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Physics-Driven Machine Learning for Computational Imaging

Recent years have witnessed a rapidly growing interest in next-generation imaging systems and their combination with machine learning. While model-based imaging schemes that incorporate physics-based forward models, noise models, and image priors laid the foundation in the emerging field of computational sensing and imaging, recent advances in machine learning, from large-scale optimization to building deep neural networks, are increasingly being applied in modern computational imaging. A wide range of machine learning techniques can be applied to enhance the effectiveness and efficiency of computational imaging systems, thus redefining state-of-the-art computational imaging algorithms.

Physics-driven machine learning has become an integral part of computational imaging

In contrast to traditional imaging methods, in which images are directly captured by the sensing device, computational imaging involves an imaging system in which computation plays a vital role in the image formation process. In particular, computational imaging can exploit the underlying physics of the imaging modality and domain knowledge, which needs to be exploited and combined with various data-driven approaches to benefit the imaging process from sensing or data acquisition to image reconstruction. There are compelling challenges for such interdisciplinary research that remain to be addressed, ranging from modeling and machine learning algorithm development and developing provable guarantees to novel imaging applications.

The main focus of this special issue of *IEEE Signal Processing Magazine* is on recent developments in physics-driven machine learning techniques that can be applied for computational imaging. Ten articles selected from the original 47 submissions are accepted in this issue, covering key theoretical topics ranging from model-based methods, such as sparse and low-rank representations and phase retrieval, to more advanced physics-informed deep learning, such as plug and play, generative models, and unrolling-based image reconstruction. Thanks to the tremendous interest from the research community, there are also many contributions for interesting applications, which will be published in the second volume of the special issue in March.

The survey and tutorial-style articles in this January special issue aim to overview the theoretical frameworks of recently proposed physics-driven learning methods, which lay the foundation for potential imaging applications. Furthermore, this issue promotes the theoretical aspect of algorithms for computational imaging, including convergence guarantees, model analysis, and so on, which are critical for reliable and interpretable computational imaging systems.

The first two articles focus on physics-driven learning methods based on shallow image models. Specifically, [A1] by Zha et al. provides an overview of the learning methods based on low-rank and group sparse models used in compressed sensing and imaging applications. A unified optimization framework for incorporating these model-based methods is demonstrated via a short tutorial, leading to various open problems and future directions in the field. The next article, [A2] by Dong et al. is a contemporary review of the phase retrieval problem from computational imaging to machine learning perspectives. It provides a useful and accurate taxonomy describing the four common forms of the phase retrieval problem: Fourier phase retrieval, coded illumination, coded detection, and random measurement matrices. It further describes the various algorithms and their use cases. It also highlights recent theoretical results on recovery guarantees.

This issue then discusses unrolling-based methods for deep imaging tasks in [A3] by Zhang et al. Here, the authors review several learned unrolled networks that are inspired by algorithms, such as the alternating direction method of multipliers, the iterative shrinkage/thresholding algorithm, and approximate message passing. They then discuss additional schemes under "beyond deep

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unrolling" that address some drawbacks of conventional unrolling methods by providing robust performance with different measurement operators or tackling the inefficiencies in information transmission in stage-by-stage unrolling. The authors conclude by discussing recent trends in the domain. The next article, [A4] by Dong et al. discusses another unfolding scheme under the framework of Bayesian deep learning. A tutorial is presented to summarize the recent advances in this approach, which combines physics-driven imaging models and learning-based priors. The promise of such an approach is demonstrated in several computational imaging applications, such as superresolution and depth map completion.

As a popular scheme for physics-driven learning, [A5] by Kamilov et al. presents how one may use image denoisers to solve general inverse problems by iteratively applying the denoiser together with some additional linear operations. The article discusses the different techniques to perform this. Specifically, it also presents the online form of the approach and the case where multiple denoisers are being used. The physics-driven methods are further surveyed in detail for magnetic resonance imaging in the work [A6] by Hammernik et al. and for full waveform seismic inversion in the work [A7] by Lin et al.

In [A8] by Chen et al. the role of using equivariance in deep learning methods for computational imaging is discussed. It is shown how one may use equivariance properties of problems to improve the design of the neural networks being used.

