

# Joint Restoration of Bi-contrast MRI Data for Intensity Non-uniformities

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**Introduction:** The static radio-frequency (RF) field in MRI is in practice inhomogeneous. This leads to non-biological intensity non-uniformities across an image that can complicate its further automated analysis [1]. In general, multiple images of different contrasts are acquired as part of an acquisition protocol that suffer from different non-uniformities [2]. This abstract presents a method for the joint restoration of two such images. It restores the statistics of the individual images as well as their joint statistics and also enforces other regularity constraints. The joint treatment of the images can improve both the accuracy as well as the efficiency of the restoration. The effectiveness of the method has been demonstrated extensively with both phantom [3] as well as real anatomic brain data.

**Image description:** Two different image sets have been considered. The first consists of seven pairs of T1 and T2 images from the BrainWeb phantom [3]. They are corrupted with simulated non-uniformities of levels  $B=0\%-20\%-40\%-60\%-80\%-100\%$  and noise  $N=5\%$  as well as  $B=40\%$  and  $N=3\%$ . The second set is ten real 4.0 Tesla brain data sets of elderly subjects. Each data set is a T1w MPRAGE and a FLAIR image of resolution  $1.0 \times 1.0 \times 1.0 \text{ mm}^3$ .

**Intensity restoration:** The method considers two co-registered images  $I_i(\mathbf{x})$ ,  $i=0,1$ , of different contrasts, where  $\mathbf{x}=(x,y,z)$  corrupted by different non-uniformity fields  $B_i$ ,  $i=0,1$ , respectively. The spatial non-uniformities multiply assumed underlying anatomic images  $I_{A,i}$ ,  $i=0,1$ . Each image is also corrupted by additive and independent Rayleigh noise,  $N_i$ ,  $i=0,1$ . That is, the images are given by  $I_i=B_i \cdot I_{A,i} + N_i$ ,  $i=0,1$ , where  $\cdot$  is the voxelwise product of the images. The statistical representation is in terms of the intensity co-occurrences over a local neighborhood,  $\Delta \mathbf{x} \in D$ , of radius  $\rho$  [3,4]. The co-occurrences of intensities  $u_0$  and  $u_1$  are defined as:

$$C(I_i, I_j, u_0, u_1) = C_{ij}(u_0, u_1) = \iint_{I_i^{-1}(u_0) \cap I_j^{-1}(u_1)} (|\mathbf{x} - \mathbf{x}'| \leq \rho) d\mathbf{x} d\mathbf{x}'$$

and give the auto-co-occurrence statistics for  $i=j$  and the joint-co-occurrence statistics for  $i \neq j$  [4,5]. The statistics of  $I_{A,i}$  and  $B_i$  are assumed to be independent. Thus, the statistics of their product correspond to the convolution of the statistics of  $I_{A,i}$  with the point spread functions corresponding to  $B_i$ . The latter are given by non-stationary Gaussian distributions,  $G(\sigma)$ . The distortion of the auto-co-occurrences can be more effectively represented in polar coordinates. The multiplicative spatial effect of the non-uniformity results in a standard deviation of the radial distortion that is linearly proportional to the distance from the origin  $\sigma_r \propto r$ . The angular point spread function is largest along the diagonal and zero along the axes. The standard deviation of the distortion of the joint-co-occurrences in Cartesian coordinates is proportional to the distance along the axes  $\sigma_{u_i} \propto u_i$  similarly to  $\sigma_r$ .

