Self-Supervised Low-Field MRI Denoising via Spatial Noise Adaptive CDLNet

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Purpose: Recent years have seen a growing interest in Low-Field MRI machines due to continued advancement in hardware, novel successes of machine-learning reconstruction, and greater overall accessibility of LFMRI machines [1]. LFMRI often necessitates averaging multiple fully sampled k-space acquisitions to obtain a signal of sufficiently high SNR. To accelerate acquisition, this averaging may be reduced or foregone, with detriment to SNR. In multi-coil setups, the corresponding image-domain reconstruction often exhibits a spatially varying noise-level due to the uniform noise-levels observed in each coil contributing to the coil-combined image via a spatially varying sensitivity map. These coil noise-levels and sensitivity maps can be estimated from the acquisition to produce an estimated spatially varying noise-level map for the coil-combined image. Deep-learning methods are well suited for tackling such a spatially varying denoising problem by implicitly learning signal and noise distribution specifics in a data-driven fashion. This work proposes a novel deep-learning framework for removing spatially varying image noise from coil-combined noisy LFMR images, without ground-truth labels. We consider our observations to be generated from some random process with a spatially varying noise-level, $\boldsymbol{y} \sim \mathcal{N}(\boldsymbol{x},\ \mathbf{diag}(\boldsymbol{\sigma}_{\mathrm{map}}))$.

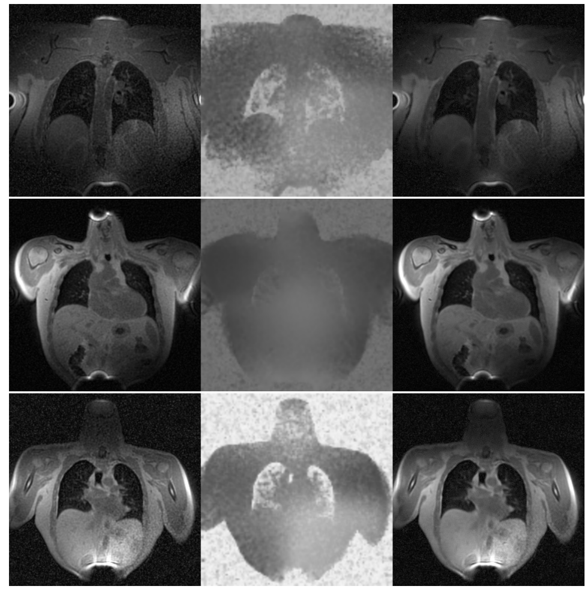

Figure 1: Left: coil-combined magnitude LFMR images. Middle: noise-level maps. Right: CDLNet denoising.

Methods: *The Convolutional Dictionary Learning Network*: The CDLNet denoising architecture [2] has its origins in basis pursuit denoising (BPDN) from the classical wavelet denoising literature, and its layers are defined as a learned iterative thresholding: $\boldsymbol{z}^{(k+1)} = \boldsymbol{T}^{(k)}\left(\boldsymbol{z}^{(k)};\ \boldsymbol{y}, \boldsymbol{\sigma}_{\mathrm{map}}, \theta^{(k)}\right)$ for K layers, where $\boldsymbol{z}^{(k)}$ is a subband latent representation and the final denoising is given by a synthesis convolutional dictionary, $\hat{\boldsymbol{x}} = f_{\Theta}(\boldsymbol{y}, \boldsymbol{\sigma}_{\mathrm{map}}) = \boldsymbol{D}\boldsymbol{z}^{(K)}$. CDLNet can tune its denoising strength at inference by augmenting the input noise-level map, as shown in Figure 2.

MCSURE Denoising: For observations contaminated by AWGN, Stein's Unbiased Risk Estimator (SURE) offers an approximation to the mean-squared error metric in the absence of ground-truth data. A Monte-Carlo approach is required to use SURE in practice [2]. This work adapts the MCSURE loss for a spatially varying noise-power to train a CDLNet denoiser in a self-supervised manner. We increase the diversity of training samples by augmenting the original noisy images $\boldsymbol{y}$ with additional AWGN from their original spatial distribution, i.e. $\tilde{\boldsymbol{y}} \sim \mathcal{N}(\boldsymbol{y},\ \alpha\boldsymbol{\sigma}_{\mathrm{map}})$ with $\alpha \sim \mathcal{U}(0, a)$. This presents the network with a wider range of noise-levels during training, which we observe as beneficial for training. The network is trained from augmented samples via the MCSURE loss, $\min_{\Theta} \sum_{\boldsymbol{y}\sim\mathcal{D}} \mathrm{MCSURE}(\boldsymbol{y},\ f_{\Theta}(\tilde{\boldsymbol{y}}, (1+\alpha)\boldsymbol{\sigma}_{\mathrm{map}}); (1+\alpha)\boldsymbol{\sigma}_{\mathrm{map}})$.

Results: Preliminary results were obtained on an unlabeled dataset of 0.55T LFMR lung images containing with a total 39 samples. A CDLNet model was trained via the self-supervised MCSURE scheme described for the denoising of complex-valued coil-combined images, with noise-level maps pre-estimated from the data. Qualitative results in Figure 1 demonstrate the learned network is able to maintain details seen in high SNR image regions while employing a stronger denoising on low SNR image regions (see Fig. 1).

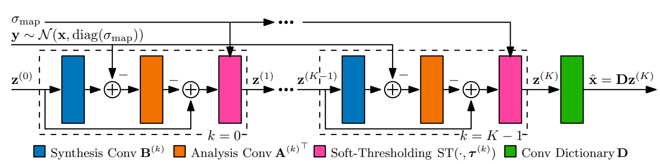

Figure 2: Block diagram of CDLNet.

Discussion and Conclusion: This work proposes a self-supervised learning scheme (based on the MCSURE loss) for removing spatially varying noise. The proposed method leverages the noise-adaptive thresholds of a convolutional dictionary learning based deep-denoiser to perform a spatially varying denoising. However, the results show undesired noise is not completely removed, and some anatomical structures are unnecessarily blurred from the denoising. This may be due to imperfect noise-level maps obtained from coil sensitivity map estimation on the original noisy samples. Future work will consider leveraging a mixture of coil-combined measurement data and individual coil data, as well as noise-level map refinement, to achieve more balanced spatially varying noise-removal results.

[1] M. Hori, A. Hagiwara, M. Goto, A. Wada, and S. Aoki, "Low-field magnetic resonance imaging: Its history and renaissance," *Invest. Radiol.*, vol. 56, no. 11, pp. 669–679, Nov. 2021.

[2] N. Janjušević, A. Khalilian-Gourtani, and Y. Wang, "CDLNet: Noise-adaptive convolutional dictionary learning network for blind denoising and demosaicing," *IEEE Open Journal of Signal Processing*, vol. 3, pp. 196–211, 2022.