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

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Learning based MR Imaging Systems - Deployment Challenges

Magnetic Resonance (MR) imaging - image reconstruction from undersampled k-space measurement plays a critical role.

Clinically deployed conventional methods (like CS-MRI) need repeated parameter tweaking and iterative computations lead to relatively long reconstruction times.

Deep learning methods have shown to provide faster and good quality MRI images.

However, translating these methods to a real MRI workstation is challenging! Reason? Deep learning based methods operate only for a specific input setting used at train time - covariate shift in the distribution of data.

Can we address this fundamental challenge in our convolutional neural network model?

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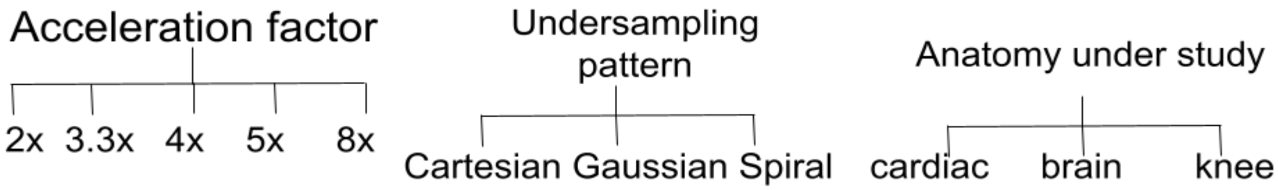
Terminology

Acquisition Context - A specific combination of three input or acquisition settings namely, the anatomy under study, undersampling mask pattern and acceleration factor for undersampling. Examples specific to MRI:



Context specific model or CSM - a model that is trained and evaluated on a particular setting i.e a particular acquisition context. Ex: Cardiac images, Gaussian undersampling with 5x acceleration.

Joint context model or JCM- a model trained using a large corpus of images obtained from various contexts.

Unseen Context - An acquisition context in which the model is evaluated and is not known by the network at train time.

Fundamental limitations of CSMs and JCMs

Model	Accuracy	Storage efficiency?	Can perform well in unseen contexts?	Different Weights for different tasks? Or Task specific weights?
CSM	✓	✗	✗	✓
JCM	✗	✓	✗	✗
Proposed method	✓	✓	✓	✓

✗ - poor ✓ - good ✓ - yes ✗ - No

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How do we bring in flexibility? Dynamic Weight Prediction

By making the network aware of the acquisition context of each training image. By feeding context information to the network along with the respective images. What is the best way?

Context vector - a numerically encoded vector to represent an acquisition context. Example: [3.3, 2, 1] where 3.3 denotes acceleration factor, 2 denotes Gaussian mask and so on.

Use an auxiliary network that learns to map the context vector with respective input-target pair -> Dynamic Weight Prediction (DWP) network.

DWP takes context vector as input generates context specific weights dynamically.

Advantage?

1. Different set of weights for different contexts are obtained! Better accuracy closer to that of the CSMs. 2. Model is storage efficient 3. Model generalized well. Model can work for unseen contexts also.

MAC-ReconNet - Contributions

We propose a multiple acquisition context-based network for MRI reconstruction, called MAC-ReconNet, consisting of a reconstruction module and a dynamic weight prediction (DWP) module.

Reconstruction module performs undersampled MRI reconstruction. The DWP module takes context vector learns context specific weights of the reconstruction module dynamically.

We show that the proposed approach can handle multiple contexts involving input settings: 1) anatomy under study: cardiac and brain, 2) undersampling (US) pattern: Cartesian and Gaussian 3) acceleration factors: 2x, 3.3x, 4x, 5x and 8x.

Results for three clinically relevant contexts show that the proposed network outperforms the JCM and gives competitive results with the CSMs both quantitatively and qualitatively.

