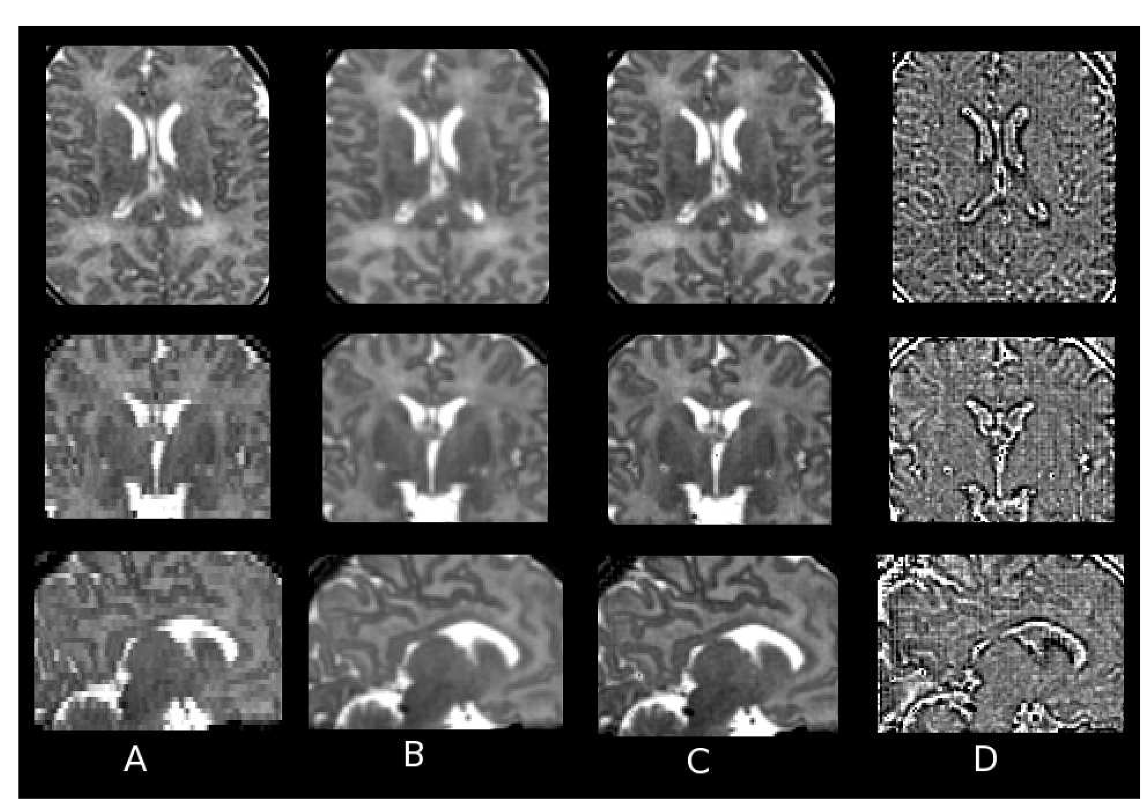



FIGURE 3: Details of reconstructed infant MR images. From left to right: A) original low resolution image, B) reconstructed image using local interpolation [2], C) proposed approach, D) difference between C and B.

### References

[1] Buades, A. and Coll, B. and Morel, J.M. A review of image denoising algorithms, with a new one *Multiscale Modeling & Simulation*, 4(2):490–530, 2005.

[2] Rousseau, F. *et al.* Registration-Based Approach for Reconstruction of High-Resolution in Utero Fetal MR Brain images *Academic Radiology*, 13(9):1072–1081, 2006.

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