Algorithm unrolling, which bridges model-based optimization and data-driven deep learning, has emerged as a powerful paradigm for designing neural networks with improved performance and interpretability. By mapping the iterations of classical optimization algorithms onto network layers, unrolled architectures not only achieve competitive results across diverse computer vision tasks but also provide insight into the underlying mechanisms—an aspect often lacking in conventional deep learning models.

This thesis develops a unified framework based on convolutional sparse coding (CSC) and algorithm unrolling, in which each iteration of a sparsity-regularized optimization algorithm is mapped to a learnable network layer. Unlike existing CSC-based unrolling networks, which are limited to ℓ_1 regularization and two-dimensional images, our proposed framework supports ℓ_0 or ℓ_1 regularization, three-dimensional data, and channel-specific modeling, enabling principled and flexible network design for diverse vision tasks.

The effectiveness of the proposed framework is demonstrated on three computer vision tasks: multi-modal image fusion (MMIF), hyperspectral unmixing (HSU), and underwater image enhancement (UIE). For MMIF, an interpretable fusion network (FNet) is designed based on an ℓ_0-regularized multi-modal CSC formulation. An inverse fusion network (IFNet) is further introduced to improve the training of FNet in the absence of ground-truth fused images. The use of ℓ_0 regularization allows preservation of salient features and contrast in the fused output images. For HSU, a three-dimensional CSC-based unrolled network (3DCSCNet) is developed within an autoencoder framework, where a 3D sparse coding block jointly captures spatial–spectral correlations in hyperspectral data cubes, together with a projected simplex volume maximization algorithm for endmember initialization. For UIE, a color channel-specific CSC model is unrolled to construct a sparsity-driven interpretable network (SINET) that explicitly accounts for wavelength-dependent degradation and enhances underwater images with improved color fidelity.

Extensive experimental evaluations on multiple benchmark datasets demonstrate that the proposed methods consistently outperform state-of-the-art techniques in terms of both quantitative metrics and qualitative visual quality. Overall, this thesis establishes sparsity-driven deep unrolling as a powerful and unifying paradigm for designing neural networks for diverse computer vision tasks.