SNAC-DL: Spatial Noise Adaptive Convolutional Dictionary Learning for MRI Enhancement

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Overview

Recent advances in machine learning based signal processing propose greater accessibility for MRI machines by using advanced algorithms to enhance Low-Field MR (LFMR) images. Low field strength of LFMR yields low SNR (noisy) measurements, which often requires averaging several acquisitions (slow and costly). Deep-learning techniques may be able to enhance noisy data from only a small number of acquisitions. However, obtaining ground-truth (clean) LFMR images, needed for supervised deep learning methods, is prohibitively costly. We leverage the following properties to tackle LFMR image enhancement without clean data:

- **Multi-Coil Acquisition** provides redundancy in the LFMR images that can be used for self-supervised deep learning training.
- **Complex-Valued** measurement data allows for low-SNR training.
- **Coil-Whitening** preprocessing eliminates spatially varying noise issues.
- **Noise-Adaptive** Convolutional Dictionary Learning (CDL) deep networks perform parameter and data-efficient restoration.

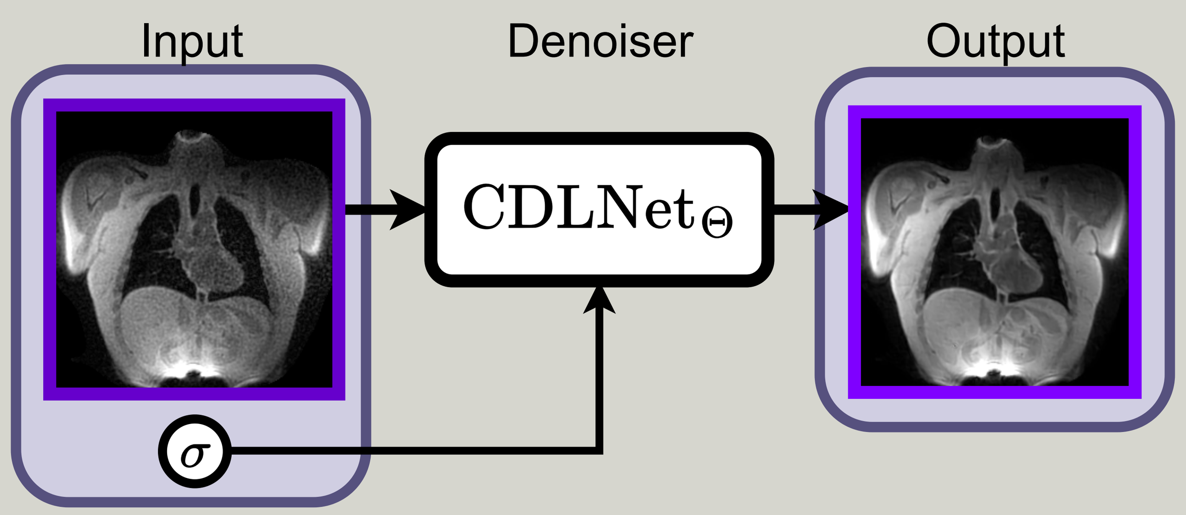

Figure 1. Noise-adaptive CDLNet denoises low-SNR coil-combined images after training.

A complex-valued Coil2Coil self-supervision can successfully train a Convolutional Dictionary Learning Network (CDLNet) for Low-Field MRI enhancement.

Data

- Two datasets of LFMR (0.55 T) lung images totaling 83 volumes, each 140 slices.
- Volumes have 12 coils of complex image data (magnitude and phase).
- Coil sensitivity estimated using the ESPiRIT algorithm.
- Coil noise covariance estimated by median abs. deviation of wavelet coefficients.
- Coil noise correlation causes difficult to remove spatially varying noise.

