A Super-FOV method for rapid SSFP banding artifact reduction

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Introduction

Balanced Steady-State Free Precession (SSFP) suffers from high sensitivity to static field inhomogeneity or susceptibility variations. In many imaging scenarios the typical dark band artifact is observed [1,2]. Several multiple acquisition methods to reduce the banding artifact have been described [1,2]. In these schemes, multiple sets of images are acquired each with a different RF phase increment from one sequence repetition to the next (RF phase cycling). The images are combined in a way to effectively reduce the dark band artifact. However, the extra cost in scan time (usually up to a factor of 4) is limiting. In this work we describe the "super Field of View" (sFOV) problem, which is a generalization of sensitivity encoding (SENSE)[3] in parallel imaging. We show that multiple acquisition SSFP can be posed as an sFOV reconstruction, significantly reducing the scan time. We further validate our method by showing in-vivo experimental results.

Theory

In an sFOV setting one measures a set of distorted, aliased small FOV representations of a larger FOV object. The distortion for each image is different, known and linear. For example, a distortion can be due to motion, blur, sensitivity mask or geometric distortion. The k-space trajectory is arbitrary and can be different for each of the images. This is a generalization of SENSE, where the distortion is due to the sensitivity of the receiver coil and the k-space trajectory is the same for all the coil images. The k-space data y_i for each image version can be written as,

$$y_i = F_i S_i m \qquad (1)$$

where m is the full FOV undistorted object, S_i is the known distortion operator of the i'th image *and* F_i is the Fourier matrix of the specific k-space trajectory. We can write this in an augmented matrix as,

$$Y = Em \qquad (2)$$

where $Y=[y_1,\ldots,y_n]^T$ is the acquisition vector and $E=[F_1S_1, \ldots F_nS_n]^T$ is an encoding matrix. This is a linear set of equations and can be solved for m in many ways [3,4]. The term sFOV was chosen to emphasize the similarity to super-resolution reconstruction in image processing. Super resolution in image processing is a method to combine several corrupted down-sampled version of an image into a single high resolution uncorrupted one. In fact, the sFOV formulation is the frequency domain analog of super-resolution reconstruction [4]. In Cartesian imaging, sFOV fills in missing lines in k-space increasing the sampling resolution of the frequency domain. We can now formulate the multiple acquisitions SSFP as an sFOV problem. The SSFP signal exhibits a high sensitivity of both magnitude and phase to off-resonance frequency. By changing the RF phase cycling the response is shifted in frequency [2]. This can be thought of as different distortions that operate on the object. Since in general, off-resonance is slow varying [5], the SSFP sensitivity (S_i) can be measured from low-resolution information with little or no overhead. Therefore, instead of acquiring multiple full k-space images we can sub-sample k-space and acquire aliased small FOV image versions with different RF phase increments. We then use Eq. 2 and unfold the aliasing using the measured low-resolution sensitivity information (S_i). This approach is general and can, in principle, be used in Cartesian, radial or spiral trajectories. Fig. 1 outlines the imaging and reconstruction process for the Cartesian acquisition.

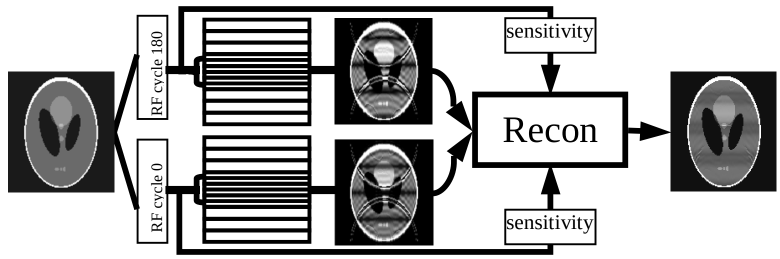

Figure 1: Outline of the imaging and reconstruction process for a Cartesian acquisition. Low-resolution information is used to estimate the SSFP sensitivity and unfold the aliasing. In this example, the field is assumed to vary linearly in the vertical direction.

Methods

To validate our approach we performed an in-vivo radial acquisition experiment. The experiment was conducted on a 1.5T GE Signa scanner with gradients capable of 40mT/m and 150mT/m/ms maximum slew-rate. Four images with corresponding 0°, 90°, 180° and 270° RF phase increments of an axial slice through the head (FOV=24cm, res=1mm) were acquired using a 2D radial balanced SSFP sequence (TR=8.32ms, TE=1.3ms, α=30°). Each image was obtained by collecting 133 spokes with a 3ms readout, which is 25% of the actual FOV (full FOV corresponds to 532 spokes). The inherent over sampling of the k-space origin was used for sensitivity estimation. The image was reconstructed using iterative conjugate-gradient method [3,4] with min-max nuFFT [6]. The result was compared to a full FOV multiple acquisition sum-of-squares [2]. It is important to note that since we acquire several different images one after the other, the k-space trajectory is different for each of the images. For example, In the radial case the first image will have the 1^{st}, 5^{th}, 9^{th} … spokes, the second image will have the 2^{nd}, 6^{th}, 10^{th}, … spokes etc. Because of this, the encoding matrix is well conditioned and the reconstruction does not suffer a significant loss in SNR as in SENSE imaging.

Results and Conclusions

Fig. 2 shows the result of the radial experiment. The sFOV reconstruction exhibits similar band suppression and resolution as a fully sampled multiple acquisitions sum-of-squares with only 25% of the data. In conclusion, sFOV can be used successfully with multiple acquisitions SSFP to reduce the total scan time. Sequences that can benefit from using sFOV SSFP are 3DPR, 3DFT, VIPR, cardiac gated and time resolved imaging. In these applications the time to transition from one steady state to another is negligible compared to the time used for data acquisition.

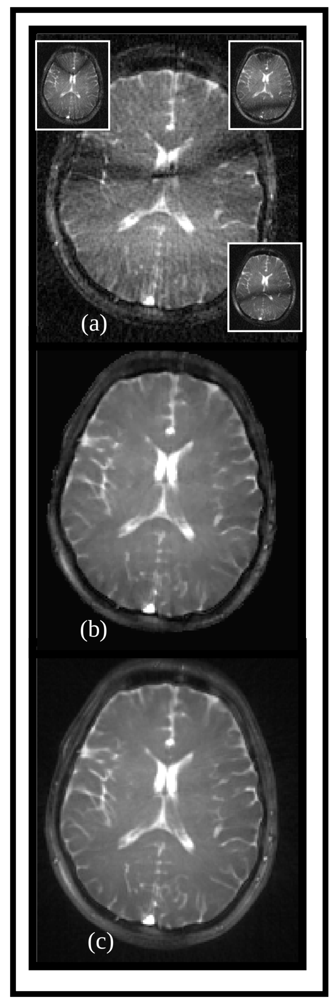

Figure 2: sFOV with radial trajectory. (a) 25% FOV RF phase cycling images. (b) sFOV reconstruction. (c) Full multiple acquisitions sum-of-squares.

References

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