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Supplementary material for MAC-ReconNet: A Multiple Acquisition Context based Convolutional Neural Network for MR Image Reconstruction using Dynamic Weight Prediction

Appendix A. Context in which only the acceleration factor is varied

Table 1: Context with fixed anatomy, fixed sampling pattern and varying acceleration factors

ゔ : 2 × 1		ZF	JCM	MAC-ReconNet (ours)	CSM
		PSNR/SSIM	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM
Gaussian	2x	34.11 ± 2.86 / 0.932 ± 0.02	45.69 ± 6.24 / 0.992 ± 0.00	46.06 ± 6.81 / 0.993 ± 0.00	46.39 ± 6.93 / 0.993 ± 0.00
	3.3x	29.2 ± 2.76 / 0.844 ± 0.04	40.81 ± 5.30 / 0.981 ± 0.01	40.92 ± 5.51 / 0.982 ± 0.01	40.99 ± 5.50 / 0.982 ± 0.01
	4x	26.96 ± 2.70 / 0.783 ± 0.04	39.14 ± 4.93 / 0.973 ± 0.02	39.24 ± 5.15 / 0.974 ± 0.02	39.14 ± 5.00 / 0.974 ± 0.02
	5x	25.56 ± 2.74 / 0.728 ± 0.05	37.45 ± 4.56 / 0.962 ± 0.03	37.53 ± 4.76 / 0.963 ± 0.03	37.35 ± 4.59 / 0.962 ± 0.03
	8x	23.3 ± 2.74 / 0.633 ± 0.06	33.32 ± 4.03 / 0.919 ± 0.04	33.51 ± 3.99 / 0.92 ± 0.05	33.42 ± 3.82 / 0.920 ± 0.04
Cartesian	2x	29.63 ± 3.17 / 0.843 ± 0.05	40.55 ± 4.15 / 0.980 ± 0.01	41.39 ± 4.95 / 0.982 ± 0.01	41.8 ± 5.37 / 0.983 ± 0.01
	3.3x	26.95 ± 3.12 / 0.790 ± 0.06	34.73 ± 3.43 / 0.946 ± 0.03	34.77 ± 3.48 / 0.946 ± 0.03	35.08 ± 3.59 / 0.95 ± 0.03
	4x	24.27 ± 3.10 / 0.699 ± 0.08	32.73 ± 3.28 / 0.919 ± 0.04	32.78 ± 3.27 / 0.920 ± 0.04	32.75 ± 3.29 / 0.919 ± 0.04
	5x	23.82 ± 3.11 / 0.674 ± 0.08	31.77 ± 3.49 / 0.906 ± 0.05	31.79 ± 3.39 / 0.906 ± 0.05	31.75 ± 3.40 / 0.905 ± 0.05
	8x	22.83 ± 3.11 / 0.634 ± 0.09	28.53 ± 3.27 / 0.838 ± 0.07	28.6 ± 3.15 / 0.838 ± 0.07	28.5 ± 3.11 / 0.836 ± 0.07

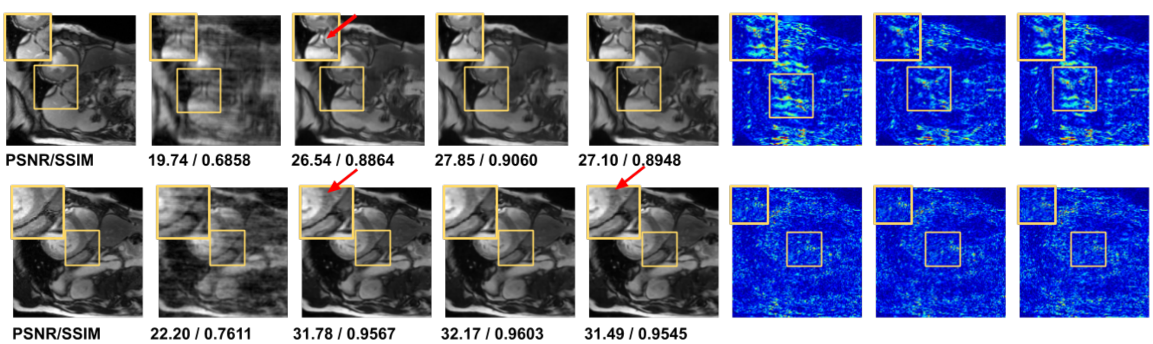

Figure 1: Context with fixed anatomy, fixed sampling pattern and varying acceleration factors.(Left to right): GT, ZF, JCM, Ours, CSM,residual image for JCM, Ours and CSM respectively. Top: Cardiac, Cartesian, 5x undersampling. Bottom: Cardiac, Gaussian, 5x undersampling: Red arrows in JCM and CSM indicate aliased regions, corresponding regions in the proposed approach structures more closer to ground truth.

