Image Enhancement via Sliding Window Method for Thermal Noise Reduction

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Introduction. We propose a *sliding window* self-calibrated parallel imaging method that reduces thermal noise and provides SNR gain over conventional SENSE reconstruction. This method calculates sensitivity profiles dynamically by using a sliding window approach: combining fully sampled data of adjacent frames in an interleaved acquisition, *i.e.*, sensitivity profiles are updated synchronously with image acquisition. No spatial smoothing is performed so as to retain thermal noise in sensitivity profiles. This *sliding window* technique is especially applicable to acquisition of high spatial-resolution images where thermal noise predominates.

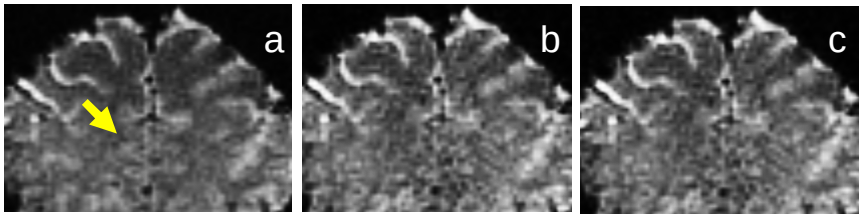
We compare this proposed *sliding window* parallel imaging technique with a conventional *reference frame* sensitivity calculation method in which four image time frames from the beginning of a time series are averaged and smoothed with spline interpolation. To demonstrate that accurate thermal noise information (retained in *sliding window* sensitivity profiles) indeed reduces reconstructed image noise, we further reconstruct images with *sliding window* profiles but smoothed with spline interpolation. Compared with smoother profiles, *sliding window* technique effectively reduces thermal noise. The improvement is most significant for high resolution, thin slice, and low SNR cases.

Theory. CG-SENSE reconstructed image can be written as $\hat{\mathbf{m}} = ((\mathbf{E}\hat{\mathbf{S}})^H \mathbf{E}\hat{\mathbf{S}})^{-1} (\mathbf{E}\hat{\mathbf{S}})^H \mathbf{d}$ where $\mathbf{d} = \mathbf{ES}(\mathbf{m} + \mathbf{p}) + \boldsymbol{\varepsilon}$ is a vector of data acquired in k-space, $\mathbf{m}$ is a vector containing the original image, $\mathbf{p}$ is a vector of physiological noise, $\boldsymbol{\varepsilon}$ is a thermal noise vector, $\mathbf{S}$ and $\hat{\mathbf{S}}$ are ideal and measured coil sensitivity matrices respectively, and $\mathbf{E}$ is the Fourier kernel matrix. $\hat{\mathbf{S}}$ is the calculated coil sensitivity matrix. Using *sliding window* method, $\hat{\mathbf{m}}$ can be expressed $\hat{\mathbf{m}} \approx \mathbf{m} + \mathbf{p} + ((\mathbf{ES})^H \mathbf{ES})^{-1} (\mathbf{ES})^H (\boldsymbol{\varepsilon} - \bar{\boldsymbol{\varepsilon}})$. When $\boldsymbol{\varepsilon}=\bar{\boldsymbol{\varepsilon}}$, $\hat{\mathbf{m}}$ is free of thermal noise; but that would occur only when no readout acceleration is provided, which is not of interest here. When minimal sliding window width is applied (R=2), then $\bar{\boldsymbol{\varepsilon}}$ is the closest approximation to $\boldsymbol{\varepsilon}$ and so $\hat{\mathbf{m}}$ will contain the least amount of noise. When sensitivity profiles (*sliding window* or *reference frame*) are smoothed, $\bar{\boldsymbol{\varepsilon}}$ is averaged to zero under a Gaussian noise assumption; thermal noise sampled in **k**-space is therefore propagated to $\hat{\mathbf{m}}$.

Methods. We demonstrate *sliding window* with a two-shot spiral-in/out trajectory providing an acceleration factor R=2. For every two repetition times (TR), two fully-sampled two-shot images (one spiral-in and one spiral-out) are reconstructed for each coil. The sensitivity profile of each coil is the ratio of the fully sampled two-shot image of that coil to the square root of the pixel-wise sum of squares of all coils. Separate sensitivity profiles are generated for spiral-in and spiral-out data. For *sliding window* (window width = 2 TRs), a new fully sampled two-shot image of each coil is formed after every TR. The sensitivity profile of each coil is then updated at every TR and used for CG-SENSE image reconstruction (1,2) at that TR. For the *reference frame* method, only one set of sensitivity profiles is used for CG-SENSE reconstruction of the entire time series. The same CG-SENSE program is used for reconstruction regardless of sensitivity profile calculation method; it generates one spiral-in image and one spiral-out image for every TR.

