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# Template Construction using a Patch-based Robust Estimator

Pierrick Coupé<sup>1</sup>, Vladimir Fonov<sup>1</sup>, José V. Manjon<sup>2</sup>, D. Louis Collins<sup>1</sup>

1 McConnell Brain Imaging Centre, Montréal Neurological Institute, McGill University 3801, University Street, Montréal, Canada H3A 2B4.

2 Biomedical Informatics Group (IBIME), ITACA Institute, Polytechnic University of Valencia, Camino de Vera, s/n. 46022 Valencia, Spain

## **Introduction**

In MR image analysis, template construction is often required to perform voxel-based morphometry analysis [Ashburner and Friston, 2000; Senjem et al., 2005] in order to create a reference used to register a population of different subjects. Usually, after a non-linear registration step used to align the MR images together, simple voxel-wise averaging is used to construct the template. The averaging approach has the advantage of being fast and simple. However this technique is not robust to registration errors, and tends to degrade small structures and contrast between tissues producing an over-smoothed result. To overcome these limitations, we propose to use a robust patch-based estimation which is less sensitive to outliers during template construction and preserves image structure continuity.

## **Methods**

In estimation problems, robust approaches such as median or M-estimators are usually preferred to sample mean, due to their ability to tolerate incorrect observations without biasing their estimations. These robust point-wise estimators are well-suited for unstructured data, but in image processing, it is possible to improve processing tasks by adding some priors on the local data organization. Recently, efficient priors have been proposed for MR denoising within a patch-based estimation scheme [Coupe et al. 2008]. The main idea of patch-based approaches is to use the similarity between patches instead of voxel intensities to perform a robust comparison of the samples. This way, estimation is driven by local geometry of the image, enabling better preservation of small structures and contrast between tissues. We propose to combine the advantages of robust statistics and patch-based approaches within an iterative template reconstruction scheme.

First, all the  $N$  subjects of the database are non-linearly co-registered and their intensities are normalized. The median of each voxel is then computed over the  $N$  subjects of the database to create the initial template. Afterward, the procedure consists in computing the intensity based distance (L2-norm) between each 3D patch within the template centered on location  $x$  and the 3D patches of each registered subject  $S_i$  at the same location. This distance is used to assign a weight for each sample within a robust function. The parameter of the robust function  $h(x)$  is locally estimated as the median of the 3D patch distances at the location  $x$ . Finally, this procedure is repeated until convergence is reached. The proposed method is mathematically described in Fig. 1.

The proposed estimator minimizes the effect of outliers (e.g. registration error or normalization inaccuracy) as well as preserves structure continuity by taking into account the local geometry of the image.

$$\widehat{T}^t(x) = \sum_{i=1}^N w(\widehat{T}^{t-1}(x), S_i(x)) \cdot S_i(x) \quad (1)$$

where  $\widehat{T}^t(x)$  is the estimation of the template intensity at iteration  $t$  and  $w(\widehat{T}^{t-1}(x), S_i(x))$  is the weight assigned to intensity of the subject  $S_i(x)$ . This weight evaluates the similarity between the intensity of patches  $\mathcal{N}(\widehat{T}^{t-1}(x))$  and  $\mathcal{N}(S_i(x))$  centered on voxels  $x$  as follows:

$$w(\widehat{T}^{t-1}(x), S_i(x)) = \frac{1}{C(x)} \exp - \frac{\|\mathcal{N}(\widehat{T}^{t-1}(x)) - \mathcal{N}(S_i(x))\|_2^2}{h(x)} \quad (2)$$

where  $C(x)$  is a normalization constant ensuring that  $\sum_i w = 1$ ,  $\|\cdot\|_2$  is the L2-norm and  $h(x)$  controls the robust function.

Figure 1. Description of the proposed method

## **Results**

During our experiments, a database of 20 T1-w images of 176x256x256 voxels of 1 mm<sup>3</sup> acquired from 20 healthy volunteers were used. These images were normalized with N3 [Zijdenbos et al. 1998] and intensity mapped into the range of the MNI152 template. Linear registration was then performed to the MNI152 space. Afterwards, the Minimum Deformation Template algorithm [Fonov et al. 2010] was applied to create the template, using ANIMAL [Collins et al. 1997] within a multi-resolution framework (non-linear deformation step size of 32, 16, 8, 4 and 2mm). For each resolution step, the template was been created using both the traditional mean and the proposed method with a 3x3x3 patch size.

An efficient template construction method should provide a template with a histogram close to the histogram of the images in database. To evaluate the method, histogram similarity is estimated with the Kullback–Leibler divergence metric [Kullback and Leibler, 1951]; smaller values of the divergence indicate more similar distributions. For all the resolution steps, the proposed approach produces a template with a histogram closer to the histograms of images in database (cf Fig. 2). The distance between template distribution and subject distributions decreases as the resolution of the deformation field increases.

