

The SNR Advantage of Radial GROWL vs. Cartesian Parallel Imaging

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Introduction

When compared with conventional Cartesian acquisitions, non-Cartesian (e.g. radial and spiral) MRI methods provide advantages in ability to achieve higher temporal-resolution [1], ultra-short echo time [2] and reduction of motion artifacts [3]. Non-Cartesian parallel imaging methods provide the additional benefits of shorter scan time. Recently, a rapid self-calibrated non-Cartesian parallel imaging method, generalized GRAPPA Operator for Wider readout Lines (GROWL), has been developed and applied to both radial and spiral acquisitions [4,5]. In this work, it is demonstrated that parallel imaging with radial GROWL provides a SNR advantage vs. Cartesian SENSE, due to the ability to use coil sensitivity profiles along orthogonal directions and easy noise regularization.

Methods

The principle of radial GROWL is shown in Fig. 1. For an undersampled radial dataset, a set of GROWL operators are calibrated using fully sampled central k-space circle (Fig. 1a), allowing estimating data on lines parallel to acquired radial line (Fig. 1b) and therefore filling up the entire k-space (Fig. 1c). A k-space adaptive Tikhonov regularization strategy can be used to achieve an optimal balance between accurate data estimation and noise amplification [4,5].

The G-factor maps for SENSE and GROWL reconstruction were evaluated in a Monte Carlo simulation [6]. A noise-free T_1 -weighted brain MR image (Fig. 2a) was downloaded from a database (<http://www.bic.mni.mcgill.ca/brainweb>). The complex sensitivity of a head coil with eight cylindrically spaced elements was computed using an analytic Biot-Savart integration (Fig. 2b). The k-space data was generated with Fourier Transform and inverse regridding. In each of 100 iterations of the Monte Carlo simulation, Gaussian distributed random noise was added to each channel, resulting in a noise standard deviation in the range of 0.1% - 10.0% of the white matter signal intensity with a sum-of-square reconstruction for a fully sampled k-space. The g-factor map and root-mean square error (RMSE) were computed for SENSE and GROWL reconstruction.

The performance of GROWL with k-space adaptive regularization [5] was further examined with an in vivo brain study. A healthy volunteer was scanned on a clinical 3.0T scanner (Achieva, Philips, the Netherlands) using an 8-channel head coil (Invivo, Gainesville). A 3D Cartesian Magnetization-Prepared Rapid Gradient Echo (MP-RAGE) sequence was modified into a hybrid radial acquisition by removing slice-encoding gradients, while rotating different encoding planes with a bit-reverse [8] angle ordering scheme. This allows the retrospective reconstruction of undersampled radial datasets with reduction factors $R = 2, 4, 8$. Scan parameters are $FOV = 230 \times 230 \times 230 \text{ mm}^3$, matrix size = 256(readout) $\times 128$ (phase-encode) $\times 128$ (view planes), $TR/TI_{\min}/TE = 2800/1000/8 \text{ ms}$, total scan time = 6 mins. GROWL reconstructions were then applied to data retrospectively undersampled to $R = 8$ (effective total scan time = 1.5 mins).

Results and Discussions

Figure 2 shows Monte Carlo simulation results. With a reduction factor $R=4$, even without regularization, GROWL gives lower RMSE and g-factor values than SENSE. G-factor map reveals that such a SNR advantage is due to the fact that Cartesian SENSE does not exploit coils distributed along the frequency encode (vertical) direction. For GROWL, k-space adaptive regularization further reduces noise, resulting in a maximal g-factor of 0.24, consistent with prior observation that k-space-based parallel imaging method can result in $g < 1$ [6]. Figure 3 shows GROWL reconstruction with an $R=8$ using an 8-channel head coil. K-space adaptive regularization [5] (Fig. 3c) significantly reduces noise when compared using a fixed regularization factor throughout k-space [4] (Fig. 3b). The GROWL is a rapid parallel imaging method due to its non-iterative nature. After an initial self-calibration step taking about 10 seconds, it only takes 300 ms to reconstruct each 2D image with GROWL.

A significant advantage of radial GROWL over Cartesian SENSE is that the regularization parameter for GROWL can be automatically determined from the noise level [4-5] without time-consuming parameter estimation [9] or iterative reconstruction [10]. In conclusion, radial parallel imaging with GROWL provides a SNR advantage vs. Cartesian SENSE, which will be particularly beneficial for applications requiring higher acceleration factors.

References

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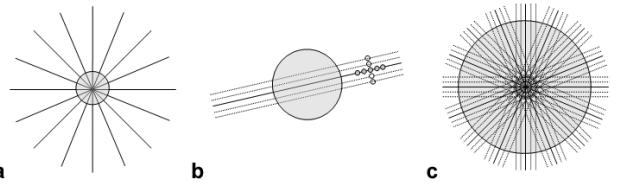


Figure 1 The basic principle of radial GROWL. (a) Undersampled radial data with a fully sampled central k-space circle that can be used for calibration. (b) A GROWL operator is calibrated for each radial direction, allowing estimating data on lines parallel to the acquired radial line. (c) The k-space coverage after applying GROWL operators.

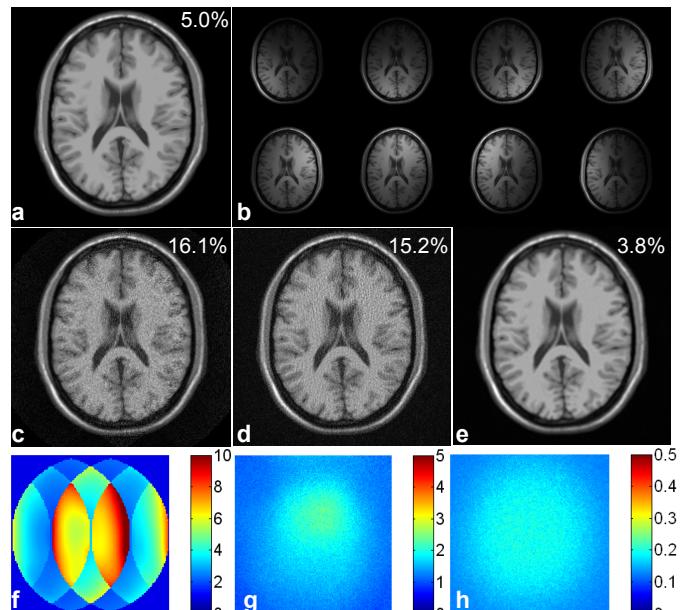


Figure 2 Monte Carlo simulation results for SENSE and GROWL. (a) Reference image (256x256). (b) Individual coil image. (c) - (e) $R=4$ (64 lines/views) reconstruction results using SENSE (c), GROWL without (d) and with k-space adaptive regularization (e). RMSE is shown in the upper left corner. (f) - (h) Corresponding g-factor maps.

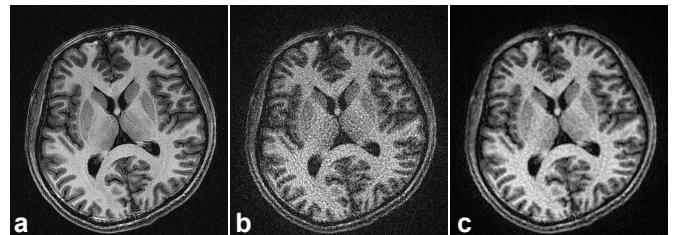


Figure 3 In vivo 3D radial MP-RAGE brain scans. (a) Reference image (256x256). (b) - (c) $R=8$ (32 views) radial GROWL image with a fixed regularization (b) and k-space adaptive regularization (c).