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

MIDL 2020 Oral paper

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Healthcare Technology Innovation Centre
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- A joint initiative of -
Indian Institute of Technology Madras
Department of Biotechnology, Ministry of Science and Technology

MIDL Lübeck 2021, 7 - 9 July 2021
Doctoral Symposium

AIM

To develop a learning framework for accelerated MR image reconstruction that is flexible to multiple acquisition contexts and generalizable to unseen contexts. Acquisition context refers to a specific combination of three MR input settings considered namely, the anatomy under study, under-sampling mask pattern and acceleration factor for under-sampling.

INTRODUCTION

Magnetic Resonance imaging (MRI) offers several benefits of non-invasive acquisition and high soft-tissue contrast but suffers from the inherent slow acquisition. The fundamental challenge in MRI is to mitigate the time-intensiveness of acquisition for the betterment of patient comfort. Existing deep learning based Magnetic Resonance (MR) image reconstruction methods operate can only for a specific input settings used at train time - Context specific models (CSM). They have to be stored separately for each setting. They do not perform well on images with different settings unseen at train time. Models jointly trained on multiple contexts also called JCM or joint context models learn a single weight set and hence not optimal for multiple contexts.

FLEXIBILITY – DYNAMIC WEIGHT PREDICTION

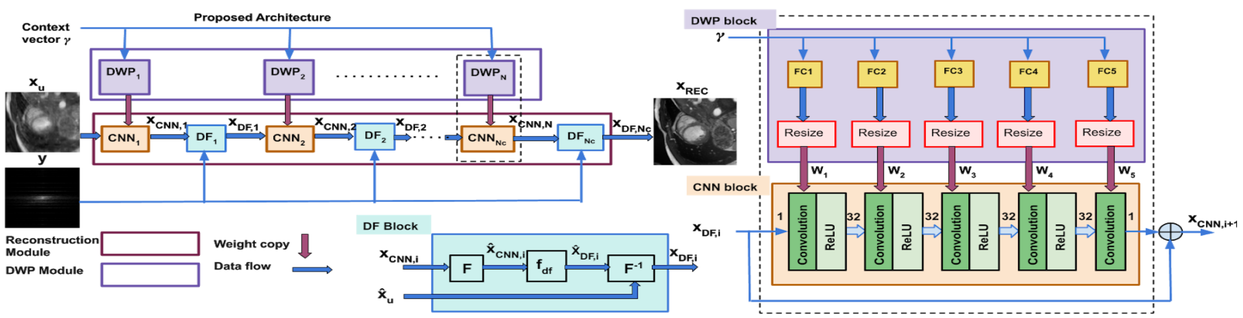
Use Dynamic Weight Prediction (DWP) network that learns to map the context information with respective input-target pair. Advantage?

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.

CONTRIBUTION

- 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 under-sampled 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) under-sampling (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.

METHOD



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

$$W^{CNN_n} = DWP_n(\vec{\gamma}) \qquad n = 1, 2..N_c$$

W^{CNN_n} Weights of the nth CNN block

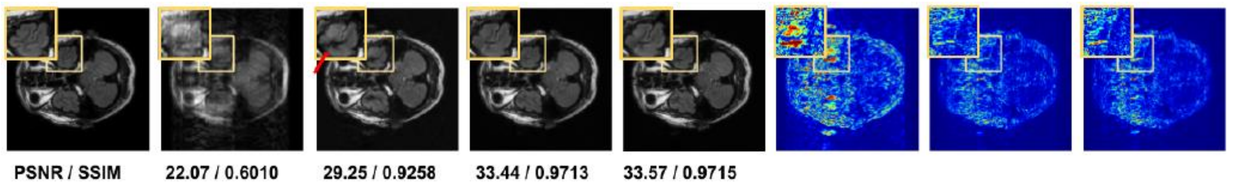
IMPLEMENTATION DETAILS

- Dataset: Cardiac Dataset - ACDC Challenge, 1841 training images ad 1076 test images of size 150x150 and 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 and the training set has under-sampled input and fully sampled target pair
- Experiments: Three contexts relevant to clinical scenarios. 1. Fixed study, varying under-sampling pattern and varying acceleration factors. 2. Fixed under sampling pattern, varying Acceleration Factors and varying studies. 3. Unseen Acceleration Factors

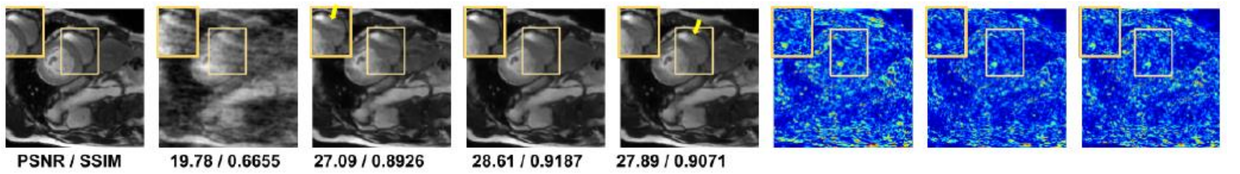
RESULTS

Fixed under sampling pattern, varying Acceleration Factors and varying studies Red - Best performance, blue - second best performance

$\vec{\gamma}$	JCM PSNR/SSIM	MAC-ReconNet (ours) PSNR/SSIM	CSM 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



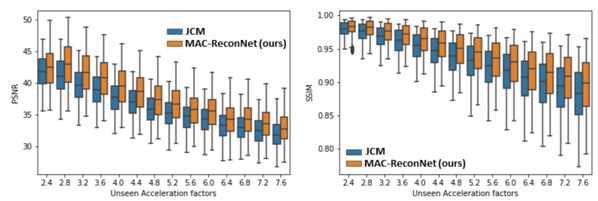
Unseen Context



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

Residual images with respect to target

Box plot shows improvement over unseen acceleration factors that on a model trained for five acceleration factors. Shows the Interpolation capability of the network over JCM.



CONCLUSIONS & 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. 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 and post the code in github soon.

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