The contrast between white and gray matter has been also computed. Ten anatomical locations for both tissue types were manually picked by an expert on the 2 mm template obtained by classical averaging. The location of these points was used to compute the normalized Michelson contrast [Michelson,1927] for each constructed template. For all the registration steps, the template obtained with the proposed approach has better contrast than the traditional mean-valued template method (cf Fig. 3).

Finally, visual inspection shows that the proposed method produces a template with better contrast preservation (cf Fig.4).

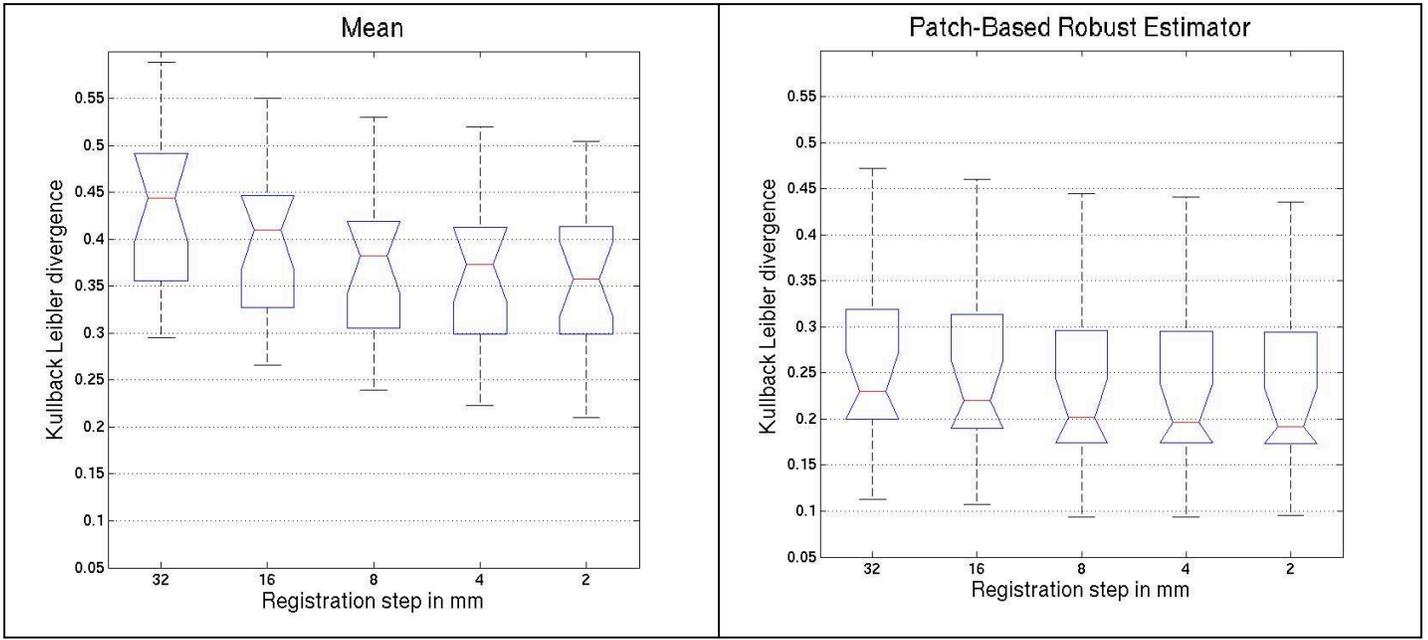


Fig 2: Comparison between the histogram of constructed templates and the histograms of each image of in database at different non-linear registration step size (32mm, 16mm, 8mm, 4mm and 2mm).

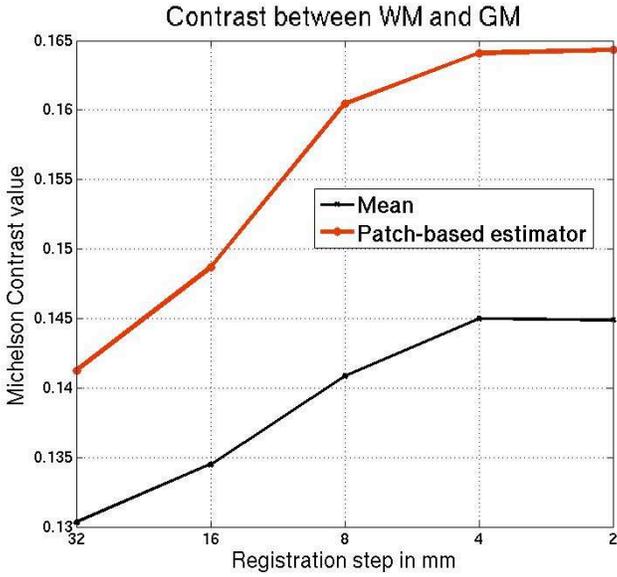


Fig 3: Contrast between White matter / Gray matter for templates obtained by using the Mean estimator and the proposed Patch-based robust estimator for each resolution.

