Subjective quality assessment of under-sampled compressed sensing and parallel imaging MRI reconstructions

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Purpose: Parallel imaging (PI) [1] and compressed sensing (CS) [2] are two major approaches to accelerating MRI acquisitions by acquiring under-sampled k-space data. Although quantitative quality measures, such as the normalized root mean square error (NRMSE), contrast-to-noise ratio (CNR), and signal-to-noise ratio (SNR), are commonly used to assess the reconstruction quality of these techniques, these measures do not necessarily correlate with the practical image quality as perceived by radiologists and other expert end users. Therefore, unless accompanied by subjective assessments, any quantitative measure of reconstruction quality will be of limited clinical impact. We present the results of our study on the subjective quality measurement of CS and combined CS and PI (where multiple-channel data are available) reconstructions.

Methods: Two common clinical applications of MRI in neuroradiology were studied: (1) Detection of white matter lesions: This task involved detection of small non-specific white matter lesions on FLAIR images. Realistic artificial lesions (approximate lesion size = 2.5mm in diameter) were incorporated into whole-brain T2-FLAIR images of a healthy volunteer (TR/TE=8000ms/120.9ms, TI=2250ms, flip angle=90˚, matrix=256x256 (Pixel spacing=0.86mm isotropic), slice thickness=2mm, slice spacing=2.5mm, BW=31.3kHz, NEX=1) in random locations in the cerebral white matter where these lesions are commonly seen clinically, with a probability of 50%. Lesion detection performance was studied for CS and low-resolution (used as a control baseline) reconstructions at under-sampling factors of 1 (i.e., no under-sampling), 2, 3, 4, and 5, each with 30 images for each reconstruction totaling to 300 images, which were viewed by 3 senior radiology residents in randomized order. The experiments involved identification of the lesion or declaring there to be none while the participants also indicated their level of confidence using a 4-score ranking system (1: non diagnostic; 2: low confidence; 3: moderate confidence; 4: high confidence). (2) Magnetic resonance angiography (MRA): Whole brain 3D time of flight (TOF) MR angiogram of a healthy volunteer was acquired at 3T using a 32-channel head coil (TR/TE=20ms/2.6ms, flip angle=15˚, matrix=216x168 (pixel spacing=1.1mmx1.4mm), slice thickness=1.4mm, slice spacing=1.4mm, BW=10.3kHz, NEX=1). Raw k-space data were retrospectively under-sampled with under-sampling factors 2, 3, 4, and 5, for PI (GRAPA), combined CS and PI, and low-resolution (lowres) reconstructions, obtaining a total of 12 whole brain under-sampled datasets, which were then reconstructed by the corresponding reconstruction technique. The reconstructions were scored by three senior radiology residents based on subjective diagnostic quality, with a 5-point scoring system. Human data used in this work were acquired using a protocol approved by the institutional office of research ethics.

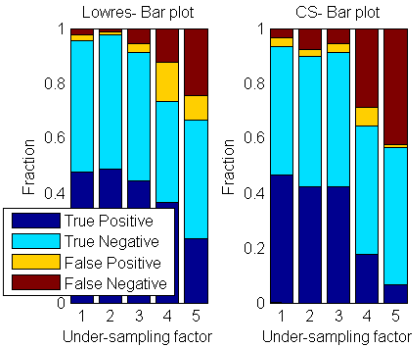

Figure 1- Lesion detection performance (pooled) for the CS and lowres reconstructions.

Results: Figure 1 shows the pooled results of the lesion detection task for the lowres and CS reconstructions. Corresponding ROC curves were computed based on the confidence levels indicated by the participants, following the methodology of Metz [3]. The area under the ROC curves (AUC) and the average NRMSE with respect to the fully-sampled reference images are shown in Table 1. MRA scoring results are shown in Table 2 and Figure 2 shows sample projection reconstructions at x5 under-sampling.