Two preliminary experiments conducted are a) Cardiac study, Cartesian mask pattern and multiple acceleration factors - 2x, 3.3x, 4x, 5x, 8x. b) Cardiac study, Gaussian mask pattern and multiple acceleration factors - 2x, 3.3x, 4x, 5x, 8x. The context vector has only one element representing the acceleration factor. The quantitative metrics are shown in Cartesian and Gaussian sections in Table 1. We observe that our proposed methods outperforms the JCM and give competitive performance as compared to the CSMs. 2) For higher acceleration factors, our methods gives better results in the Cartesian case. 3) The Gaussian undersampled images exhibit higher PSNR/SSIM metrics than the Cartesian couterparts as intended. Figure 1 shows that the structures are recovered much better using the proposed method as compared to the JCM and the CSM models.

Appendix B. Undersampling masks

A fixed 1D Cartesian mask under-sampled in the phase-encoding direction for each acceleration factor is used with ten lowest spatial frequencies and remaining following a zero-mean Gaussian distribution. A fixed 2D Gaussian undersampling mask for each acceleration factor with lowest frequencies lying in the centre disc of radius 5 and remaining following a zero-mean 2D Gaussian distribution is chosen. Figures 2 and 3 show masks used for cardiac dataset and Figure 4 shows masks for brain dataset.

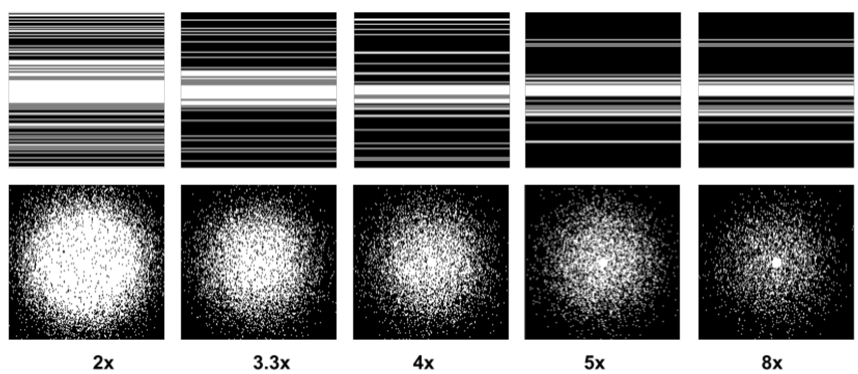

Figure 2: Cartesian (top) and Gaussian (bottom) undersampling patterns for Cardiac MRI images used for training the model. Acceleration factors - 2, 3.3, 4, 5, 8

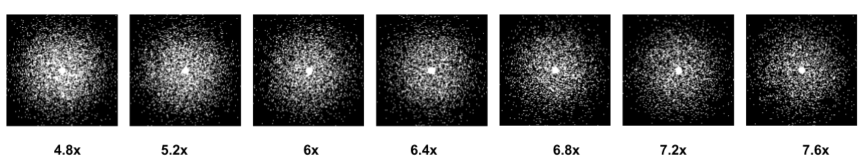

Figure 3: Gaussian undersampling patterns used for Cardiac MRI images for testing the model for unseen contexts. Acceleration factors - 2, 3.3, 4, 5, 8

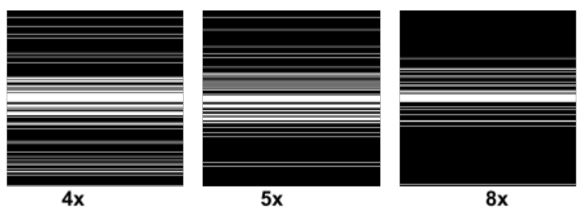

Figure 4: Cartesian undersampling patterns for Brain MRI images used for training the model. Acceleration factors - 4, 5, 8