Three subjects were scanned at four slice thicknesses (2-5mm) on a GE 3T whole-body scanner (GE Signa, WI). An 8-channel head coil (MRI Devices Corp., WI) was used for all image acquisitions. Subjects were instructed to relax while 64 time frames were collected. TE/TR/matrix size/FOV = 35.4 ms/2s/128x128/20cm. Two sets of data were gathered: flip-angle = 70° and 0°. Standard spiral trajectory gridded-reconstruction is used to make two-shot images from each coil's data. A fast T1 mapping scan (3) was utilized to obtain images for later gray matter segmentation; one for each and every slice thickness. This mask is used to extract gray matter pixel time-series from data at flip-angle = 70°. The temporal standard deviation of each gray matter pixel is recorded and then averaged over three slices; this gives the total noise σ. Thermal noise σ_o is calculated by the same procedure using images with flip-angle = 0°, and the resulting standard deviation is corrected for the Rayleigh distribution of Gaussian noise in magnitude images. (4,5) Physiological noise σ_p is then calculated from $\sigma^2 = \sigma_p^2 + \sigma_o^2$. (6)

Results. Figure 1 shows typical images (zoomed in) using (a) *sliding window*, (b) *reference frame*, and (c) smoothed *sliding window* sensitivity profiles and the profiles themselves (from coil 1) from a 2mm spiral-out data set. Smoothing sensitivity profiles (*reference frame* or *sliding window*) results in visibly noisier images. SNR of the time series to which these images belong are 21.3±1.1, 16.9±1.1, and 17.3±0.9 respectively. Figure 2 illustrates the signal magnitude in gray matter, thermal noise, and physiological noise averaged among all slices in all subjects. While signal magnitude and physiological noise are consistent over choice of reconstruction methods, thermal noise is greatly reduced by *sliding window* technique. Because both physiological noise and signal magnitude decrease as voxel size decreases, thermal noise remains constant and so predominates at high resolution. Our proposed *sliding window* method is especially effective for improving SNR when imaging at high resolution.



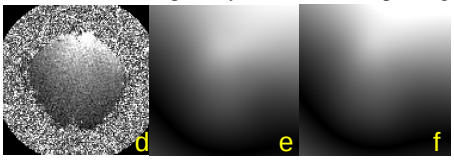


Fig. 1. 2mm data reconstructed using (a) *sliding window* method, (b) *reference frame* method, and (c) *sliding window* method but smoothed by spline interpolation. Arrow points to area where gray matter can be identified in (a) but hardly in (b) or (c). (d-f) are corresponding sensitivity profiles to (a-c).

Discussion. As the demand of PI and higher imaging resolution increases, thermal noise becomes of significant concern. Our method significantly reduces noise in reconstructed images by retaining thermal noise in sensitivity profiles. Admitting noise into sensitivity profiles appears to contradict conventional wisdom that sensitivity profiles should be smooth since receiver coil sensitivity is slowing varying in space. But the *sliding window* technique not only provides an estimation of intrinsic coil sensitivity, it also provides an estimate of thermal noise. This estimate reduces noise in the final image from the reconstruction process. Our technique may be incorporated into any interleaved acquisition and can benefit all dynamic SENSE applications such as fMRI, cardiac, and flow imaging.

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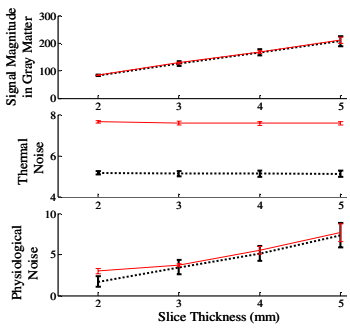

Fig. 2. Signal magnitude in gray matter, thermal noise, and physiological noise using *sliding window* (dotted line) and *reference frame* (solid) methods across various slice thickness.

Reference. 1. Pruessmann et al., MRM. 2001; 46(4):638-51. 2. Liu et al., MRM. 2005; 54(6):1412-22. 3. Hsu et al., JMR 2006; 181(1):98-106. 4. Gudbjartsson et al., MRM. 1995; 34(6):910 -4. 5. Kellman et al., MRM. 2005 ; 54(6) :1439-47. 6. Kruger et al., MRM. 2001 ; 46(4) :631-7.