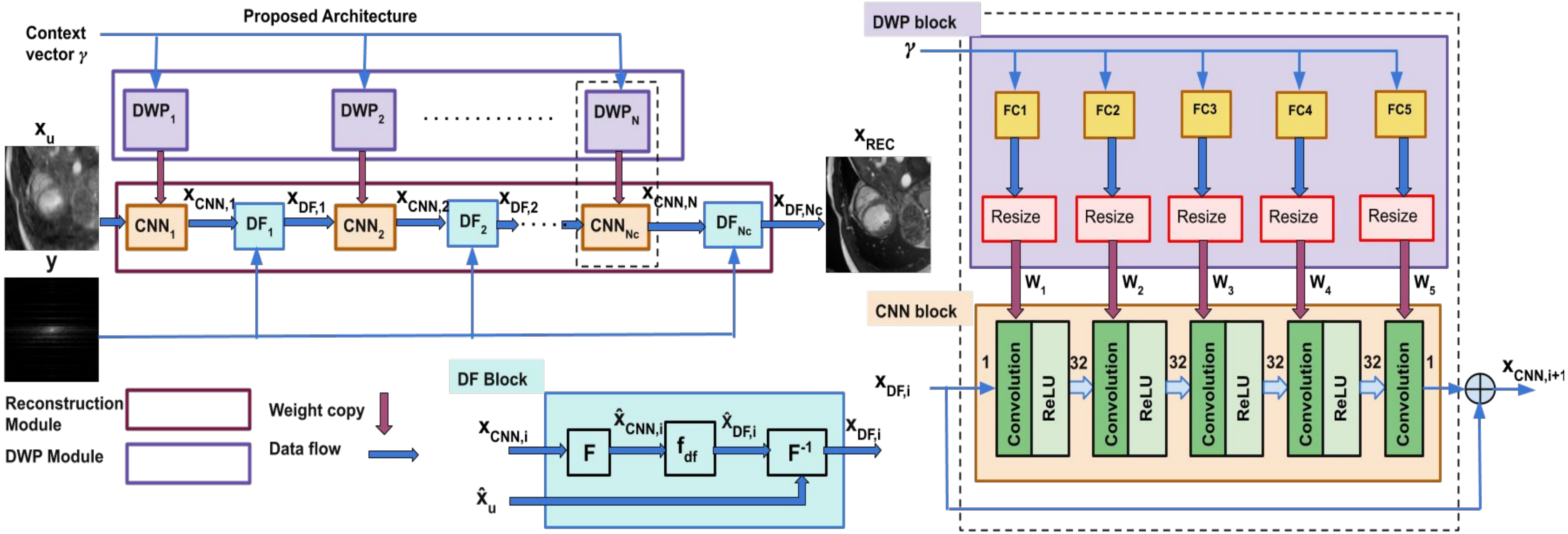
Problem formulation

A CNN-based MRI reconstruction can be formulated as an optimization problem:

$$\underset{x, W^{CNN}}{\operatorname{argmin}} \quad ||x - CNN(x_u|W^{CNN})||_2^2 + \alpha||F_u x - y||_2^2$$

$x_u = F_u^H y$	Zero-filled reconstruction
$x_{CNN} = CNN(x_u \| W^{CNN})$	CNN reconstruction of the undersampled image
$x \in C^N$	The desired image to be reconstructed from undersampled k-space measurements, y
$y \in C^M,\ M << N, y = F_u x$	
$W^{CNN} = (W_1, W_2, ..., W_n) = DWP(\vec{\gamma})$	Weights of the CNN given by a mapping function h
$\vec{\gamma}$	Numerically encoded vector representing aquisition context
$\hat{x}_{df} = \begin{cases} \hat{x}_{CNN}(k) & k \notin \Omega \\ \frac{\hat{x}_{CNN}(k) + \lambda \hat{x}_u(k)}{1+\lambda} & k \in \Omega \end{cases}$	Data fidelity operation
$\hat{x}_{CNN} = F_f x_{CNN}$	Fourier encoding of the CNN reconstruction
$\hat{x}_u = F_f x_u$	Undersampled k-space measurements
Ω	Index set of known k-space data

Architecture of MAC-ReconNet



$$x_{CNN,n} = CNN_n(x_{df,n-1}) + x_{df,n-1}$$

$$x_{df,n} = DF_n(x_{CNN,n}) \qquad n = 1, 2..N_c$$

$$W^{CNN_n} = DWP_n(\vec{\gamma})$$

W^{CNN_n} Weights of the nth CNN block

Architecture - Layer weights

Weights are resized and assigned.

