Local Mutual information guidied denoising for self-calibrated PPI

W. Guo[1], and F. Huang[2]

[1]Department of Mathematics, University of Alabama, Tuscaloosa, AL, United States, [2]Advanced concept development, Invivo Corporation, Gainesville, FL, United States

Introduction : The application of partially parallel imaging (PPI) [1, 2] techniques to regular clinical images has brought about the benefit of significantly faster acquisitions but at the cost of amplified and non-uniform noise. In the images reconstructed by SENSE [1], the noise distribution is described by g-factor map; and that information can be used to guide denoising [3]. The noise distibution in an image reconstructed by GRAPPA [2] cannot be described by the same g-factor map as the one for SENSE. However, GRAPPA, as a self-calibrated technique, uses fully acquired central *k*-space data for calibration. The central *k*-space data can be used to generate a high signal to noise ratio (SNR) image. It is proposed in this work that the local mutual information [4] between the image reconstructed by fully acquired central *k*-space data and the image by GRAPPA can be used to detect the noise distribution, and hence guide the adaptive noise suppression. Experimental results show that the proposed method significantly improved SNR without reducing the high frequency information.

Theory : Let H be an image reconstructed by GRAPPA, L be the image reconstructed with the self-calibration signal for GRAPPA. The local mutual information LMI (H, L) measures the local similarity of H and L. H is more similar to L at locations with less noise; hence LMI(H, L) has higher value at regions with less artifacts; and vice versa. Therefore the value of LMI (H, L) describes the distribution of noises. Fig. 1 shows one example. Fig. 1a is the noisy image reconstructed by GRAPPA. Fig. 1b shows 1/(1+100LMI), a function that is reversely proportional to local mutual information. It can be observed that Fig. 1b has higher value at regions with higher noise level (as shown in Figs. 1a and 1b), lower value at less noisy regions (left bottom corner). This demonstrates the feasibility of using LMI to describe the distribution of noise. Furthermore, a nice feature of LMI is that it has high value near edges. Hence the boundary information can be automatically detected. With the knowledge of the location of edges, it is possible to better preserve the image sharpness. With these two important properties, LMI is proposed to be used as a guidance for image denoising. Self-calibrated PPI, such as GRAPPA, intrinsically provides a high spatial resolution but low SNR image, and a low spatial resolution but high SNR image. Therefore, it is nature to use LMI for guided denoising for GRAPPA.

Methods : **Simulated data**: Shepp-Logan phantom and sensitivity maps of a 4-channel cardiac coil were used to simulate the phantom data set. The matrix size of the simulated data set was 256×256×4. The PE direction was along the vertical direction in the image. Random noise was added during simulation. Acceleration factor 4 with 64 central auto-calibration signal (ACS) lines were simulated. **In vivo data**: Cadiac cine data were collected on a SIEMENS Avanto system using a cine true FISP sequence with a 32-channel cardiac coil for the oblique images. Acceleration factor was 6 along anterior-posterior direction. 24 extra ACS lines were acquired. Brain anatomy data were collected on a 3T GE system using the T1 FLAIR sequence with an 8-channel head coil. The matrix size was 512×512×8. Acceleration factor was 4 along anterior-posterior direction. The number of extra ACS lines was 56**. Reconstruction**: Images were reconstructed by GRAPPA with convolution kernel size 4×5. The central ACS lines were used to generate the low-resolution but high SNR image for calculation of LMI. **Denoising**: One specific implementation of LMI guided denoising technique was applied. Model (1) shows the total-variation (TV) [5] based method. A function J that minimizes the energy in 1 provides the denoised image.

$$\min_{J_i} \int_{\Omega} | J_i(x) - H_i(x) |^2 \, dx + \frac{\lambda}{1+\alpha \cdot LMI(H_i, L_i)} | \nabla J_i(x) | dx \qquad (1)$$

'*i*' is the index for channel. Channel-by-channel denoising was used in our implementation. λ and α are two predefined positive factors. α was fixed to be 100 in all experiments. In regular TV model, the smoothing term $|\nabla J_i|$ is weighted only by a fixed parameter λ, a bigger λ can remove more artifacts but may blur the edges. In the proposed model 1, the weight of the smoothing term is a function of amplitude of noise. In our implementations, λ was a value between 10 and 30. In this implementation, LMI is used to adaptively adjust λ. At noiser regions, LMI is small and hence more smoothing is processed to remove the noise. At regions with lower noise level or near edges, LMI is high and hence the weight for smoothing becomes small to preserve the sharpness.

