Zero-Shot Physics-Guided Deep Learning for Subject-Specific MRI Reconstruction

Burhaneddin Yaman[1,2], Seyed Amir Hossein Hosseini[1,2], and Mehmet Akçakaya[1,2]

[1]Electrical and Computer Engineering, and [2]Center for Magnetic Resonance Research, University of Minnesota, Minneapolis, MN

DATABASE DEEP LEARNING

- Physics-guided deep learning reconstruction (PG-DLR): Emerging alternative technique for accelerated MRI [1-4]
- Supervised PG-DLR requires fully-sampled data for training
- Self-supervised learning via data undersampling (SSDU) enables MRI reconstruction without fully-sampled data [5-6]
- Challenges:
  1) Lack of large datasets due to physiological and physical constraints
  2) Risk of generalization due to mismatch between training and test data (e.g. anatomy shift, SNR, sampling pattern)

ZERO-SHOT SELF-SUPERVISED LEARNING (ZS-SSL)

- Enable subject-specific training without any external dataset
- ZS-SSL partitions available measurements into three disjoint sets that are respectively used in PG-DLR network, to define training loss and to establish an early stopping strategy
- ZS-SSL self-validation strategy tackles overfitting seen in zero-shot learning frameworks
- In presence of pretrained models it can be combined with transfer learning to tackle database associated challenges [7]

DISCUSSION & CONCLUSION

- We proposed to perform subject-specific training with a well-defined stopping criterion
- Results on knee and brain MRI shows that ZS-SSL:
  - achieves on-par performance with supervised PG-DLR when training & testing data follow same distribution
  - outperforms supervised PG-DLR if there is a mismatch between training & testing data

METHODS

SSDU:

- Acquired k-space locations Ω, split into two disjoint sets
- $\Omega = \Theta \cup \Lambda$, $\Theta = \Omega \backslash \Lambda$
- Θ: Data consistency units, Λ: To define loss in k-space
- End-to-end minimization
- $\min_{\boldsymbol{\theta}} \frac{1}{N}\sum_{i=1}^{N} \mathcal{L}\left(\mathbf{y}_{\Lambda}^{i}, \mathbf{E}_{\Lambda}^{i}\left(f\left(\mathbf{y}_{\Theta}^{i}, \mathbf{E}_{\Theta}^{i}; \boldsymbol{\theta}\right)\right)\right)$
- Loss is measured on k-space at unseen locations in training, Λ

Proposed Zero-Shot Self-Supervised Learning (ZS-SSL):

- A validation set Γ is chosen from acquired k-space locations Ω as $\Gamma \subset \Omega$
- The remaining measurements $\Omega\backslash\Gamma$ are retrospectively partitioned into multiple sets as in [6]

  $\Omega\backslash\Gamma = \Theta_k \cup \Lambda_k$, k=1,…,$K$
- End-to-end minimization

$$\min_{\boldsymbol{\theta}} \frac{1}{K}\sum_{k=1}^{K} \mathcal{L}\left(\mathbf{y}_{\Lambda_k}, \mathbf{E}_{\Lambda_k}\left(f\left(\mathbf{y}_{\Theta_k}, \mathbf{E}_{\Theta_k}; \boldsymbol{\theta}\right)\right)\right)$$

- Validation loss :

$$\mathcal{L}\left(\mathbf{y}_{\Gamma}, \mathbf{E}_{\Gamma}\left(f\left(\mathbf{y}_{\Omega\backslash\Gamma}, \mathbf{E}_{\Omega\backslash\Gamma}; \boldsymbol{\theta}^{(l)}\right)\right)\right)$$

