# **G-factor Maps of Conjugate Gradient SENSE Reconstruction**

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## **INTRODUCTION:**

In parallel imaging with Cartesian sampling, the spatially varying g-factor represents the loss in signal to noise ratio (SNR) due to ill-conditioning of the matrix inverse in SENSE reconstruction, and depends on the acceleration rate, the number of coils, and coil geometry. However, the spatially dependent g-factor of other trajectories (e.g. variable-density or non-Cartesian trajectory) is not well understood. The reconstruction SNR (average over the entire image) has been used to loosely calculate the average g-factor as  $SNR_{full}/(\sqrt{R}SNR_{red})$  where R is the acceleration factor. In this abstract, we propose a method to calculate the generalized spatially varying g-factor map for conjugate gradient (CG) SENSE reconstruction with

arbitrary trajectories. The method allows us to analyze how different trajectories and number of iterations in CG affect the SNR in a spatially dependent way.

# THEORY:

For Cartesian SENSE, the image is reconstructed by solving  $\mathbf{v} = (\mathbf{S}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{S})^{-1} \mathbf{S}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{a}$  [1] pixel by pixel where v is the desired image vector,  $\mathbf{a}$  is the vector of aliased images from all channels, S is the sensitivity matrix (1),  $\Psi$  is receiver noise matrix. In this case, the g-factor is defined as  $g_{\rho} = \sqrt{\left[(\mathbf{S}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{S})^{-1}\right]_{\rho,\rho}} (\mathbf{S}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{S})_{\rho,\rho}}$  [2] at pixel  $\rho$ . For arbitrary trajectories, the image can be reconstructed by solving  $(\mathbf{E}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{E})^{\mathbf{v}} = \mathbf{E}^{\mathbf{H}} \mathbf{m}$  [3] ( $\mathbf{m}$  is sampled *k*-space data,  $\mathbf{E}$  is the encoding matrix as in (1,2)) iteratively using CG method to approximate  $\mathbf{v} = (\mathbf{E}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{E})^{-1} \mathbf{E}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{m}$  [4] numerically. In this case, the g-facor is given by  $g_{\rho} = \sqrt{\left[(\mathbf{E}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{E})^{-1}\right]_{\rho,\rho}} (\mathbf{E}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{E})_{\rho,\rho}}$  [5]. The same iterative CG method can be used to calculate the first term  $\left[(\mathbf{E}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{E})^{-1}\right]_{\rho,\rho}$  in Eq. [5]. Specially, we calculate  $(\mathbf{E}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{E})^{\mathbf{v}} = \mathbf{b}$  using the the iterative CG method, where  $\mathbf{b}$  denotes an all-zero image except at pixel  $\rho$  whose value is unit one. After several iterations, the value of the obtained "image"  $\tilde{\mathbf{v}}$  at the corresponsing pixel  $\rho$  gives the approximation of  $\left[(\mathbf{E}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{E})^{-1}\right]_{\rho,\rho}$ . The second term in Eq. [5]  $(\mathbf{E}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{E})_{\rho,\rho}$  does not need matrix inversion and can be easily obtained by taking the pixel  $\rho$  of the image obtained by a forward encoding  $(\mathbf{E}^{\mathbf{H}} \mathbf{\Psi}^{-1} \mathbf{E})\mathbf{b}$ .

### METHOD AND RESULTS:

We acquired a water phantom data on a Hitachi Airis Elite (Kashiwa, Chiba, Japap) 0.3T permanent magnet scanner with a four-channel head coil and a single slice spin echo sequence (TE/TR = 40/1000ms, 8.4KHZ bw, 256\*256 matrix size, FOV = 220 mm<sup>2</sup>). The sensitivity maps were estimated using the full k-space data. We compared the g-factors at a reduction factor of 4 for three cases: (a) basic SENSE (using matrix inversion) with uniform Cartesian trajectory; (b) CG SENSE with uniform Cartesian trajectory; and (c) CG SENSE with variable-density (VD) Cartesian trajectory (32 fully sampled central lines and reduction factor of 4 outside). We also compared the g-factors after 3 and 8 CG iterations. The results are shown in Figure 1.





#### DISCUSSION:

Our results show that the g-factor of the CG SENSE reconstruction has similar spatial variation pattern as that of the basic SENSE reconstruction. However, the value of g-factor in CG SENSE depends on and increases with the number of iterations. It explains the semi-converge property of CG SENSE (3): increasing iterations reduces the aliasing artifacts but increases the noise at the same time, which can be observed in VD-CG case. Proper stopping criterion should be used to balance the aliasing artifacts and noise. In addition, our results show the VD trajectory improves the g-factor at small number of iterations, but does not improve much as iteration number increases. The proposed method can be used to calculate the g-factor for spiral and radial trajectories, as well as to evaluate the SNR improvement by the regularization technique for non-Cartesian SENSE (4).

## **REFERENCES:**

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