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

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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:
  o achieves on-par performance with supervised PG-DLR when training & testing data follow same distribution
  o outperforms supervised PG-DLR if there is a mismatch between training & testing data

METHODS
Proposed Zero-Shot Self-Supervised Learning (ZS-SSL):
• A validation set \( \Gamma \) is chosen from acquired k-space locations \( \Omega \) as \( \Gamma \subset \Omega \)
• The remaining measurements \( \Omega \setminus \Gamma \) are retrospectively partitioned into multiple sets as in [6]
  \( \Omega \setminus \Gamma = \Theta_1 \cup \Lambda_1, \ldots, K \)
• End-to-end minimization
  \[ \min_{\Theta} \sum_{k=1}^{K} \mathcal{L} \left( y_{\Theta_k}, E_{\Lambda_k} \left( f \left( y_{\Theta_k}, E_{\Lambda_k}; \theta \right) \right) \right) \]
• Validation loss:
  \[ \mathcal{L} \left( y_{\Omega}, E_{\Gamma} \left( f \left( y_{\Omega_{\Gamma}}, E_{\Omega_{\Gamma}}; \theta \right) \right) \right) \]

REFERENCES

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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.