Selection of an Undersampling pattern in the Phase-encoded Plane

L. Zhang[1], D. L. Parker[1], E. Kholmovshi[1], J-Y. Guo[1], J. Roberts[1]
[1]University of Utah, Salt Lake City, Utah, United States

Introduction:

In high resolution MRA, more k-space data needs to be acquired to increase the spatial resolution while keeping the field of view (FOV) unchanged. This makes the technique very time-consuming, especially when it is performed in 3D. Undersampled projection reconstruction (PR) has been investigated to reduce the scan times without sacrificing much of the resolution [1]. And often, in undersample PR, the saving of time comes from the reduction of the projection angles. All data is obtained using frequency encoding and is sampled on polar grid. The common reconstruction techniques for PR are filtered backprojection (FBP) [2] and regridding followed by FFT [3]. Here we propose another way of unersampling the 3D MRA data, which acquires data on Cartesian grid like what has been done in conventional MRA. But the total number of phase encoding is decreased. On the PE plane, the data distribution can be chosen to be an approximate radial pattern or simply a random pattern. And we used compensated FFT to reconstruct the data.

Methods:

We took a 3D high resolution MRA data set with matrix size 280×192×64. The 280 points along Kx were collected in fractional echoes (55% asymmetric echoes) to recover the 220mm FOV in x direction. 192 points were symmetrically phase-encoded in Ky to ensure 3 quarters of FOV in y direction as in x direction. In Kz, there were 64 phase encodings to give a 64mm FOV in z direction. The full k-space data set was first taken to create the 3D image by FFT. It was then used as our object. To concentrate on investigation of undersampling in PE plane, we took only one slice in y-z plane from the 3D object, which is shown in Figure 1.e. Next, we applied 2D FFT to the slice to get the full k-space data for that slice. Then, the data was undersampled and reconstructed. Finally the reconstructed image was compared with the original image of the chosen slice.

The first undersampling pattern is shown in Figure 1.a. It selects all the data on the Cartesian grid within an ellipse with semimajor axis of 19 grid points in Ky direction and semiminor axis of 9 grid points in Kz direction. As it goes out, it behaves like a radial pattern with radial interval being ΔKy and incremental angle Δθ given by

$$\Delta\theta = 2\pi / N_\theta, \quad with \quad N_\theta = 50 \qquad (1)$$

So, the data was greatly undersampled in this pattern. Then all the data on radial was rounded to the nearest rectangular grid to form an approximate radial distribution. The second sampling pattern is shown in Figure 1.b. It differs from the first one in that the outer portion of the samples is randomly distributed in k-space. It was obtained by shifting each point in the first pattern randomly. This resulted in less number of points because of the inevitable colliding of points during the shifting. We have tried to avoid this as much as possible. And we ended up with 3218 points in this random pattern, which is still less than the 3293 points in the radial pattern.

The reconstruction was done by using compensated FFT (CFFT). We have also tried the method of regridding with FFT (RFFT). It turned out that the result was very similar. The compensation function was calculated iteratively as suggested by James Pipe [4].

Results:

Figure 1.c shows the magnitude of the image reconstructed from the sampling pattern in Figure 1.a. And Figure 1.d is the reconstructed image corresponding to Figure 1.b. It can be visually discerned that Figure 1.d has better image quality than Figure 1.c. It has less streak artifact caused by radial undersampleing. It also gives better information at the edge. To analyze further the quality of the reconstructed images, subtraction was done between each of these images and the reference image (the magnitude image reconstructed using 3D FFT of the fully sampled data). Then root mean squared error and relative error were computed for both images in Figures 1.c and 1.d. The relative errors were calculated by the following formula:

$$\delta_i = \sum_{all} \frac{(m_i - m_0)^2}{{m_0}^2} \qquad (2)$$

where δi (i =1, 2) is the relative error, and m0 is the reference image, mi (i = 1, 2) corresponds to the image in Figures 1.c and 1.d, respectively. And the summation is over all elements in the images. The results are listed in table I for comparison. From table I, we can see that the random pattern gives smaller error than the radial pattern does, even though it has less number of sampling points. This is in agreement with our visual deception. This result suggests that the random pattern is the better choice between the above two undersampling patterns.

Conclusions:

The two undersampling patterns have the same number of low frequency data. But the random pattern has less number of points in the outer portion. However, it leads to better reconstructed image than the radial pattern. So, it is better to choose the random undersampling pattern in the PE plane to save time for 3D high-resolution MRA scanningl

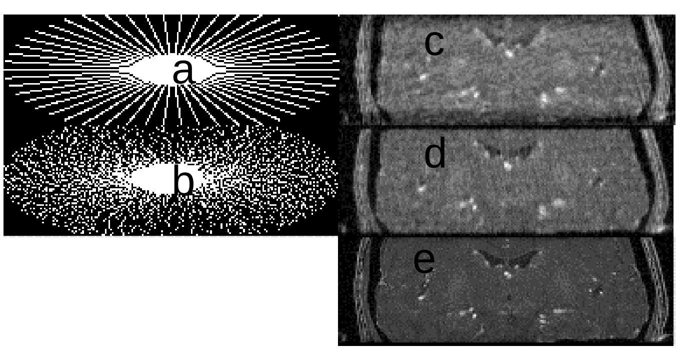

Figure 1.a approximate radial pattern, **b** random pattern, **c,** reconstructed image from a, **d** reconstructed image from b, **e** original image.

Pattern	rms error	Relative error
Radial	27.1	2.3
Random	20.4	1.3

Table1. Comparison of error between the two patterns.

References:

[1] Dana C. Peters, Frank R. Korosec, et al,. MRM 43:91-101 (2000).
[2] Stefan Schaller, Ph.D thesis, Erlangen,1998.
[3] John I. Jackson, Craig H. Meyer, et al,. IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL.10, No3, Sep. 1991.
[4] James G. Pipe, Padmanabhan Menon, MRM 41:179-186, 1999.