KD-MRI: A knowledge distillation framework for image reconstruction and image restoration in MRI workflow

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Motivation

- Magnetic Resonance Imaging (MRI) workflow consists of image acquisition, reconstruction, restoration, registration and analysis.
- Deep learning networks have shown encouraging results for every stage in the MRI workflow.
- Deep learning networks are specific to task, dataset (anatomical study, contrast).
- For MRI reconstruction, deep learning networks are also specific to type of degradation (acceleration factor, undersampling mask).
- Integration of deep learning models to MRI workflow demands larger storage and compute power.
- Development of memory-efficient model is required.

Solution

- Model compression - Deploying state-of-the-art deep networks in low-power and resource limited devices without significant drop in accuracy.
- Knowledge distillation (KD) - Develop compact models with ease of deployment.
- KD - student model (memory efficient, lower performance network) learns from teacher model (memory intensive, higher performance network) to improve the student's accuracy.
- For MRI reconstruction and restoration, we propose:
  - Attention-based feature distillation - Student learn the intermediate representation of the teacher.
  - Imitation loss - Regularizer to the reconstruction loss.

MRI reconstruction

- MRI reconstruction
  - Transformation of Fourier space (k-space) data to image domain.
  - MRI is a slow acquisition modality, acceleration is done by under sampling k-space.
  - De-alias the artifact due to undersampling and provide reconstruction equivalent of fully sampled k-space.
- Deep Cascade - Convolution Neural Network (DC-CNN)
  - Cascade of convolutional neural networks (CNN) and a data consistency (DC) layer.
  - CNN - To learn Image-to-Image mapping, DC - To provide consistency in Fourier domain.
  - n_c cascades, every cascade has n_d convolution layers and 1 DC layer.
- Teacher DC-CNN
  - $n_c = 5, n_d = 5$
- Student DC-CNN
  - $n_c = 5,\ n_d = 3$

KD for MRI reconstruction

- Attention based feature distillation
  - Attention transfer loss for information distillation:

$$L_{AT} = \sum_{j \in I} || \frac{Q_S^j}{||Q_S^j||_2} - \frac{Q_T^j}{||Q_T^j||_2} ||_2 \tag{1}$$

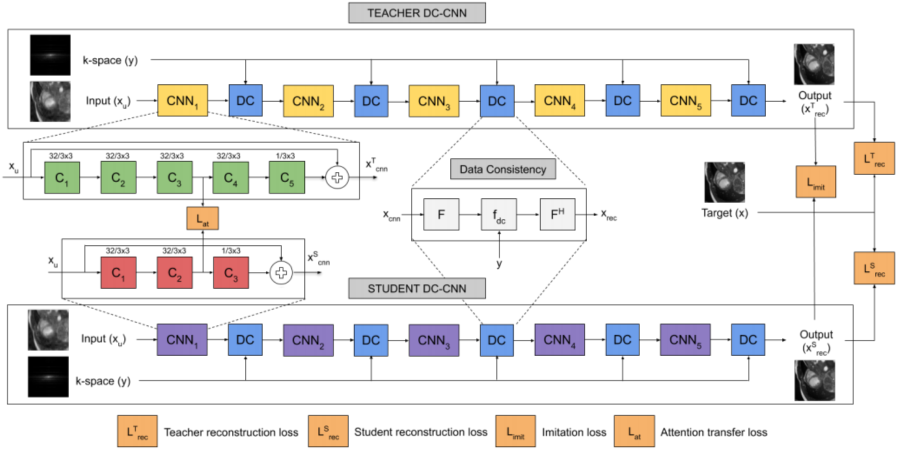
where $Q_S^j = vec(F_{sum}(A_S^j))$, $Q_T^j = vec(F_{sum}(A_T^j))$, $F_{sum}(A) = \sum_{i=1}^{C} |A_i|^2$ and I denote the set of teacher-student convolution layers which is selected for attention transfer

- Imitation Loss
  - Regularizer to the student reconstruction loss

$$L_{total}^S = \alpha L_{rec}^S + (1 - \alpha) L_{imit} \tag{2}$$

where $L_{rec}^S = ||x - x_{rec}^S||$ is the loss between student prediction and target, $L_{imit} = ||x_{rec}^T - x_{rec}^S||$ is the imitation loss between teacher and student prediction

