On the Limits of Image Noise Suppression in High-Speed Cardiac MR Parallel Acquisition

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Introduction
SMASH and SENSE based parallel imaging techniques have become important tools in improving acquisition speeds for cardiac MRI data. However, since these techniques utilize partial acquisition of full *k*-space, there is a trade-off between temporal resolution and the signal-to-noise ratio (SNR) in the reconstructed images due to the physics of acquisition. For a given field-of-view, increasing the parallel imaging rate in general will lead to a corresponding deterioration in signal quality; the faster the acquisition is, the poorer are the resultant images. Image denoising techniques when used as a post-processing step can provide a means to push the existing limits of temporal resolution of the cardiac cycle while maintaining image quality for high-speed acquisition protocols. In this abstract, we explored the feasibility of a state-of-art denoising technique [1] in improving the SNR of cardiac imaging during such fast acquisition.

Method
A pre-developed image denoising method [1] is used based on wavelet coefficient thresholding on a 3D dyadic overcomplete multi-scale expansion. First, the threshold for each level of the expansion is automatically estimated based on each input image; a soft thresholding approach is then applied to each level of expansion as described in [1]; finally, the denoised image is reconstructed by computing an inverse wavelet transformation on this redundant representation. For phantom studies, the ACR MR phantom was imaged using a Siemens Avanto 1.5T MR scanner. Both *k*-space-based (using generalized auto-calibrating partially parallel acquisitions; GRAPPA) and image-domain based (using sensitivity encoding, mSENSE) parallel-imaging approaches were used with different parallel imaging rates (or acceleration factors, R). A balanced-SSFP image without parallel acquisition was also acquired as the "best available quality" image. For GRAPPA and mSENSE, protocols with R=3 (using 24 and 36 reference lines) and R=4 (using 24, 36, and 48 reference lines) were acquired with additional images at different noise level. Image SNR for each image was computed using the method described in [2] (SNR = mean(ROI)/std(ROI) for homogeneous ROI) within the first three columns of tubes. To explore the feasibility of our denoising approach on clinical data, a healthy volunteer was scanned using a Siemens 1.5T scanner. Cardiac cine images using GRAPPA and mSENSE with R = 2, 3 and 4 with 35 reference lines were acquired. Image SNR for each image was computed within manually picked regions of interest (ROI) within the blood pool in the left ventricle. Relative changes in SNR were used instead of absolute changes to factor out the SNR dependency on the brightness within each ROI.

Results
Figure 1 shows the effectiveness of denoising on a GRAPPA(rate 4 with 24 reference lines) acquisition on the phantom. The zoomed ROI shows qualitatively that the noise level on the original image is much higher than the denoised image. Similar results can be observed from the intensity profile (taken from the original ROI as indicated in Figures 1 and 2). The intensity profile also suggests that the denoising method primarily removed the noise with minimal effects on important features of the object.. Figure 2 illustrates the results for denoising an mSENSE (rate 4) human volunteer dataset. Similar conclusions can be drawn as from the phantom study. The percent change in the SNR between that for original images and denoised ones are shown in Figures 3 and 4 (phantom and human data respectively) for each protocol, from which we can see that the denosing method improved image SNR. For GRAPPA parallel imaging, the denoising approach can improve the SNR of the clinical images by a minimum of 24%, while the SNR improvement for mSENSE ranged between 16% and 55%. It is interesting to note that in the phantom, this method provides up to 25% improvement in SNR for the situation where fewer reference lines are acquired in rate 4 mSENSE acquisition.

Conclusions
An automated denoising approach was applied to images acquired by parallel acquisition techniques in cardiac imaging. Denoising with redundant multiscale representations can improve the SNR and image quality to the level of non-parallel techniques for most of the cases while preserving important anatomic dynamic features. This study suggests that with proper denoising, the limits of temporal resolution due to the SNR-resolution trade-offs can be unfettered.

References
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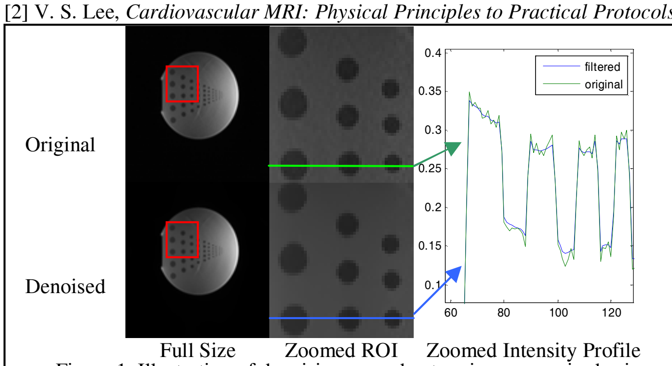

Figure 1. Illustration of denoising on a phantom image acquired using GRAPPA (Rate 4 with 24 ref lines).

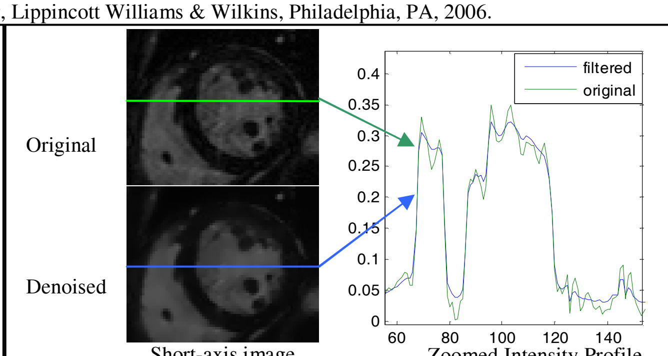

Figure 2. Illustration of denoising on cardiac data acquired using mSENSE (Rate 4 with 35 reference lines).

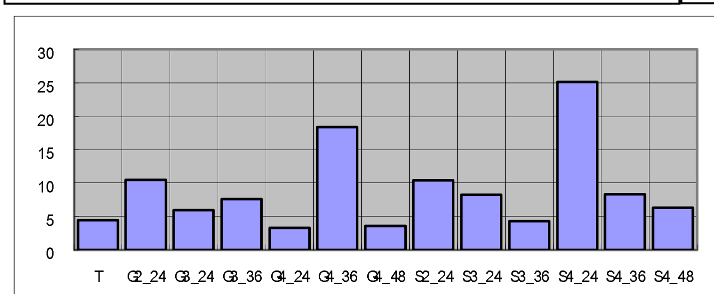

Figure 3. SNR result on phantom. T: TrueFISP; G: GRAPPA; S: mSense. The 1st number is rate R; the 2nd number is the number of reference lines.

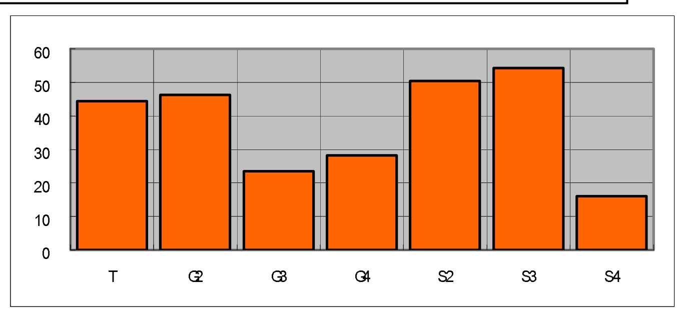

Figure 4. SNR result on clinical data. T: TrueFISP; G: GRAPPA; S: mSense. The number is rate R.