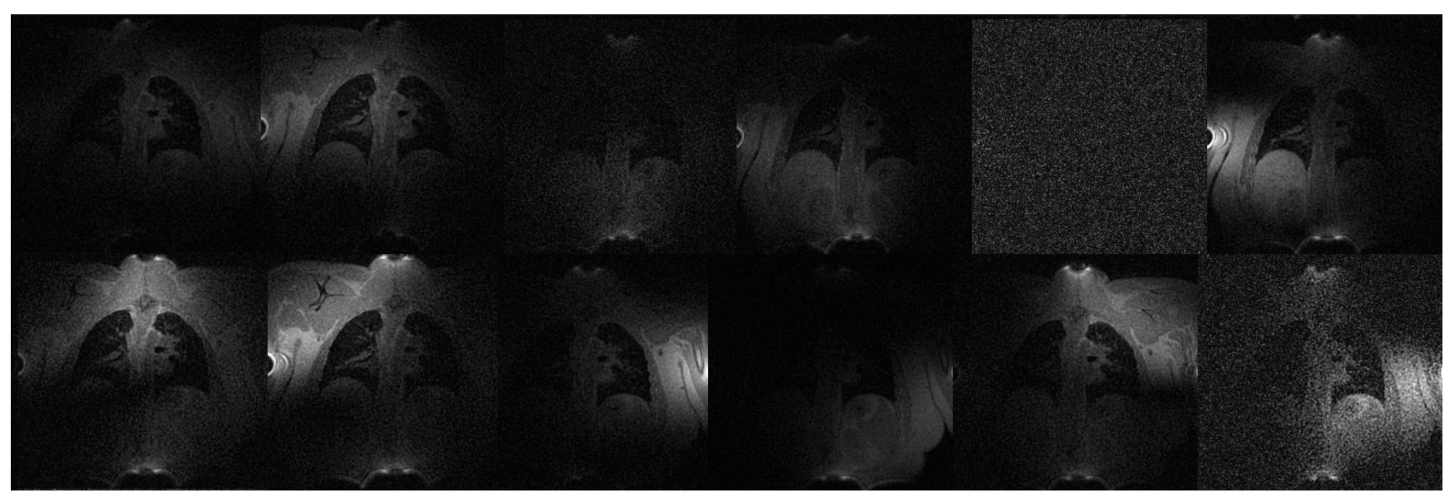

Figure 2. Single slice of a multi-coil volume. Magnitude images shown for display purpose.

Methods

Convolutional Dictionary Learning Network

- A light-weight deep network derived from a complex-valued basis pursuit denoising / ISTA.
- Network weights given by analysis / synthesis filterbanks and thresholds of each layer.
- Thresholds $\tau = \tau_0 + \tau_1 \hat{\sigma}$ constrained to increase with the estimated input-noise level.

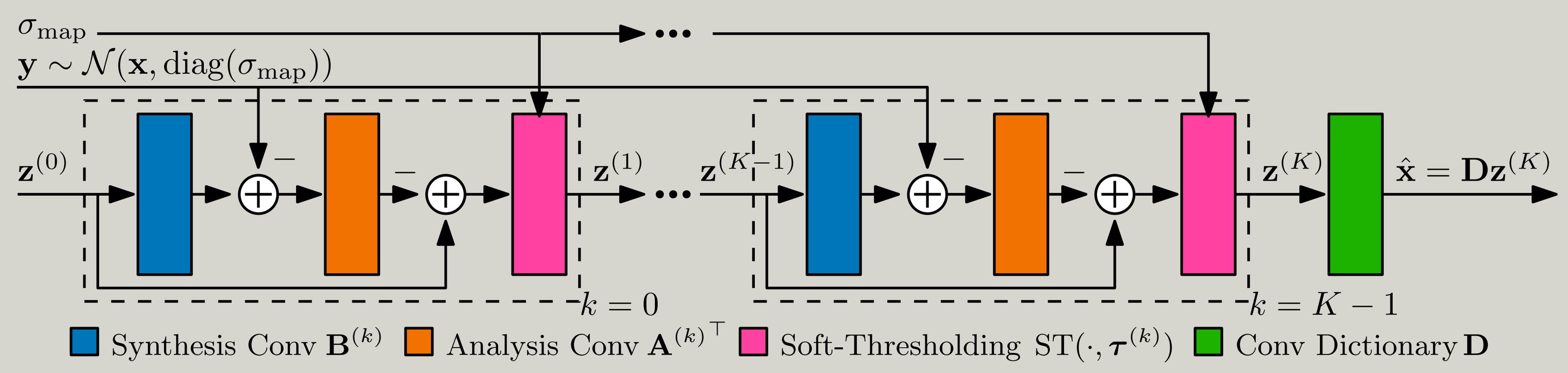

Figure 3. Noise Adaptive CDLNet block diagram.

Observation Model:

- Model the clean complex images of each coil as contaminated with circularly-symmetric complex-valued additive Gaussian white noise (AWGN), with a coil variance matrix Σ.

$$\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{\nu} \in \mathbb{C}, \quad \mathcal{N}(0, \Sigma).$$

Coil Whitening:

- Estimate Σ and decompose it into its Cholesky factors: $\Sigma = LL^H$. Compute:

$$\boldsymbol{y}_{\text{white}} = \alpha L^{-1}\boldsymbol{y}, \quad \alpha = \sqrt{\lambda_{\min}(\Sigma)}.$$

- Whitened coil data $\boldsymbol{y}_{\text{white}}$ has approximately spatially uniform noise-level $\sigma = \alpha$.

