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Perspectives on the Past, Present, and Future of Astronomical Image Deconvolution

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Abstract. Astronomical image deconvolution has evolved from early linear regularization to modern deep learning approaches. This article provides a concise overview of the historical milestones, methodological breakthroughs, and current challenges in the field, with emphasis on sparsity, compressed sensing, and the role of deep learning in large astronomical surveys.

Keywords. astronomical image deconvolution, sparsity, compressed sensing, deep learning

1. From Early Developments to the Mathematical Era

Image deconvolution seeks to recover an underlying astronomical signal X from blurred and noisy measurements: $Y = HX + N$, where H represents the point spread function (PSF) of the instrument and N denotes noise. The ill-posed nature of this problem means that without additional constraints or priors, the inversion is unstable and non-unique. This difficulty has motivated a long line of methodological innovations, beginning with linear solutions and progressing toward sophisticated nonlinear regularization.

The earliest attempts, developed before 1980, were rooted in linear inverse theory. The Wiener filter, introduced in 1948, provided an optimal linear estimator under Gaussian noise and signal assumptions, but was severely limited by its reliance on second-order statistics. In the 1950s and 1960s, iterative methods such as the Landweber iteration Landweber (1951) and quadratic penalization via Tikhonov regularization Tikhonov et al. (1987) improved stability by balancing fidelity to the data with smoothness constraints. The Richardson-Lucy algorithm Lucy (1974) marked a major advance by introducing a positivity-preserving iterative scheme. Around the same period, maximum entropy methods Frieden (1998) offered a statistical interpretation by favoring solutions with maximum information entropy, ensuring positivity and smoothness. Despite these advances, all of these early approaches struggled with complex astronomical structures where fine features coexist with diffuse emission.

The 1980s brought a significant shift as mathematicians entered the field of deconvolution, introducing powerful new tools for regularization. Total Variation (TV) regularization Rudin et al. (1992) was a landmark contribution. By penalizing the ℓ_1 norm of the image gradient, TV preserved edges while denoising flat regions, a property well suited to astronomical scenes containing both sharp point sources and diffuse nebulosity. The 1990s extended this progress with the emergence of wavelet analysis Meyer (1990). Wavelets provided sparse multiscale representations that could efficiently capture localized features across a range of scales. They became central to astronomical image processing, especially in the correction of early Hubble Space Telescope data, where aberrated images could be substantially improved through wavelet-based deconvolution

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Starck et al. (1995). The combination of statistical regularization, multiscale analysis, and computational algorithms marked the consolidation of a mathematical framework for inverse problems in astronomy Starck and Murtagh (2006). By the end of the 20th century, deconvolution had evolved from heuristic iterative schemes into a rigorous field supported by functional analysis and variational methods.

2. Geometric Representations and Compressed Sensing

In the 2000s, the theory of sparse representation deepened with the introduction of geometric multiscale transforms Mallat (2008); Starck et al. (2015) designed to capture anisotropic and elongated structures. Whereas wavelets were optimal for representing isotropic point-like features, new constructions such as ridgelets or curvelets proved far more efficient for edges, filaments, and curvilinear structures that frequently occur in astrophysical data Starck et al. (2003). This period also coincided with the emergence of compressed sensing Candès (2006); Donoho (2006), a paradigm shift in sampling theory. Compressed sensing established that a signal sparse in an appropriate dictionary could be recovered from a number of random measurements dramatically smaller than its ambient dimension. In formal terms, recovery was possible by solving an ℓ_1 minimization problem,

$$\min_X \|X\|_1 \quad \text{s.t. } Y = HX. \tag{1}$$

This principle had important implications for astronomy Bobin et al. (2008), where instrumental limitations and observing time constrain data acquisition, as for example coded-mask telescopes for gamma-ray imaging or radio interferometry. Proximal algorithms, such as iterative thresholding and forward-backward splitting, became practical tools to implement these reconstructions at scale Combettes and Wajs (2005). The synergy between geometric sparse representations and compressed sensing created a new generation of deconvolution methods, combining theoretical optimality with practical efficiency. By 2015, these techniques were widely adopted in astrophysical imaging, forming a bridge between rigorous mathematical theory and real-world astronomical applications.

3. The Deep Learning Era

The mid-2010s marked a paradigm shift with the arrival of deep learning. Convolutional neural networks, and in particular the U-Net architecture, provided powerful nonlinear mappings that implicitly captured sparsity and multiscale features through their layered design Ronneberger et al. (2015). Unlike traditional variational approaches, these methods learned effective priors directly from data, enabling unprecedented performance in tasks such as galaxy image deconvolution Nammour et al. (2022). Hybrid strategies have also been developed, where physical modeling is retained in a linear inversion step, followed by neural network-based denoising. Other approaches include unrolled optimization networks, generative adversarial networks, and Bayesian deep inversion frameworks.