$$W_i = W_i^{FC} \vec{\gamma} + B_i^{FC}$$

W_i Weights of the ith CNN layer. Size - $N_{out}\ ,\ N_{in}\ ,\ k\ ,\ k$

W_i^{FC} Weights of the ith DWP layer. Size - (N_w, N_γ)

$$N_w = N_{out} * N_{in} * k * k$$

N_γ Dimension of the context vector. Size - $N_\gamma \times 1$

B_i^{FC} Bias of the ith DWP layer. Size - $(N_w, 1)$

Results and discussions - preliminaries

Dataset:

- Cardiac Dataset - ACDC Challenge, 1841 training images ad 1076 test images of size 150x150
- MRBrains - T1 and FLAIR images each with size 240x240 with 240 training and 96 test slices

Loss function: L1 loss between predicted image and fully sampled target image, D is the training set with undersampled input and fully sampled target pair

$$L(\theta) = \sum_{(x_u, x_t) \in D} ||x_t - x_{cnn}||_2^2$$

Experiments: Three contexts relevant to clinical scenarios

1. Fixed study, varying undersampling pattern and varying acceleration factors
2. Fixed under sampling pattern, varying Acceleration Factors and varying studies.
3. Unseen Acceleration Factors

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1. Fixed study, varying undersampling pattern and varying acceleration factors

Red - Best performance, blue - second best performance

$\vec{\gamma}$		ZF	JCM	MAC-ReconNet (ours)	CSM
		PSNR/SSIM	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM
Gaussian	2x	34.11 ± 2.86 / 0.932 ± 0.02	45.37 ± 5.98 / 0.992 ± 0.00	46.12 ± 6.82 / 0.994 ± 0.00	46.39 ± 6.93 / 0.994 ± 0.00
	3.3x	29.2 ± 2.76 / 0.844 ± 0.04	40.45 ± 5.01 / 0.98 ± 0.01	41.02 ± 5.53 / 0.982 ± 0.01	40.99 ± 5.50 / 0.982 ± 0.01
	4x	26.96 ± 2.70 / 0.783 ± 0.04	38.78 ± 4.62 / 0.972 ± 0.02	39.35 ± 5.16 / 0.975 ± 0.02	39.14 ± 5.00 / 0.974 ± 0.02
	5x	25.56 ± 2.74 / 0.728 ± 0.05	37.13 ± 4.27 / 0.961 ± 0.03	37.66 ± 4.77 / 0.964 ± 0.03	37.35 ± 4.59 / 0.963 ± 0.03
	8x	23.30 ± 2.74 / 0.633 ± 0.04	33.27 ± 3.78 / 0.918 ± 0.04	33.68 ± 3.99 / 0.923 ± 0.04	33.42 ± 3.82 / 0.92 ± 0.04
Cartesian	2x	29.63 ± 3.17 / 0.843 ± 0.05	40.97 ± 4.49 / 0.981 ± 0.01	41.64 ± 5.14 / 0.983 ± 0.01	41.8 ± 5.37 / 0.983 ± 0.01
	3.3x	26.95 ± 3.12 / 0.790 ± 0.06	34.81 ± 3.49 / 0.946 ± 0.03	34.98 ± 3.54 / 0.948 ± 0.03	35.08 ± 3.59 / 0.95 ± 0.03
	4x	24.27 ± 3.10 / 0.699 ± 0.08	32.79 ± 3.36 / 0.920 ± 0.04	33.03 ± 3.36 / 0.923 ± 0.04	32.75 ± 3.29 / 0.919 ± 0.04
	5x	23.82 ± 3.11 / 0.674 ± 0.08	31.79 ± 3.59 / 0.907 ± 0.05	32.05 ± 3.47 / 0.909 ± 0.04	31.75 ± 3.40 / 0.905 ± 0.05
	8x	22.83 ± 3.11 / 0.634 ± 0.09	28.53 ± 3.29 / 0.838 ± 0.07	28.78 ± 3.21 / 0.842 ± 0.07	28.5 ± 3.11 / 0.836 ± 0.07

Context vector has two elements - [Acceleration factor undersampling mask pattern]