Whitened data satisfies uncorrelated noise of input-target pair assumptions for C2C training.

Complex Coil2Coil Loss

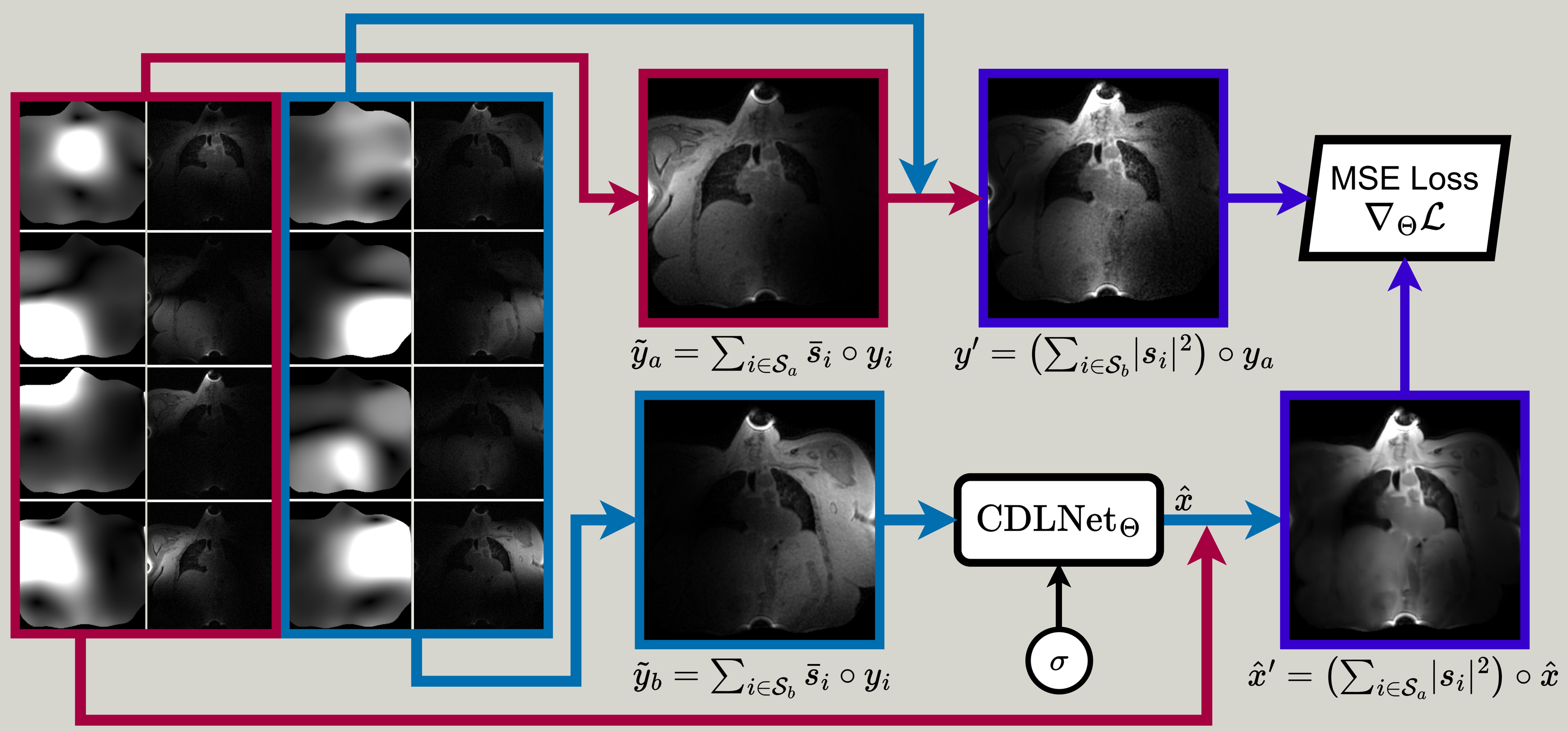

Figure 4. Self-supervised training of CDLNet denoiser via Coil2Coil loss function on complex image data. Coils and sensitivity maps are split in half, with one serving as the input data (blue) and the other as target data (red). Normalization by the other coil's sensitivities is performed after the network to ensure proper scaling. An MSE loss function between the normalized target ($\boldsymbol{y}'$) and reconstruction ($\hat{\boldsymbol{x}}'$) is used to update the parameters of CDLNet (Θ) via stochastic gradient descent and back-propagation.