The article [A9] by Zhao et al. provides an overview of a few generative modeling techniques, such as variational auto-encoder and generative adversarial networks as well as more recent developments in score-based generative models. Through different imaging applications, the article highlights how the generative modeling techniques are effectively combined with the physics of the imaging problem, e.g., the measurement forward model and physical properties of the target objects, to solve inverse problems. In [A10] by Mukherjee et al., the authors specify relevant notions of convergence for data-driven image reconstruction and provide a survey of learned methods with mathematically rigorous reconstruction guarantees. They also offer the possibility to combine the power of deep learning with classical convex regularization theory.

Although the original computational imaging is based on several decades of separate research activities in physics, signal processing, and so on, the recent rapid developments in this field owe to the interdisciplinary collaboration in research in physics, signal processing, machine learning, statistics, and computer vision. This special issue is dedicated to further fostering such collaboration across multiple fields to enable breakthrough developments in imaging.

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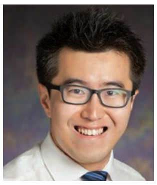
Guest Editors



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Appendix: Related Articles

[A1] Z. Zha, B. Wen, X. Yuan, S. Ravishankar, J. Zhou, and C. Zhu, "Learning nonlocal sparse and low-rank models for image compressive sensing: Nonlocal sparse and low-rank modeling," *IEEE Signal Process. Mag.*, vol. 40, no. 1, pp. 30–42, Jan. 2023, doi: 10.1109/MSP.2022.3217936.

[A2] J. Dong, L. Valzania, A. Maillard, T.-a. Pham, S. Gigan, and M. Unser, "Phase retrieval: From computational imaging to machine learning — A tutorial," *IEEE Signal Process. Mag.*, vol. 40, no. 1, pp. 43–55, Jan. 2023, doi: 10.1109/MSP.2022.3219240.

[A3] J. Zhang, B. Chen, R. Xiong, and Y. Zhang, "Physics-inspired compressive sensing: Beyond deep unrolling," *IEEE Signal Process. Mag.*, vol. 40, no. 1, pp. 56–70, Jan. 2023, doi: 10.1109/MSP.2022.3208394.

[A4] W. Dong, J. Wu, L. Li, G. Shi, and X. Li, "Bayesian deep learning for image reconstruction: From structured sparsity to uncertainty estimation," *IEEE Signal Process. Mag.*, vol. 40, no. 1, pp. 71–82, Jan. 2023, doi: 10.1109/MSP.2022.3176421.

[A5] U. S. Kamilov, C. A. Bouman, G. T. Buzzard, and B. Wohlberg, "Plug-and-play methods for integrating physical and learned models in computational imaging: Theory, algorithms, and applications," *IEEE Signal Process. Mag.*, vol. 40, no. 1, pp. 83–95, Jan. 2023, doi: 10.1109/MSP.2022.3199595.

[A6] K. Hammernik, T. Küstner, B. Yaman, Z. Huang, D. Rueckert, F. Knoll, and M. Akçakaya, "Physics-driven deep learning for computational magnetic resonance imaging: Combining physics and machine learning for improved medical imaging," *IEEE Signal Process. Mag.*, vol. 40, no. 1, pp. 96–112, Jan. 2023, doi: 10.1109/MSP.2022.3215288.

[A7] Y. Lin, J. Theiler, and B. Wohlberg, "Physics-guided data-driven seismic inversion: Recent progress and future opportunities in full-waveform inversion," *IEEE Signal Process. Mag.*, vol. 40, no. 1, pp. 113–131, Jan. 2023, doi: 10.1109/MSP.2022.3217658.

[A8] D. Chen, M. Davies, M. J. Ehrhardt, C.-B. Schönlieb, F. Sherry, and J. Tachella, "Imaging with equivariant deep learning: From unrolled network design to fully unsupervised learning," *IEEE Signal Process. Mag.*, vol. 40, no. 1, pp. 132–145, Jan. 2023, doi: 10.1109/MSP.2022.3205430.

[A9] Z. Zhao, J. C. Ye, and Y. Bresler, "Generative models for inverse imaging problems: From mathematical foundations to physics-driven applications," *IEEE Signal Process. Mag.*, vol. 40, no. 1, pp. 146–161, Jan. 2023, doi: 10.1109/MSP.2022.3215282.

[A10] S. Mukherjee, A. Hauptmann, O. Öktem, M. Pereyra, and C.-B. Schönlieb, "Learned reconstruction methods with convergence guarantees: A survey of concepts and applications," *IEEE Signal Process. Mag.*, vol. 40, no. 1, pp. 162–180, Jan. 2023, doi: 10.1109/MSP.2022.3207451.

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