Results :Fig. 1 shows the results of the phantom. Fig. 1c represents the denoised image by the proposed method. Fig. 1d is the result of TV with a fixed λ, which is optimized for TV model. It can be seen that both Figs. 1c and 1d have significantly reduced noise level, however, Fig. 1c removed more noise/artifacts (as shown by the arrow in Fig. 1d) and preserve the edges better than Fig. 1d. Figs. 1e and 1f illustrate the difference maps between Fig. 1a and Fig. 1c, Fig. 1d respectively. No structure information can be observed in 1e. On the contrary, significant signals were removed by TV model as shown in Fig. 1f. Further,10 spots were picked from Figs. 1c and 1d at the same corresponding locations to calculated sharpness. Small-sample Student t-test gives one tailed p value of 0.001847, two tailed p value of 0.003693, both of which are small enough to conclude that Fig. 1c shows significantly better sharpness statistically. Figs. 2 and 3 show the results of cardiac and brain data. Figs. 2a and 3a are the results of GRAPPA before denoising; Figs. 2b and 3b show the denoised result using model 1; Figs. 2c and 3c show the difference maps between the images before (Figs. 2a, 3a) and after (Figs. 2b, 3b) denoising. Again, it can be seen that the proposed method can efficiently denoise images with a better protection of edges. The difference maps (Figs. 2c, 3c) show the adaptively removed noise; and again there is no structure can be observed except the boundaries between images and background.

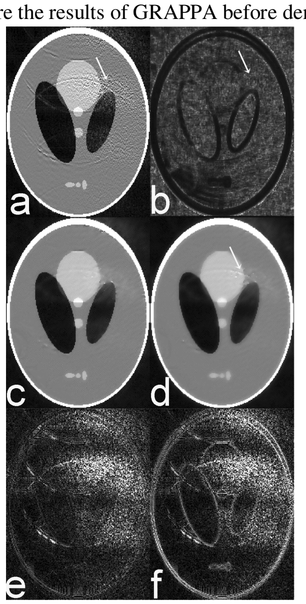

Figure . 1

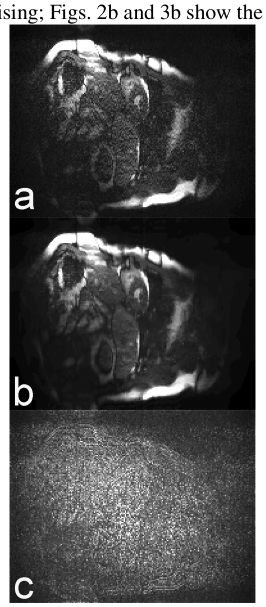

Figure . 2

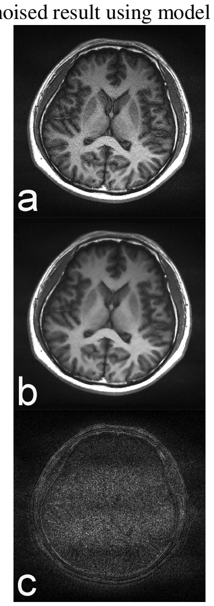

Figure. 3

Difference maps (Figs. 1e, 1f, 2c, and 3c) were brightened 5 times for visibility.

Discussion and Conclusion: In this work, it is proposed to use LMI, between the result of GRAPPA and the image with ACS lines, as a guidance for automatic adaptive image smoothing. One specific implementation of application of LMI using TV model is proposed. One considerable advantage of LMI is that the location of edges can be automatically detected as well as the distribution of noise. Therefore, LMI guided denoising technique can automatically protect the edges. Experimental results show the proposed method adaptively removed the noise and preserved the edges. Further improvements of this method is under research. In conclusion, LMI can automatically detect the noise distrubution and the location of edges. The application of LMI for images reconstructed by GRAPPA presrves the edges while efficiently removes noise.

References: [1] Pruessmann KP, *et. al.,* MRM 1999; 42:952-962. [2] Griswold MA, *et. al.,* MRM 2002;47:1202-1210. [3] Vijayakumar S, *et. al.*, ISMRM 2006; Seattle, Washington, USA. p 2357. [4] Guiasu, Silviu (1977), Information Theory with Applications, McGraw-Hill, New York [5] Rudin LI, *et. al.*, Physica D 1992;60:259-268.