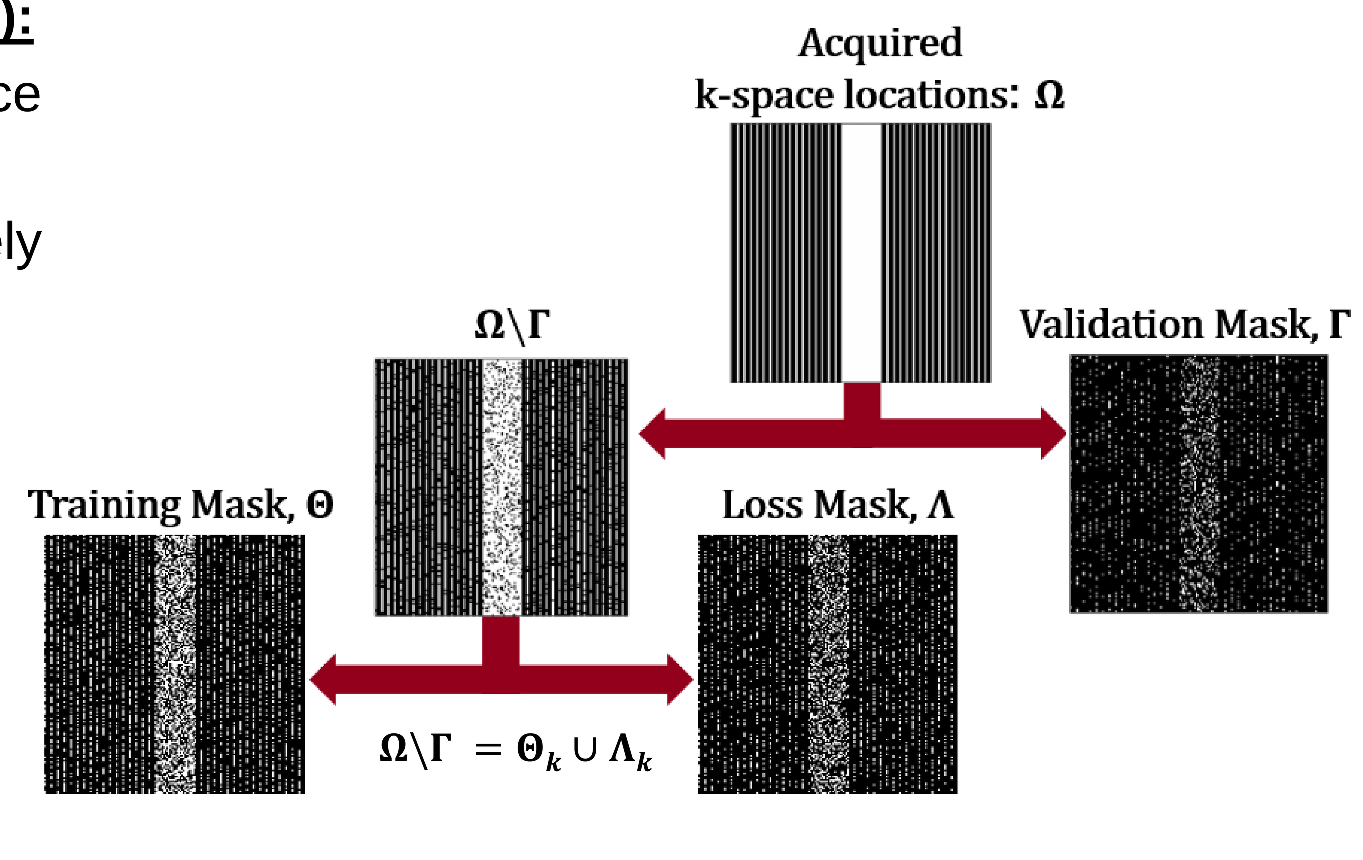

Figure 1: Proposed ZS-SSL partitioning framework

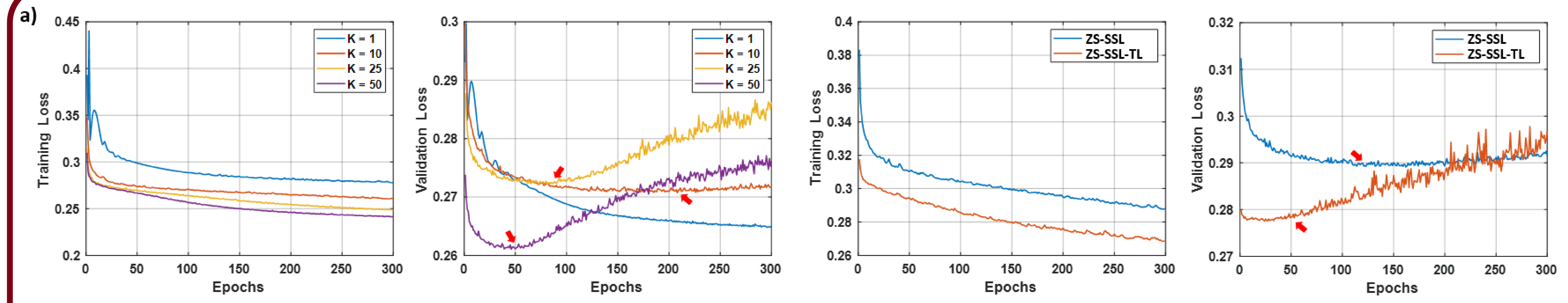

Figure 2: a) Training and validation loss curves with varying *K* for ZS-SSL at R=4. For K > 1 the validation loss forms an L-curve, whose breaking point (red arrows) dictates the automated early stopping