Acceleration factor - 2, 3.3, 4, 5, 8

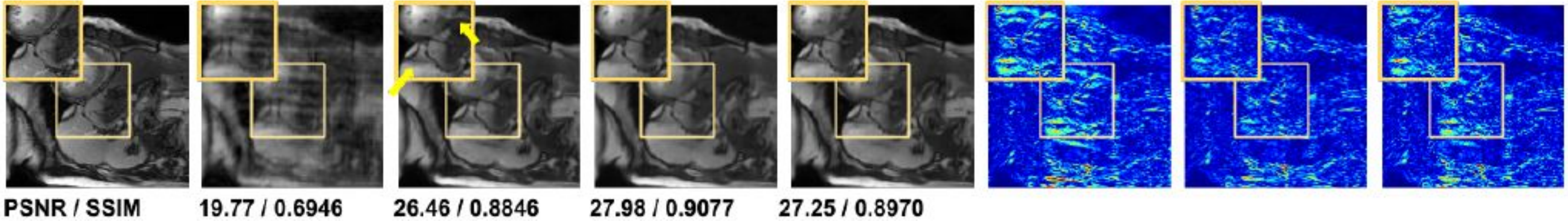
Undersampling mask pattern - Cartesian - 1 Gaussian - 2

Dataset is cardiac is fixed

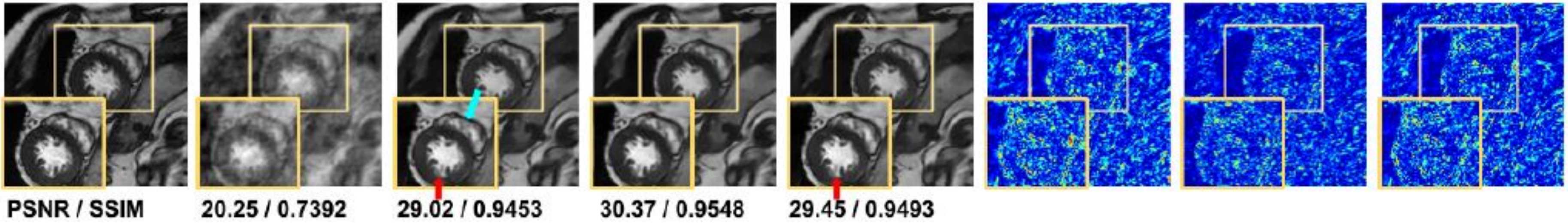
1. Fixed study, varying undersampling pattern and varying acceleration factors

Cardiac, Cartesian, 5x undersampling

Residual images with respect to target



Cardiac, Gaussian, 5x undersampling



Target Zero-filled CSM JCM MAC-ReconNet JCM MAC-ReconNet CSM

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2. Fixed under sampling pattern, varying acceleration factors and varying studies

Red - Best performance, blue - second best performance

$\vec{\gamma}: 2 \times 1$		ZF	JCM	MAC-ReconNet (ours)	CSM
		PSNR/SSIM	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM
T1	4x	31.38 ± 1.02 / 0.665 ± 0.02	37.05 ± 1.44 / 0.946 ± 0.00	39.35 ± 2.04 / 0.968 ± 0.00	40.37 ± 2.09 / 0.980 ± 0.00
	5x	29.93 ± 0.80 / 0.630 ± 0.02	35.75 ± 1.01 / 0.935 ± 0.00	38.65 ± 1.75 / 0.954 ± 0.00	39.5 ± 1.63 / 0.974 ± 0.00
	8x	29.93 ± 0.80 / 0.630 ± 0.02	33.47 ± 1.15 / 0.905 ± 0.01	34.3 ± 0.59 / 0.907 ± 0.00	35.21 ± 1.34 / 0.939 ± 0.00
T2	4x	28.4 ± 0.84 / 0.642 ± 0.02	35.4 ± 0.09 / 0.94 ± 0.00	37.43 ± 0.37 / 0.966 ± 0.00	39.35 ± 2.04 / 0.968 ± 0.00
	5x	26.99 ± 0.74 / 0.609 ± 0.02	33.99 ± 0.22 / 0.924 ± 0.00	37.09 ± 0.23 / 0.956 ± 0.00	37.81 ± 0.05 / 0.970 ± 0.00
	8x	26.49 ± 0.79 / 0.588 ± 0.03	31.7 ± 0.03 / 0.899 ± 0.00	32.68 ± 0.91 / 0.912 ± 0.00	33.35 ± 0.27 / 0.93 ± 0.00

Context vector has two elements - [Acceleration factor Anatomy under study]

