One Stone Three Birds: Three-Dimensional Implicit Neural Network for Compression and Continuous Representation of Multi-Altitude Climate Data

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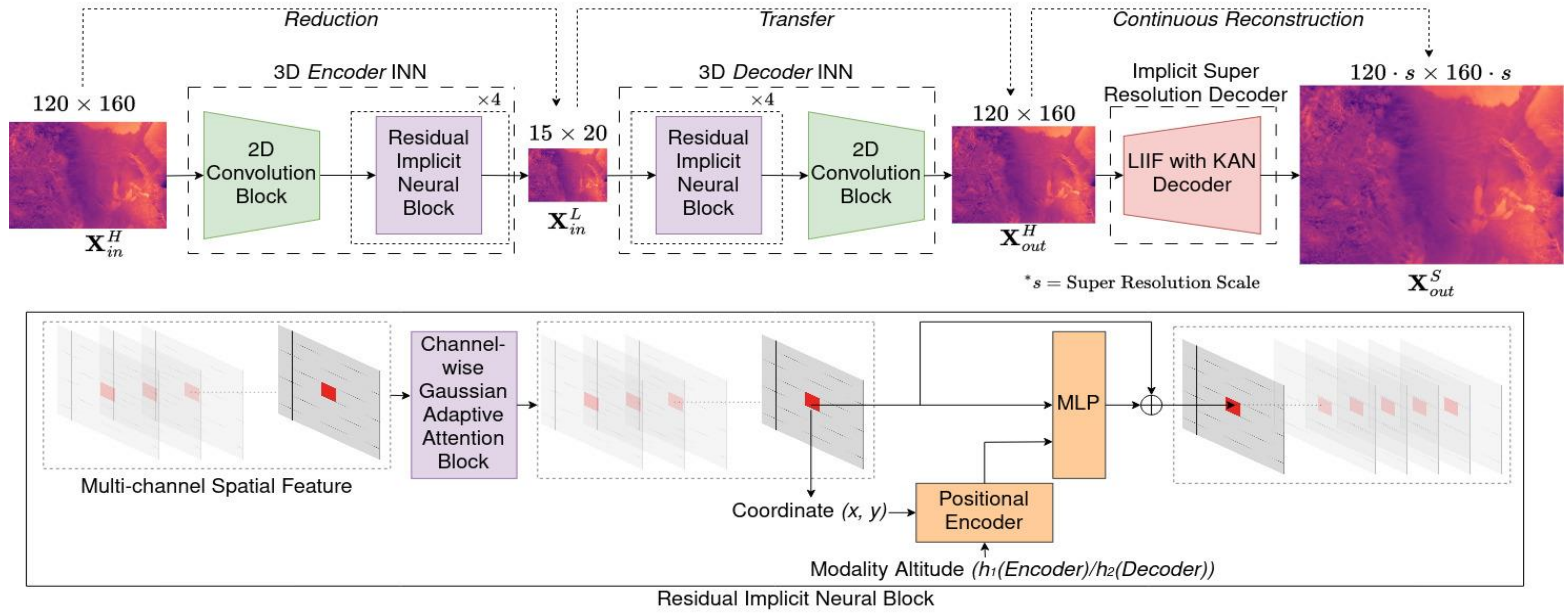

Figure 1. Overview of the proposed method, which jointly enables (a) data reduction, (b) transfer across modalities, and (c) continuous representation and arbitrary-scale super resolution.

Motivation

Wind energy stands out as a promising clean and renewable energy alternative, not only for its potential to combat global warming but also for its capacity to meet the ever-growing demand for energy. However, analysis of wind data to fully harness the benefits of wind energy demands tackling several related challenges:

- **Resolution**: Identifying the most suitable sites for wind turbines necessitates data with high resolution. However, most wind farm simulations do not achieve this resolution, limiting our capacity to enhance the efficiency of wind energy farms.
- **Data Storage**: As the granularity of simulated data and the accumulation of field measurements increase, the resulting growth in data size requires advanced storage solutions.
- **Generalization**: Setting up wind measurement stations in specific locations can be challenging due to the high costs of transportation and maintenance. This necessitates cross-altitude inference, such as estimating high-altitude wind speeds from ground-level measurements.

Problem Statement

We aim to achieve *simultaneous* data dimension reduction and cross-altitude continuous reconstruction of a particular data instance. Our goal is to design a model capable of pertaining the following tasks (kill three birds):

- **Bird 1.Data Dimensionality Reduction**: Reduce the dimensionality of input data at one altitude.
- **Bird 2.Continuous Reconstruction:** Reconstruct the data in a continuous domain from reduced dimensional format.
- **Bird 3.Cross-Altitude Reconstruction:** Perform the reconstruction in a cross-altitude manner (input data altitude ≠ target data altitude).

OSTB (One Stone Three Bird)

Simultaneous Dimension Reduction & Continuous Reconstruction

We propose an encoder–decoder (transfer)--decoder(continuous reconstructor) framework, comprises three primary components:

- **Encoder**: The three-dimensional implicit neural network that encodes the discrete input data at altitude of input modality to a low-dimensional representation.
- **Decoder (Transfer):** The three-dimensional implicit neural network that transforms the discrete low-resolution representation of the input altitude into the discrete high-resolution representation of the target altitude.
- **Decoder (Continuous Reconstructor):** The implicit continuous decoder that utilizes the altitude-transferred discrete high-resolution representation to predict wind data at specific coordinate.

Figure 1 summarizes the proposed **OSTB** model.