The restoration separates  $I_i$  into the products of the distortion  $I_{A,i}$  and  $B_i$ . Several regularity constraints are also imposed for the restoration that are contradictory. The restoration is performed iteratively with coordinate descent. Each iteration,  $t$ , provides an estimate of the non-uniformities  $B_{i,t}$ ,  $i=0,1$  and of the underlying anatomic images  $I_{A,i,t}$ ,  $i=0,1$ . The co-occurrence statistics are restored with non-stationary Wiener filtering  $f=G/(|G|_2^2 + \epsilon)$ . The restored statistics are then forced back to the images. The auto-co-occurrence statistics provide restored intensities in polar form as:  $(r_i', \phi_i') = (C_{ii}(\sigma_{r,i}, \sigma_{\phi,i}) f_i^*(r_i, \phi_i)) / (C_{ii}(\sigma_{r,i}, \sigma_{\phi,i}) f_i^*(1, 1))$  and the resulting restoration matrix as  $R_{i,t}^s(r, \phi) = r_i' / r_i$ . The restoration of the joint-co-occurrence intensity statistics provide coordinates  $(u_0', u_1') = (C_{01} f_{01}(\sigma_{u_0}, \sigma_{u_1})^*(u_0, u_1)) / (C_{01} f_{01}(\sigma_{u_0}, \sigma_{u_1})^*(1, 1))$  and the resulting restoration matrices are  $R_{i,t}^b(u_0, u_1) = u_i' / u_i$  for the two images. The three restoration matrices are back-projected to the images to provide an initial estimate of the restorations  $W_{i,t}'(\mathbf{x}) = (1/2) E_{\Delta \mathbf{x} \in D} (R_{i,t}^s(I_i(\mathbf{x}), I_i(\mathbf{x} + \Delta \mathbf{x})) + R_{i,t}^b(I_0(\mathbf{x}), I_1(\mathbf{x} + \Delta \mathbf{x}))), i=0,1$ . These estimates are subsequently filtered spatially with a Gaussian  $G(\sigma_s)$  to enforce the smoothness constrain of the non-uniformities  $W_{i,t}'' = W_{i,t}' * G(\sigma_s)$ ,  $i=0,1$ . The restored images are also altered to preserve their  $L_1$  norm,  $|I_{0,t}|_1 = |I_0|_1$  and  $|I_{1,t}|_1 = |I_1|_1$ . The end condition of the iterations uses the entropy of the auto-co-occurrence statistics  $S_{i,t}$  and the entropy of the joint-co-occurrence statistics  $S_{01,t}$ . The iterations stop when  $(S_{i,t+1} - S_{i,t})/S_{i,t} > \eta$ , for  $i=0,1$ , or  $(S_{01,t+1} - S_{01,t})/S_{01,t} > \eta$ .

**Implementation:** The computation of the non-uniformity in an image is physically meaningful only over its signal region. In images only partly occupied by signal, this region must first be identified. The noise in the non-signal region is represented by a Rayleigh distribution. The signal region is also denoised topologically. The non-uniformities computed over the valid image region are then extrapolated to the entire image. The parameters of the algorithm are  $\sigma_r$  and  $\sigma_s$ . To improve the efficiency of the restoration, the computation of the co-occurrences uses sub-sampling in  $D$  and the spatial Gaussian filtering uses separability.

**Experimental results and discussion:** The entropy of the statistical distributions decreases for all test images. This is achieved despite the high noise of the phantom datasets. The noisy phantom with zero non-uniformity is minimally affected. Also, the real images are restored despite the high non-uniformities of the high field 4Tesla data. An example phantom and an example real bi-contrast restoration are shown in Figure 1. The method uses regularity constraints imposed from the non-uniformity and the anatomy. It can restore disconnected gray matter regions as opposed to methods based on total variation. It is also robust to the contrast mechanism as well as subject and can also decrease the need for calibration scans. The intensity restoration of the pairs of T1w and FLAIR brain data can improve the accuracy of the detection of white matter lesions and the computation of biomarkers from the gray matter.

## References:

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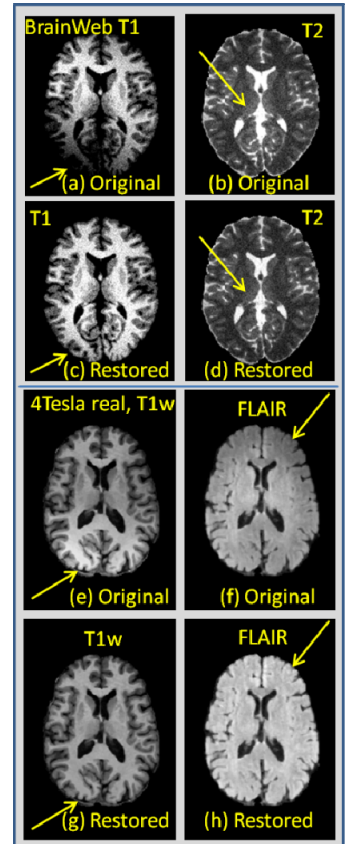


Figure 1 Coronal slices of original and restored images. The phantom of  $B=80\%/N=5\%$  is in (a-d) and a real is in (e-h).