Results

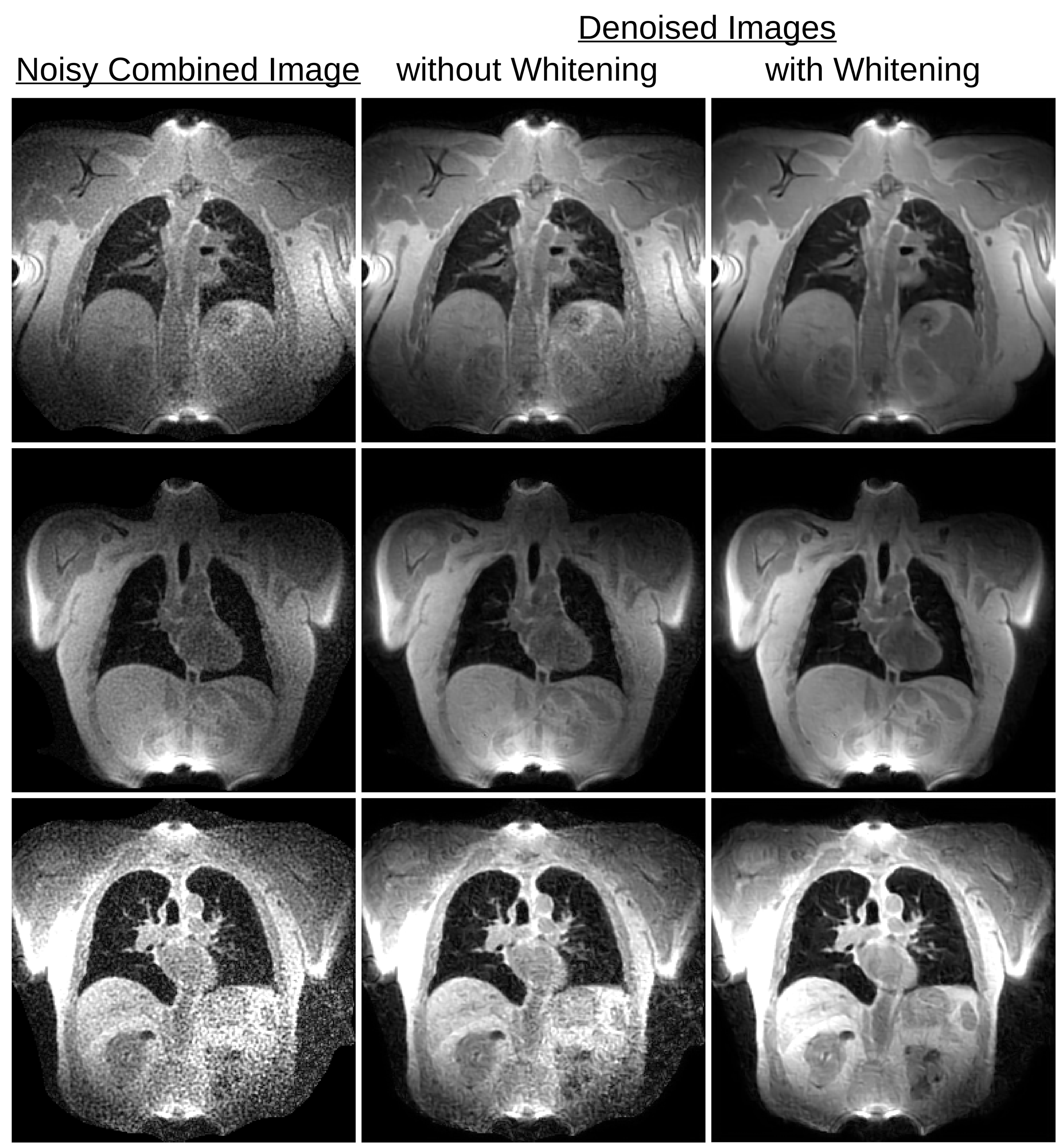

Figure 5. Successful denoising of LFMR images without ground-truth data via Complex Coil2Coil Loss training. Coil whitening preprocessing improves denoising performance.

Conclusion

- Self-supervised training techniques (Coil2Coil) can be extended to the low-SNR regime by leveraging complex-valued data.
- Coil whitening preprocessing greatly improves denoising.
- Quantitative (synthetic noise) study needed to further validate methods.

References

- Janjušević, N., et al. "CDLNet: Noise-Adaptive Convolutional Dictionary Learning Network for Blind Denoising and Demosaicing," IEEE OJSP (2022).
- Park, J., et al. "Coil2Coil: Self-supervised MR image denoising using phased-array coil images." arXiv (2022).

https://nikopj.github.io | Grant Acknowledgements: R01EB031083

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