UF	AUC		NRMSE	
	lowres	CS	lowres	CS
1	0.99	0.96	0	0
2	1.0	0.97	0.013	0.0081
3	0.96	0.97	0.024	0.012
4	0.81	0.77	0.033	0.023
5	0.78	0.67	0.042	0.038

Table 1- Area under ROC curves (AUC) and the average NRMSE for different under-sampling factors (UF) in the lesion detection task (pooled results).

Discussion: While CS reconstruction of the FLAIR images results in significantly lower NRMSE values than the corresponding lowres reconstruction, the results show no improvement in lesion detection accuracy with CS over lowres. In fact, better detection performance is observed with a simple lowres reconstruction. However, for MRAs, while the subjective diagnostic quality score drops for the GRAPPA and lowres reconstructions very rapidly with increasing under-sampling factor, the combined CS+PI reconstruction maintains a reasonably high score up to an under-sampling factor of 3, suggesting that diagnostic quality (i.e., a subjective score of 4 or higher) images are achievable with under-sampling factors as high as 3 by combined CS and PI.

UF	Recon.	Avg. score	NRMSE
	GRAPPA	5	0.0082
2	**lowres**	4	0.029
	CS+PI	4.7	0.014
	GRAPPA	1.7	0.11
3	**lowres**	3	0.037
	CS+PI	4	0.025
	GRAPPA	1	0.14
4	**lowres**	2	0.045
	CS+PI	3.3	0.027
	GRAPPA	1	0.15
5	**lowres**	2	0.051
	CS+PI	3	0.030

Table 2- Average subjective scores given by three participants for the MRA scoring task and the NRMSE of the corresponding reconstructions with respect to fully-sampled reference.

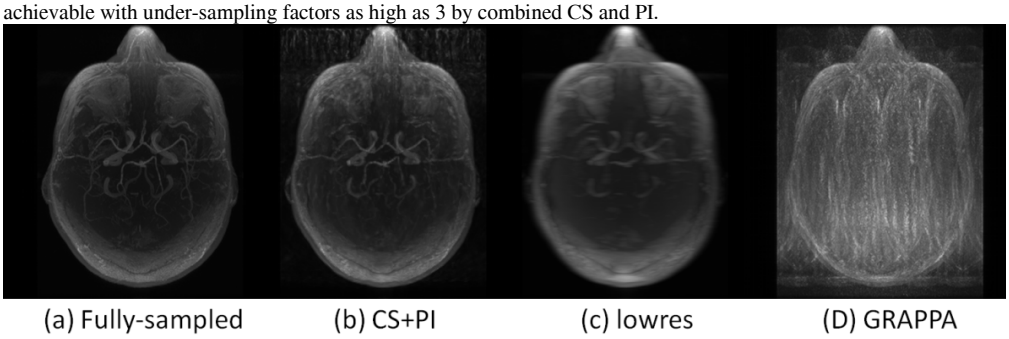

Figure 2- Axial MRA projection reconstruction: (a) fully-sampled (b,c,d) 5x under-sampled.

Conclusion: The results primarily suggest that the advantages of CS depend on the application. For example, while they indicate that higher under-sampling factors while maintaining the diagnostic quality are achievable with combined CS+PI for MRAs, no improvement over a simple lowres acquisition is achieved by CS in the lesion detection task. While for some applications, especially those requiring high resolution, CS may be of advantage, for some others, e.g., certain lesion detection tasks, one might simply reduce the acquisition time by appropriately reducing the resolution.

Reference: **1**. Larkman, D. J. & Nunes, R. G. Parallel magnetic resonance imaging. *Phys. Med. Biol.* **52,** R15–55 (2007). **2**. Lustig, M., Donoho, D. & Pauly, J. M. Sparse MRI: The application of compressed sensing for rapid MR imaging. *Magn. Reson. Med.* **58,** 1182–1195 (2007). **3**.Metz, C. E. *Applications of Roc Analysis in Diagnostic Image Evaluation*. (Chicago Univ., IL (USA); Franklin McLean Memorial Research Inst., Chicago, IL (USA), 1979).