Acceleration factor - 4, 5, 8

Anatomy under study - T1 - 1 T2 - 2

Undersampling pattern is fixed

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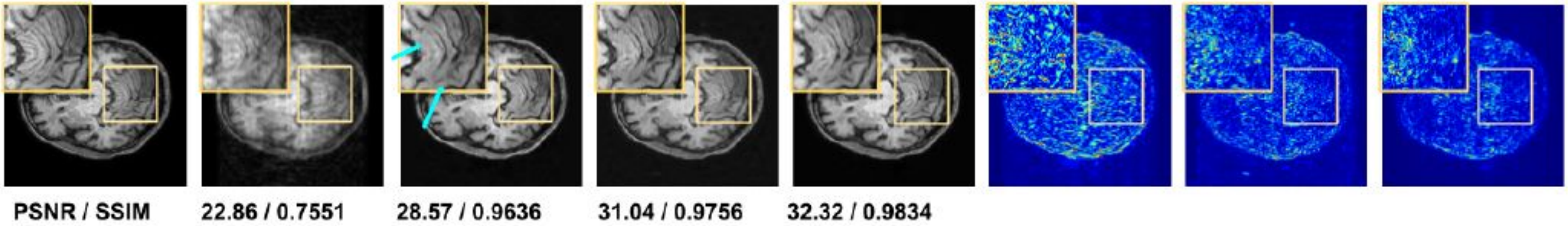
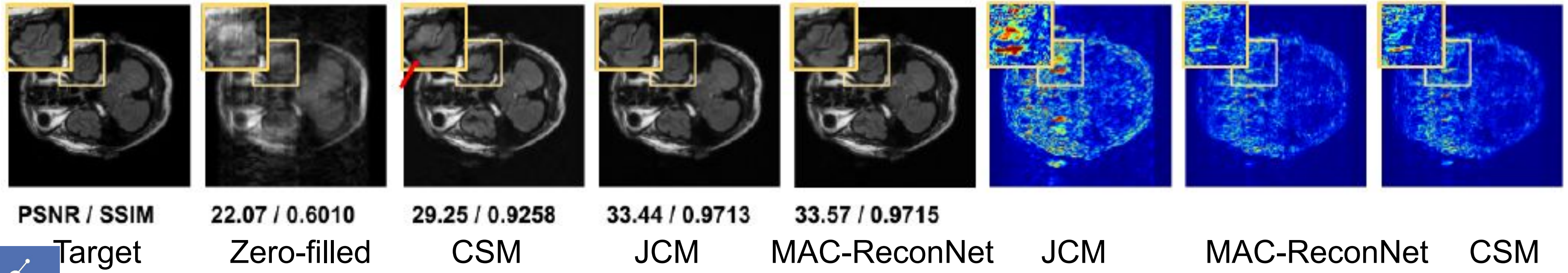
2. Fixed under sampling pattern, varying Acceleration Factors and varying studies

T1 Brain, Cartesian, 5x undersampling

Residual images with respect to target



Flair Brain, Cartesian, 5x undersampling



2. Unseen Context

Red - Best performance, blue - second best performance

$\vec{\gamma}$	JCM	MAC-ReconNet (ours)	CSM
	PSNR/SSIM	PSNR/SSIM	PSNR/SSIM
4.8	35.57 +/- 3.75 / 0.9493 +/- 0.03	36.97 +/- 4.79 / 0.9594 +/- 0.03	36.85 +/- 4.46 / 0.9592 +/- 0.03
5.2	34.92 +/- 3.71 / 0.9434 +/- 0.03	36.34 +/- 4.64 / 0.9546 +/- 0.03	36.37 +/- 4.53 / 0.9541 +/- 0.03
6	33.96 +/- 3.57 / 0.9301 +/- 0.03	35.21 +/- 4.32 / 0.9425 +/- 0.04	35.06 +/- 4.06 / 0.9418 +/- 0.03
6.4	33.02 +/- 3.58 / 0.9193 +/- 0.04	33.99 +/- 4.26 / 0.9321 +/- 0.04	34.03 +/- 3.89 / 0.9315 +/- 0.04
6.8	32.68 +/- 3.55 / 0.913 +/- 0.04	33.93 +/- 4.21 / 0.9284 +/- 0.04	33.98 +/- 3.98 / 0.9277 +/- 0.04
7.2	32.15 +/- 3.60 / 0.904 +/- 0.04	33.29 +/- 4.04 / 0.9203 +/- 0.05	33.18 +/- 3.72 / 0.9189 +/- 0.04
7.6	31.58 +/- 3.58 / 0.8955 +/- 0.05	32.58 +/- 3.93 / 0.9115 +/- 0.05	32.55 +/- 3.68 / 0.9102 +/- 0.05

Train a network with fixed dataset type and undersampling pattern (Gaussian) and varying acceleration factors (2x, 3.3x, 4x, 5x, 8x) on unseen contexts.

