Combine Reconstructions Using Non-local Operator and Its Application in PPI

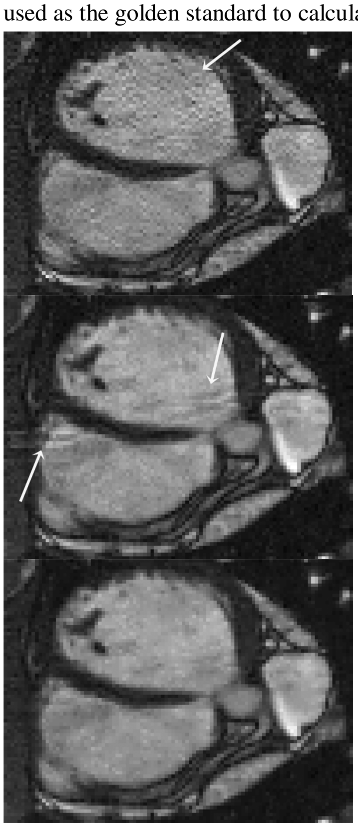
W. Guo[1], H. Cheng[2], and F. Huang[3]
[1]Department of Mathematics, University of Alabama, Tuscaloosa, AL, United States, [2]Department of Psychological and Brain Sciences, Indiana University, IN, United States, [3]Advanced Concept Development, Invivo Corporation, Gainesville, FL, United States

Introduction: Given a set of reconstructions with different noise/artifact distribution, it is possible to generate an image with higher signal to noise ratio (SNR) than each single reconstruction through weighted summation. One example is the sensitivity weighted summation proposed by Roemer *et al.* [1] for reconstructions from multi-channel. It is well known that the reconstructions of GRAPPA [2] and SENSE [3] have different noise distribution. The noise in images reconstructed by GRAPPA has a more uniform spatial distribution. However, SENSE-reconstructed images usually have lower noise level at regions with lower g-factor level. Hence it is possible to combine pros of these two reconstructions to come up with an image with reduced noise/artifact level without changing the spatial resolution through weighted summation. An efficient method of weight calculation is proposed in this work.

Method: Let $G(x)$ and $S(x)$ be images reconstructed from the same set of K-space data using two different reconstructions, say GRAPPA and SENSE respectively. We aim to linearly combine $G(x)$ and $S(x)$ to create an image, $I(x) = P(x)G(x) + (1-P(x))S(x)$, with minimized non-local L_2 norm of gradient. A main advantage of non-local L_2 [4] over regular L_2 is the ability to handle better textures and repetitive structures. The pixel-wisely defined weight $P(x)$ is calculated by minimizing the energy functional

$$E(P(x)) = \int_{\Omega}\int_{N(x)} w(x,y)(P(x)G(x) + (1-P(x))S(x) - P(y)G(y) - (1-P(y))S(y))^2\,dydx \qquad [1]$$

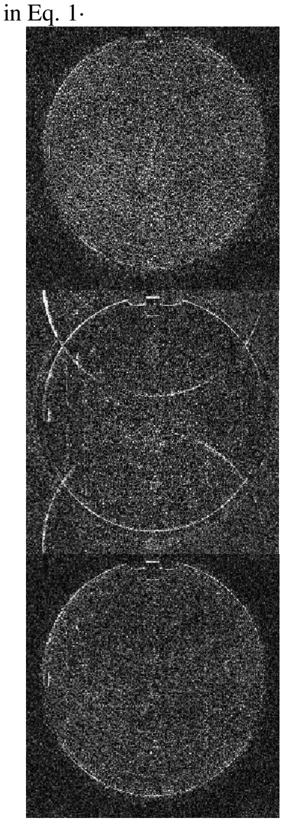
under the constraint $0 \le P(x) \le 1$, where Ω can be either the whole image domain or a predefined region of interest (ROI), $N(x)$ is a window (size set to be 21x21 in experiments) centered at x, $w(x,y) = \dfrac{1}{1 + G_a * |G(x+) - G(y+)|^2)(0)/h^2}$ is the weight between x and y, with G_a a Gaussian kernel, * denoting convolution, h controlling the amount of smoothing [5]. The linear combination using this $P(x)$ is optimized in the sense of SNR. Through minimizing the energy E, we enforce the intensity of the resulting image I at x to be close to an average intensity. This average is calculated among non-local neighbors [4], instead of the spatial neighbors, of x. Therefore, boundaries and fine structures can be better preserved or even enhanced while removing noise/artifact sufficiently. To show the performance of the proposed method, two data sets, one phantom data set and one in vivo data set, were acquired on a SIEMENS 1.5 T system (Erlangen, Germany). Full k-space data were acquired, but only partial data were used for reconstruction to simulate partially parallel acquisition. Images were reconstructed by SENSE and GRAPPA separately. The final reconstruction is the combination of these two reconstructions using the weight calculated by Eq. 1. Image reconstructed with full k-space data was used as the golden standard to calculate the root mean square error (RMSE). The whole image domain was used as Ω in Eq. 1.



Result: Images on the left and the table below show the results for the in vivo data set, those images from top to bottom are GRAPPA, SENSE, and linear combination respectively. Clearly, the combination has reduced noise level than that by GRAPPA, and reduced artifact level than that by SENSE. Compared to the golden standard, the RMSEs of these images from top to bottom are 9.7%, 10.4%, and 8.5% respectively. The spatial resolutions of these images are visually identical. Table below compares SNR of the three reconstructions at 8 regions, the combined result has statistically better (p-value < 10^{-3}) SNR than GRAPPA and SENSE.

G	8.90	10.7	10.5	11.2	13.2	13.0	7.58	10.5
S	17.3	18.3	20.2	13.4	21.1	15.6	10.1	18.4
I	21.7	19.7	22.7	15.6	24.1	17.7	11.5	22.8

From top to bottom, images on the right show difference maps of GRAPPA, SENSE and linear combination respectively with golden standard for the phantom data set. The smallest difference (darkest intensity) is observed in the combined image almost point wisely.



Discussion: The proposed model automatically and adaptively integrates advantages of GRAPPA and SENSE reconstruction to create an image that is more informative than each of them. Quantitative and qualitative results have shown advantages of the proposed model. Since the combined image I is a liner combination of G and S, the spatial resolution of I is not less than the minimum spatial resolution of G and S. This nice property guarantees the resolution preservation. The idea can be generalized to combining any number of any types of reconstruction.

References: [1] Roemer PB et al., MRM 1990; 16:192-225. [2]Pruessmann KP et al., MRM 1999; 42:952-962. [3] Griswold MA et al., MRM 2002;47:1202-1210. [4] Gilboa G et al., UCLA CAM Report 2007;07-23. [5] Buades A et al., CVPR 2005;2:60-65.