Joint Reconstruction of Under-Sampled Multiple Contrast Images Using Mutual Information

Eric Wong[1]
[1]Radiology/Psychiatry, UC San Diego, La Jolla, CA, United States

Introduction: For many MRI scanning procedures, images of the same anatomy are collected with two or more types of image contrast (ie T1 and T2). Because these images contain nearly the same anatomical information, the mutual information (MI) between them is very high, and this property is widely used for registration of images with different contrast, and even across imaging modalities (1,2). We introduce here a simple method to use mutual information to jointly reconstruct under-sampled images with multiple contrasts. This method is similar in motivation to the recently introduced joint Bayesian CS reconstruction (3).

Methods: The mutual information *I(X;Y)* between two images *X* and *Y* is given by $I(X;Y) = H(X) + H(Y) - H(X,Y)$, where *H(X)* and *H(Y)* are the entropies of the individual images and *H(X,Y)* the joint entropy of the pair. The entropy is in turn given by $H = -\sum p \log_2(p)$, where *p* is the marginal or joint probability density function (pdf) of the image intensities. MI is maximized when the joint entropy is minimized, and this occurs when the joint pdf is sparse. Based on this principle, we use the following iterative procedure to jointly reconstruct under-sampled images of the same anatomy with two different contrasts. First, initial image estimates are obtained from by Fourier Transform of zero filled under-sampled K-space data. The joint pdf is constructed from these image estimates, smoothed using a Gaussian filter, and the gradient field of the pdf calculated. The intensity of each pixel is then modified so as to move up the local gradient of the pdf, thus decreasing the joint entropy. These modified images are transformed back to K-space where the original data, where it exists, replaces the current estimate, and the process iterates. For the example shown here, images were scaled to range from 0-256 in intensity, and the step size for moving up the gradient of the pdf was randomly chosen between 0 and 1 for each voxel at each iteration. This randomness was found to help avoid local minima.

Results: T1 and T2 weighted images from the MNI BrainWeb database (4) along with the joint pdf thereof are shown in the top row of Figure 1. Image resolution was 208x180, with 1mm resolution in plane, and three adjacent 1mm slices were averaged to generate partial volume effects. These images were transformed into K-space and undersampled using the odd and even numbered lines from the T1 and T2 weighted images, respectively, in addition to the center 8 lines from both, to form the source data. The data was thus 94/180=52% of the fully sampled data for both images. The initial image estimates and joint pdf are shown in the second row, and after 20 iterations in the third row. Residual errors at the beginning and end of the iterations are shown in rows 4 and 5. Reconstruction took less than one second running in Matlab.

Discussion: We have demonstrated here a fast and simple method to jointly reconstruct under-sampled images with multiple contrasts based on the use of mutual information. Many modifications of this algorithm are easily imagined, including methods for calculation of gradients in pdf space, methods for initial estimation of the images, schedules for adaptive step sizes in pdf space, sensitivity to undersampling patterns, convergence criteria, etc., and are currently under investigation.

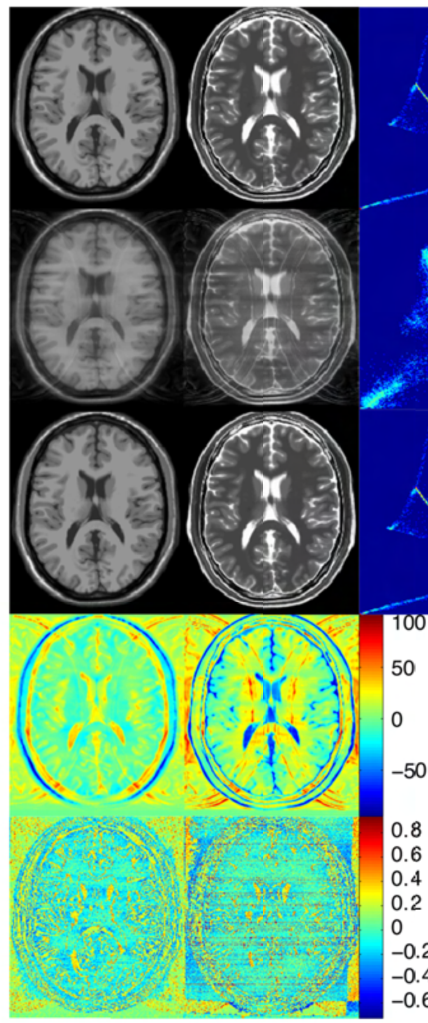

Figure 1: From Left: T1 and T2 weighted images, and joint pdf. From top: fully sampled; reconstructed from zero filled undersampled data; after 20 iterations. Rows 4 and 5 are residual errors before and after iterations. Note the difference in scale between rows 4 and 5.

References

1. Maes et al, IEEE TMI, 16(2), p.187, 1997.
2. Pluim et al, IEEE TMI, 22(8), p.986, 2003.
3. Bilgic et al, ISMRM 2011, p.71.
4. http://www.bic.mni.mcgill.ca/brainweb/