criterion for training. b) Loss curves for ZS-SSL with/without TL for K = 10. ZS-SSL with TL converges faster in time compared to ZS-SSL (red arrows).

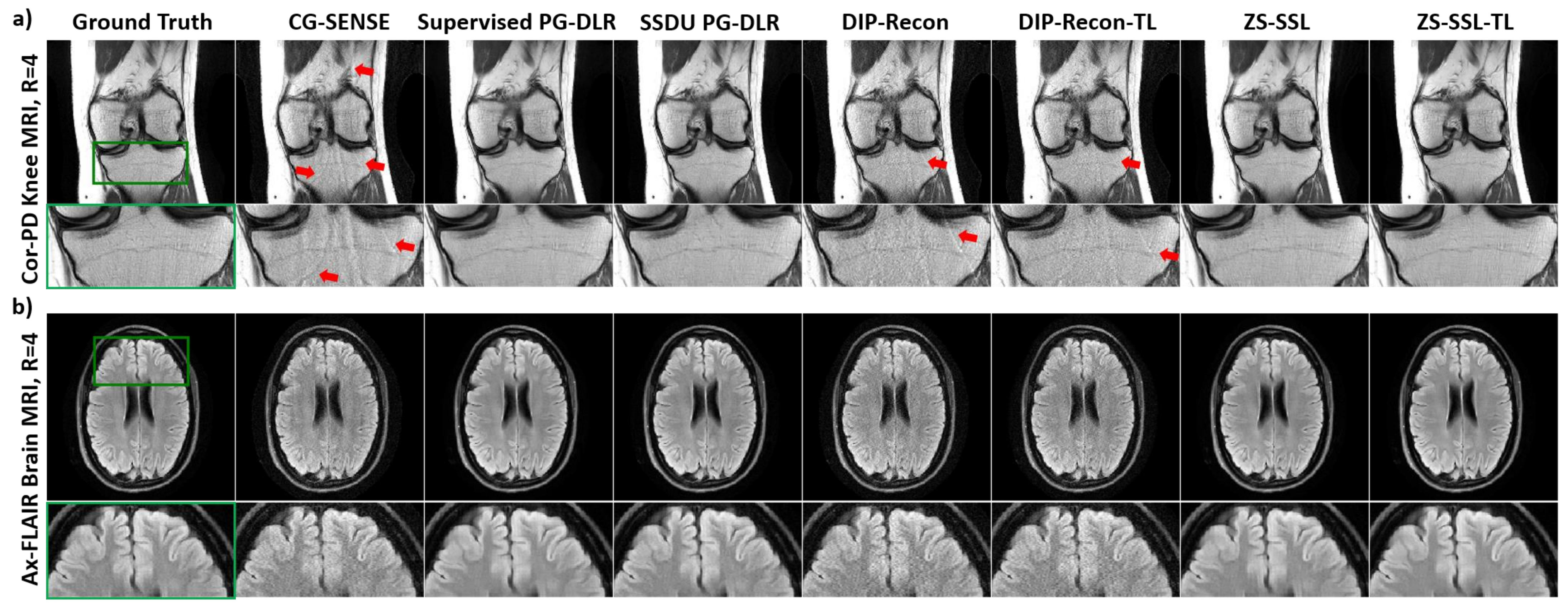

Figure 3: Reconstruction results for database (Supervised & SSDU PG-DLR) and zero-shot deep learning (DIP-Recon & proposed ZS-SSL) approaches.