Block Diagram



Training procedure

- Step1: Train the teacher DC-CNN f^{T}_{cnn} weights θ^{T} using teacher reconstruction loss $L^{T}_{rec} = ||x - x^{T}_{rec}||$
- Step2: Train the student DC-CNN f^{S}_{cnn} weights θ^{S} using attention transfer loss $L_{AT} = ||Q_T - Q_S||$ between teacher and student
- Step3: Load the weights θ^{S} from Step2 and re-train f^{S}_{cnn} weights θ^{S} using student reconstruction and imitation loss $L^{S}_{total} = \alpha||x - x^{S}_{rec}|| + (1-\alpha)||x^{T}_{rec} - x^{S}_{rec}||$

Quantitative comparison

		4x		5x		8x	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Cardiac	ZF	24.27 ± 3.10	0.6996 ± 0.08	23.82 ± 3.11	0.6742 ± 0.08	22.83 ± 3.11	0.6344 ± 0.09
	Teacher	32.51 ± 3.23	0.9157 ± 0.04	31.49 ± 3.32	0.9002 ± 0.04	28.43 ± 3.13	0.8335 ± 0.06
	Student	31.92 ± 3.17	0.9053 ± 0.04	30.79 ± 3.24	0.8863 ± 0.05	27.87 ± 3.11	0.8156 ± 0.07
	Ours	32.07 ± 3.21	0.9084 ± 0.04	31.01 ± 3.27	0.8913 ± 0.04	28.11 ± 3.17	0.8236 ± 0.07
Brain	ZF	31.38 ± 1.02	0.6651 ± 0.02	29.93 ± 0.80	0.6304 ± 0.02	29.37 ± 0.98	0.6065 ± 0.03
	Teacher	40.03 ± 2.00	0.9781 ± 0.00	39.03 ± 1.28	0.971 ± 0.00	35.04 ± 1.38	0.9374 ± 0.01
	Student	39.36 ± 1.82	0.9753 ± 0.00	38.58 ± 1.28	0.9674 ± 0.00	34.39 ± 1.26	0.9281 ± 0.01
	Ours	39.8 ± 1.89	0.977 ± 0.00	38.78 ± 1.24	0.9688 ± 0.00	34.83 ± 1.35	0.9337 ± 0.01
Knee	ZF	29.66 ± 3.86	0.8066 ± 0.08	29.2 ± 3.87	0.8007 ± 0.08	28.71 ± 3.88	0.7985 ± 0.08
	Teacher	37.15 ± 3.55	0.9436 ± 0.03	35.16 ± 3.46	0.9231 ± 0.03	32.53 ± 3.49	0.8887 ± 0.05
	Student	36.37 ± 3.53	0.9367 ± 0.03	34.37 ± 3.47	0.9144 ± 0.04	31.92 ± 3.58	0.8804 ± 0.05
	Ours	36.7 ± 3.52	0.9392 ± 0.03	34.71 ± 3.44	0.9181 ± 0.04	32.32 ± 3.57	0.8867 ± 0.05

Qualitative comparison

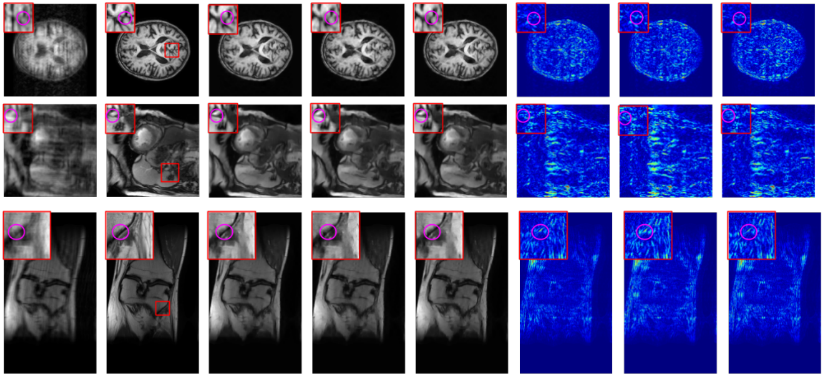


Figure: From Left to Right: Zero-filled, Target, Teacher, Student, Ours (KD-MRI), Teacher Residue, Student Residue, KD-MRI Residue

Conclusion

- We proposed a knowledge distillation (KD) framework for image to image problems in the MRI workflow in order to develop compact, low-parameter models without a significant drop in performance.
- We propose obtaining teacher supervision through a combination of attention transfer and imitation loss.
- We demonstrated its efficacy on the DC-CNN network and show consistent improvements in student reconstruction across datasets and acceleration factors.

Thank you

- Paper - https://arxiv.org/abs/2004.05319
- Code - https://github.com/Bala93/KD-MRI
- Contact - balamurali@htic.iitm.ac.in