Beyond raw performance, deep learning has been applied to specific astrophysical contexts. Weak lensing mass maps have been reconstructed with higher fidelity than Wiener filtering using architectures such as DeepMass Jeffrey et al. (2020).. Probabilistic extensions have enabled uncertainty quantification using Bayesian sampling techniques Remy et al. (2023) or conformalized regression to estimate credible intervals on recovered structures Leterme et al. (2025).

Physics-informed networks have further bridged the gap between black-box learning and forward modeling, integrating differentiable optics and PSF descriptions directly into the network design. These applications underscore the diversity of deep learning strategies, from supervised end-to-end learning to hybrid physics-aware models Liaudat et al. (2023).

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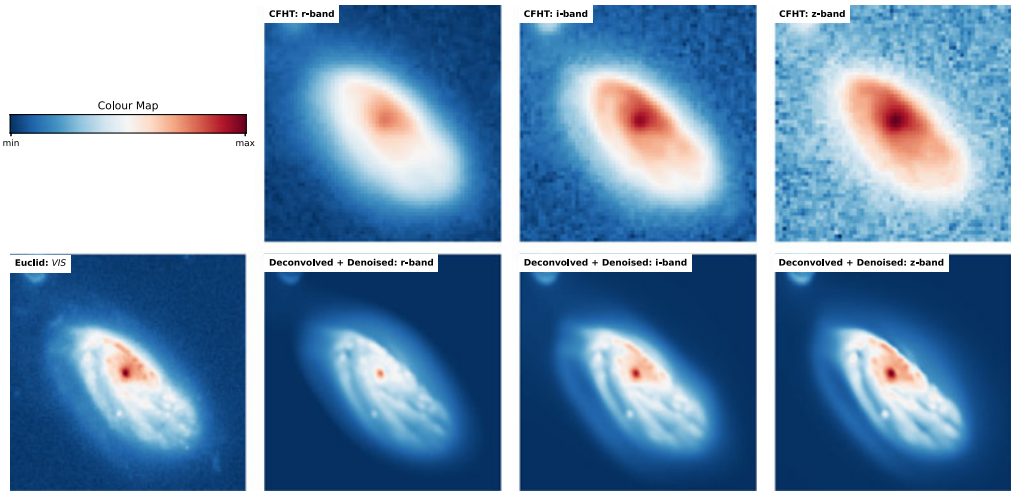


Figure 1. Joint multiband deconvolution of an extended galaxy from the Perseus cluster. The top row shows the input $0.2''$ CFHT images in the r, i, and z bands, with the corresponding deconvolved-and-denoised outputs shown directly below. The $0.1''$ Euclid image is included at the bottom left for visual comparison. The images demonstrate the method's impressive performance and generalization, showing successful recovery of high-frequency details like spiral arms and accurate preservation of color variations across different photometric bands. Image credit: Utsav Akhaury.

Despite their success, deep learning approaches face important challenges. Their generalization across instruments and noise regimes is limited, raising concerns about robustness in large surveys. They can also be unstable, with small perturbations in the input producing spurious artifacts, or even hallucinating features that appear realistic but lack physical basis. These issues highlight the tension between realism and physical consistency, and motivate ongoing research into more interpretable neural architectures such as Learnlets Akhaury et al. (2022) or SUNet Akhaury, U. et al. (2024).

4. Conclusions and Perspectives

An example of deconvolved and denoised galaxy with extended features is shown in Fig. 1. The results demonstrate that the method performs impressively on the CFHT images and generalizes extremely well. It successfully recovers high-frequency details, such as spiral arms, and accurately captures the colour gradients from one photometric band to another.

Deep learning techniques are now being integrated into the data processing pipelines of major astronomical projects such as the Dark Energy Survey (DES), Hyper Suprime-Cam (HSC), Euclid, and Rubin/LSST. Joint multiband deconvolution methods leveraging Euclid and Rubin data demonstrate the potential of combining physical priors, spectral energy distributions, and machine learning for high-precision galaxy shape and photometry measurements Akhaury, U. et al. (2025). These efforts show that deep learning is transitioning from experimental tests to production-level tools in survey pipelines.

The trajectory of astronomical deconvolution reflects a continuous shift in methodology: from linear regularization to nonlinear variational methods, from multiscale sparse representations to compressed sensing, and now to deep learning. While neural networks deliver state-of-the-art performance, they also introduce new questions regarding robustness, interpretability, and trustworthiness. Future research must address these limitations while also grappling with scalability for petabyte-scale datasets and the potential role

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of foundation models for inverse problems. The challenge ahead is to strike a balance between high performance and methodological frugality. Ultimately, the integration of physics-based models, sparse priors, and deep architectures promises a new generation of deconvolution methods adapted to the demands of 21st-century astronomy.

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