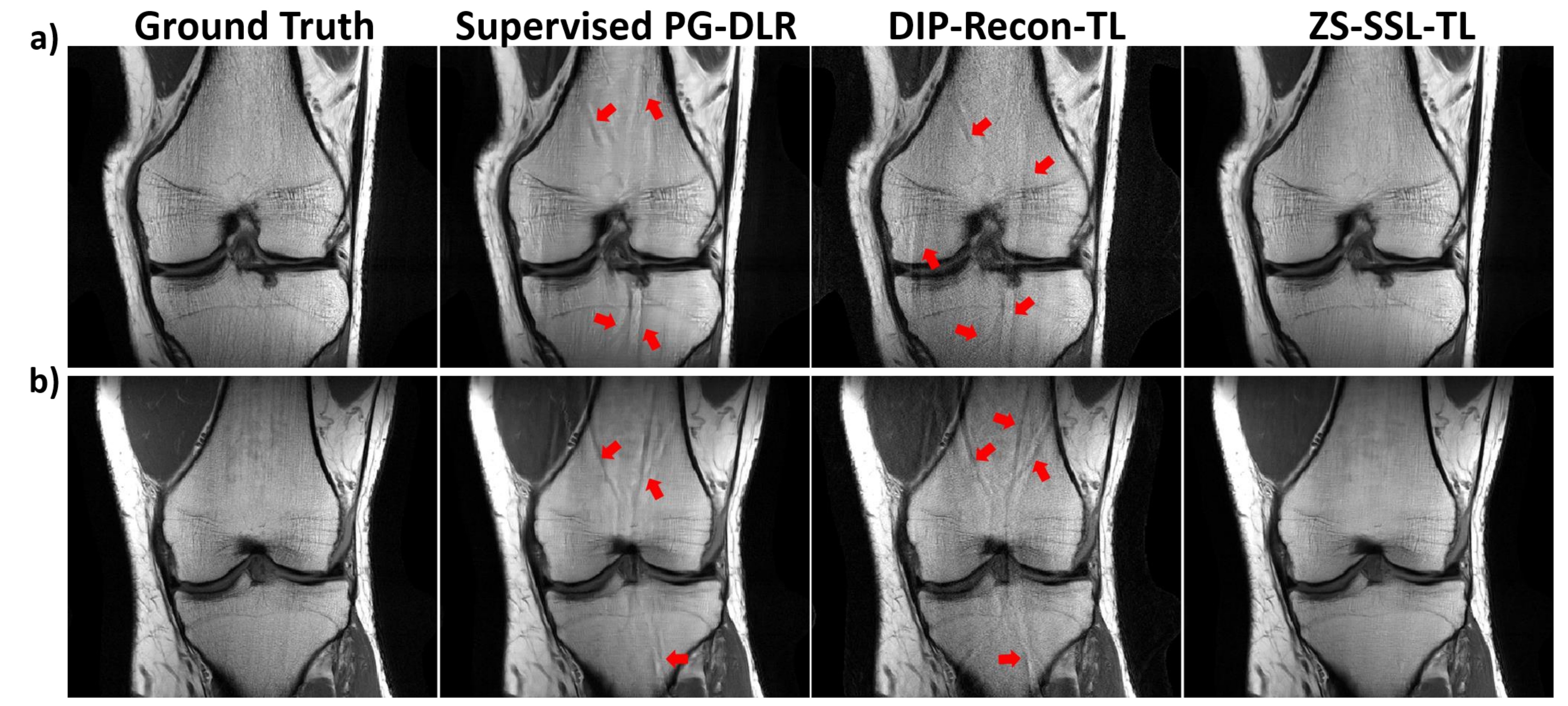

Figure 4: Using pre-trained a) Cor-PDFS (low-SNR) and b) Ax-FLAIR (brain MRI) models for Cor-PD (knee). While supervised PG-DLR and DIP-Recon-TL suffer from artifacts, ZS-SSL-TL successfully removes noise and artifacts for both cases.

REFERENCES

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