**Conclusion**

A patch-based robust estimator has been proposed for MR anatomical template construction. Compared to the classical approach using the mean, the proposed method enables the construction of a template with a histogram closer to the histogram of the images in the database. Moreover, the proposed estimator produces a template with higher contrast. Finally, as shown with our validation on multi-

resolution registration, the proposed method is more robust to registration error than the mean estimator. Further work on the impact the proposed method on analysis or processing tasks such as registration and segmentation will be the subject of investigation.

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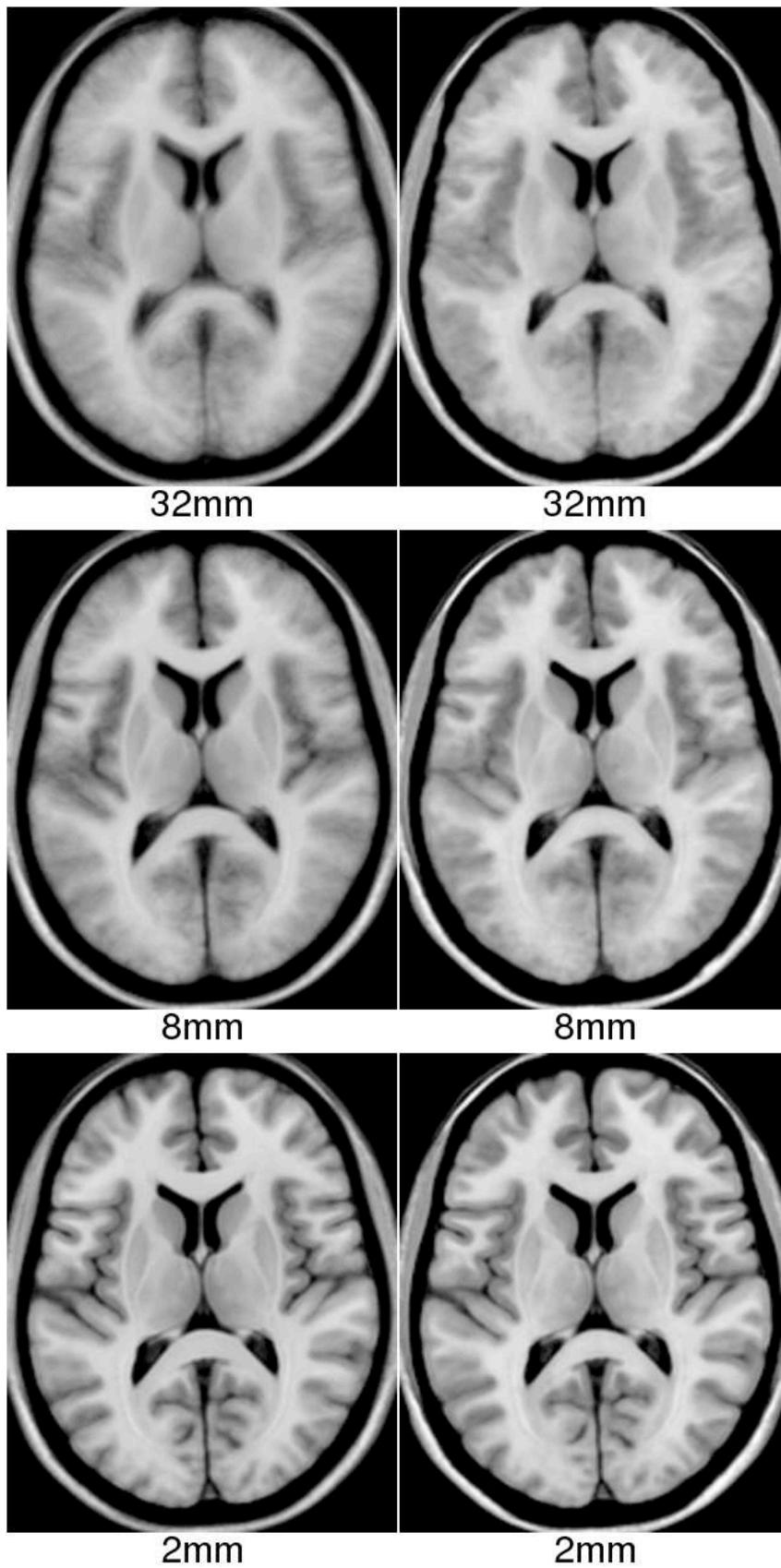


Fig 4. Left : templates obtained with mean estimator. Right : templates obtained with the proposed robust method. Results are shown for different resolution steps.