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研究拓展及知识转移处 RESEARCH DEVELOPMENT AND KNOWLEDGE TRANSFER OFFICE

GUANGDONG AND HONG KONG UNIVERSITIES

"1+1+1" Joint Research Collaboration Scheme

粵港高校「1+1+1」聯合資助計劃

A Study on Deep Learning Methods for Inverse Scattering Problems

Guangdong and Hong Kong Universities "1+1+1" Joint Research Collaboration Scheme

Principal Investigators: Yuliang Wang, Jun Fan

Project Overview

Inverse scattering is widely used in medical imaging, geophysical exploration, and nondestructive testing, but traditional methods often suffer from nonlinearity, ill-posedness, and noise sensitivity. This project develops a physics-informed deep learning framework for inverse scattering, combining mathematical modeling with data-driven methods to improve reconstruction accuracy, efficiency, robustness, and interpretability. By incorporating tailored neural architectures, multi-frequency strategies, Bayesian inference, and uncertainty quantification, the project aims to provide both theoretical support and practical solutions for complex inverse scattering problems.

Research Achievements

Inverse Reconstruction

Develop high-accuracy reconstruction methods that couple physical priors, numerical methods, and deep learning under sparse, limited-aperture, and ill-posed observation settings.

A two-stage framework was developed for limited-aperture grating reconstruction, where a dual-branch cross-attention network first recovers missing data and a Newton-type method then reconstructs the profile with high robustness.

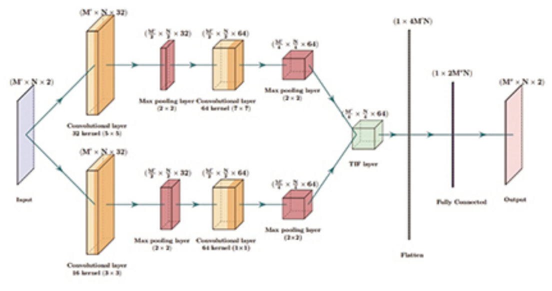


Figure 1: The illustrations of network architecture.

A Fourier-based physics-informed method was combined with a U-Net to achieve robust inverse source reconstruction from sparse far-field data, with strong performance under high noise and incomplete low-frequency information[1].

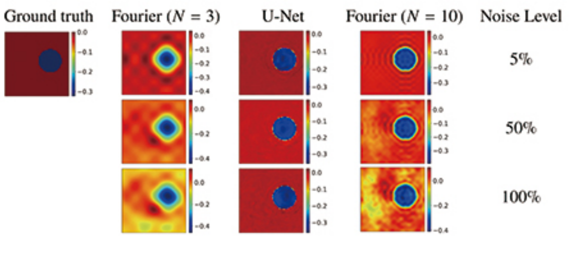
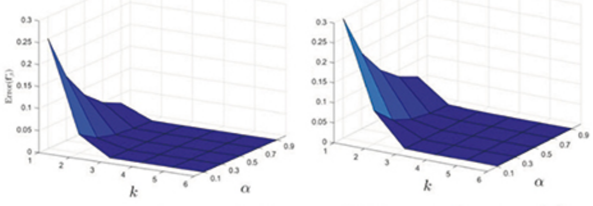


Figure 2: Reconstruction results for disk sources under 5%, 50%, and 100% noise levels.

An efficient matching Schur complement preconditioning technique was developed for time-fractional diffusion inverse source problems, establishing size and regularization independent linear convergence of the PCG solver and enabling stable, efficient inversion for ill-conditioned systems under noisy data[2].



(a) $\delta = 10^{-3},\ \beta = \epsilon^{k/2}$ (b) $\delta = 10^{-4},\ \beta = \epsilon^{k/2}$

Figure 3: The surface plots of Error.

Theoretical Foundations

Provide interpretable error analysis and expressive support for deep models in inverse problems from the perspectives of approximation theory, generalization theory, and operator learning.

- The adaptive approximation and estimation ability of deep neural networks was analyzed, showing that they can accommodate nonuniform function regularity and nonuniform data distributions[3].
- Approximation and generalization theory was developed for neural operators with prescribed structures, clarifying how differentiability and operator design influence learning performance[4].

Structural Representation

Explore structural recovery, low-rank modeling, and feature extraction for incomplete, degraded, and high-dimensional observations, providing stable information representations for complex inverse problems.

- A deep low-rank tensor representation framework was developed for recovering degraded multi-dimensional data, improving the preservation of intrinsic structure in complex observations[5].

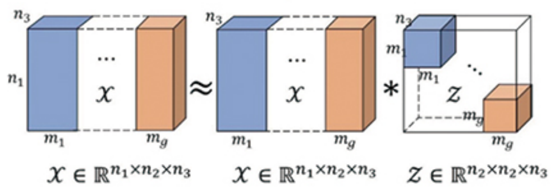


Figure 4: Illustration of tensor self-representation.

- A PCA-based model was proposed to recover surfaces from incomplete point clouds by extracting local geometric information and using it as structural regularization[6].
- An unsupervised feature selection method was designed to preserve both global distributional information and local structural information while reducing redundancy in high-dimensional data[7].

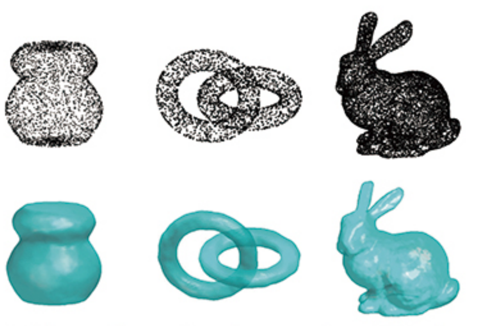


Figure 5: Three-dimensional examples of Surface Reconstruction from Incomplete Point Clouds.

Publications and Projects

References

[1] Chen H, Chang Y, Guo Y, et al. A deep learning-enhanced fourier method for the multi-frequency inverse source problem with sparse far-field data[J]. Communications in Computational Physics, accepted, 2026.
[2] Lin X, Ke R, Hon S Y, et al. A matching schur complement preconditioning technique for a discrete time fractional diffusion inverse source problem[J]. Journal of Scientific Computing, 2026, 106(2): 37-60.
[3] Liu H, Cheng J, Liao W. Deep neural networks are adaptive to function regularity and data distribution in approximation and estimation[J]. Journal of Machine Learning Research. 2025;26(213):1-56.
[4] Cheng K, Fan J, Song L, et al. Learning fréchet differentiable operators via prespecified neural operators[J]. Applied and Computational Harmonic Analysis, 2026, 84: 101878.
[5] Yang G W, Yang L, Jiang T X, et al. DELTA: deep low-rank tensor representation for multi-dimensional data recovery[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2026, 48(3): 3018-3035.
[6] Liu H. A PCA based model for surface reconstruction from incomplete point clouds[J]. SIAM Journal on Imaging Sciences, 2026, 19(1): 1-34.
[7] Cao C, Zhang Y, Ai Y, et al. Unsupervised feature selection via unifying distribution alignment and structure preservation[J]. Information Fusion. 2025, 26:103544.

And including the results highlighted above, the project produced 10 SCI papers.

Projects

[1]王玉亮.高温合金材料的数学机理建模与高性能计算驱动优化设计（课题：材料高分辨率表征和高效参数反演算法,国家自然科学基金委员会,国家重点研发计划, 2025.12-2030.11.

[2] Hao Liu. A Framework for Mathematical Model-Guided Deep Neural Networks in Image Processing. Research Grants Council of Hong Kong, General Research Fund, 2026.01.01-2028.12.31.