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LANTERN: learn analysis transform network for dynamic magnetic resonance imaging.
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Summary: This paper proposes to learn analysis transform network for dynamic magnetic resonance imaging (LANTERN). Integrating the strength of CS-MRI and deep learning, the proposed framework is highlighted in three components: (i) The spatial and temporal domains are sparsely constrained by adaptively trained convolutional filters; (ii) We introduce an end-to-end framework to learn the parameters in LANTERN to solve the difficulty of parameter selection in traditional methods; (iii) Compared to existing deep learning reconstruction methods, our experimental results show that our paper has encouraging capability in exploiting the spatial and temporal redundancy of dynamic MR images. We performed quantitative and qualitative analysis of cardiac reconstructions at different acceleration factors ($2\times$ - $11\times$) with different undersampling patterns. In comparison with two state-of-the-art methods, experimental results show that our method achieved encouraging performances.

MSC:

- [78A46](#) Inverse problems (including inverse scattering) in optics and electromagnetic theory
- [78A70](#) Biological applications of optics and electromagnetic theory
- [78-05](#) Experimental work for problems pertaining to optics and electromagnetic theory
- [78M50](#) Optimization problems in optics and electromagnetic theory
- [65K10](#) Numerical optimization and variational techniques
- [65T50](#) Numerical methods for discrete and fast Fourier transforms
- [68T07](#) Artificial neural networks and deep learning
- [92C55](#) Biomedical imaging and signal processing
- [68U10](#) Computing methodologies for image processing

Keywords:

dynamic MR imaging; deep learning; CS-MRI

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