Context is a scalar with only one element - Acceleration factor - 2, 3.3, 4, 5, 8

Dataset and undersampling pattern are fixed.

Test the network with undersampling images with factors from 2.4x to 7.6x in increments of 2

Out of the 28 unseen context 26 of them showed improvements qualitatively and quantitatively

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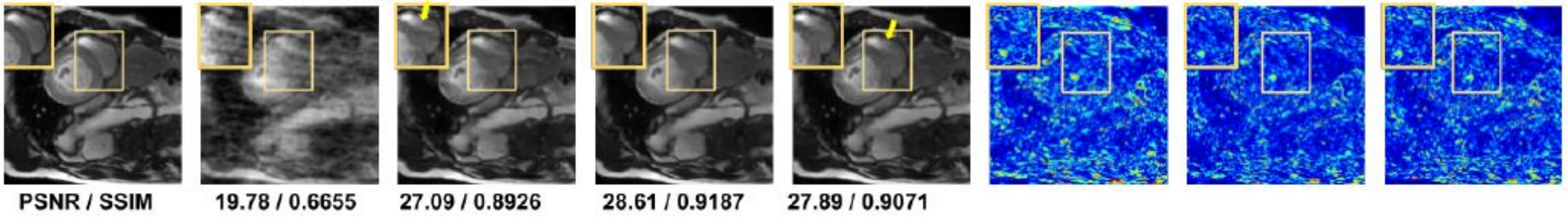
2. Unseen Context

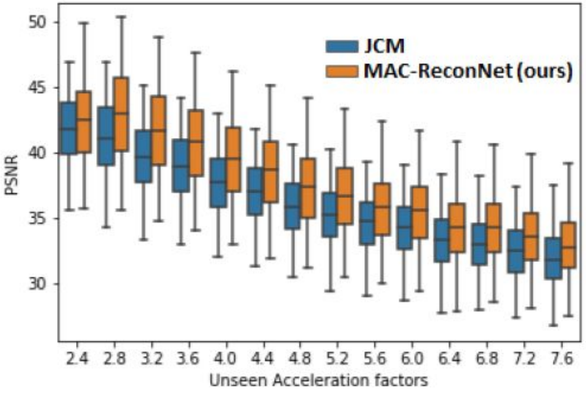
Cardiac, Gaussian, 7.6x undersampling

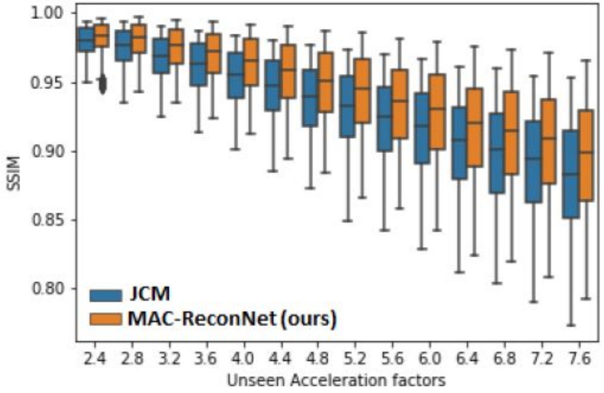
Residual images with respect to target



Target | Zero-filled | CSM | JCM | MAC-ReconNet | JCM | MAC-ReconNet | CSM

Residuals





Conclusions and Future work

We see that a CNN-based MR reconstruction that exhibits flexibility to multiple acquisition contexts could be more appropriate for a clinical scenario

MAC-ReconNet incorporates flexibility to multiple contexts in a single model, by using a dynamic weight prediction module to generate context-specific weights to our MR reconstruction module.

Future work:

We are currently working for a journal extension of our work towards improving the architecture to suit more clinical scenarios, extend the model to complex and parallel MRI datasets and so on.

Thank you!

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