Experiment

Dataset: National Renewable Energy Laboratory's Wind Integration National Database (WIND) Toolkit provides high spatial and temporal resolution wind power, wind power forecasting, and meteorological data for over 126,000 locations across the continental United States during a 7-year span [1].

Baselines: Due to the lack of existing methodologies for simultaneous dimension reduction and reconstruction through super-resolution, we use the following three methods as baselines:

- **MAINN (Multi-Altitude Implicit Neural Network)**: Multi-altitude simultaneous reduction and continuous reconstruction through multi-modal implicit neural network [2].
- **GINO (Geometry Informed Neural Operator)**: Bicubic downscaling followed by Geometry-Informed Neural Operator (GINO) [3].
- **WindLaw**: We used the wind power law $(v_1/v_2) = (h_1/h_2)^{\alpha}$ with our proposed OSTB model. We eliminated the *3D Decoder INN* and trained 4 different models for 4 altitudes, and then used the wind power law for cross-altitude prediction.

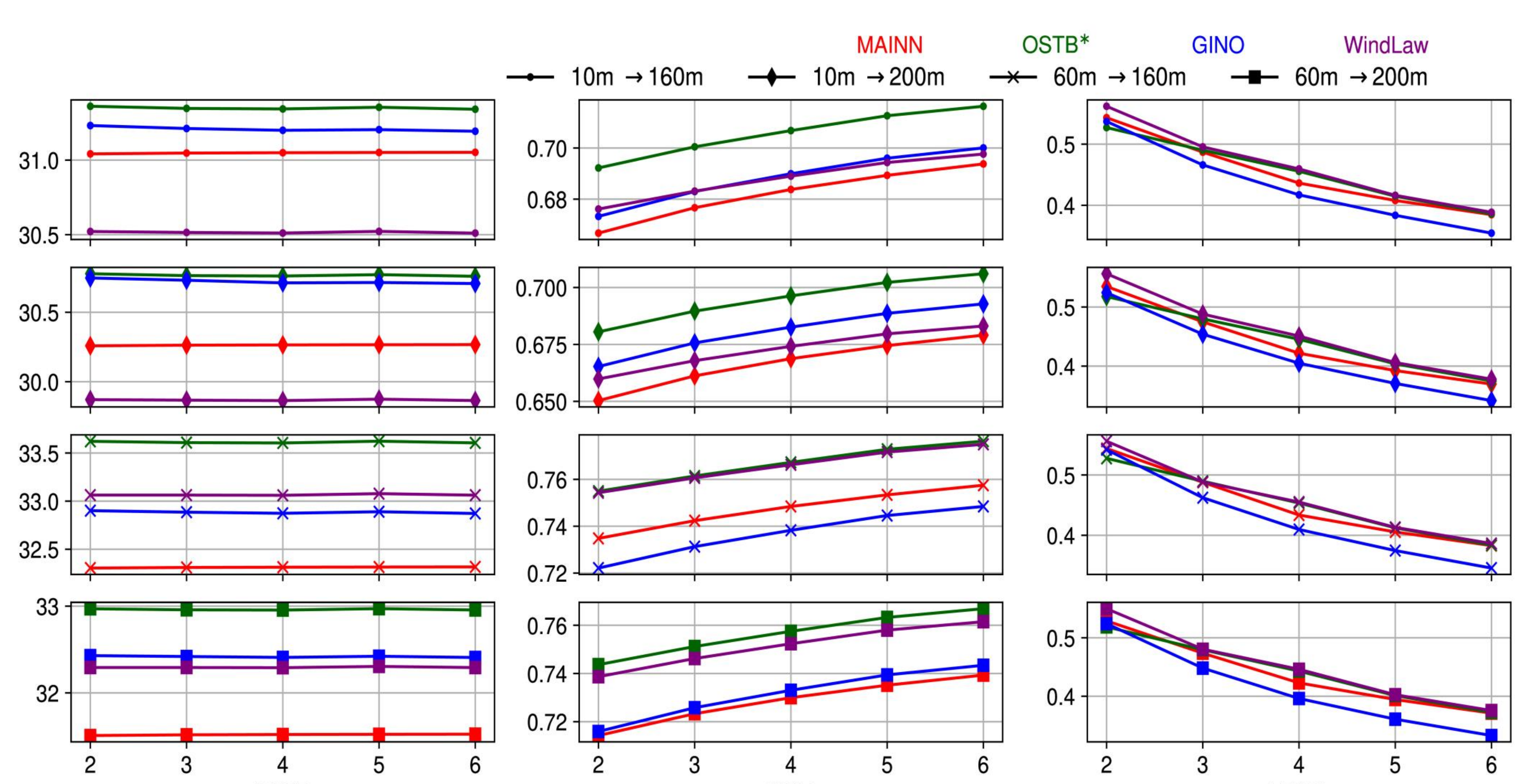

Figure 2: Comparative Results with Baselines. x−axis shows different super resolution scales for all three subplots.

Reference

[1]. C. Draxl, A. Clifton, B.-M. Hodge, and J. McCaa. The wind integration national dataset (WIND) toolkit. Applied Energy, 151:355–366, 2015. ISSN 0306-2619.
[2]. A. B. A. Qayyum, X. Luo, N. M. Urban, X. Qian, and B.-J. Yoon. Implicit neural representations for simultaneous reduction and continuous reconstruction of multi-altitude climate data. In 2024 IEEE 34th International Workshop on Machine Learning for Signal Processing (MLSP), pages 1–6, 2024.
[3]. Z. Li, N. Kovachki, C. Choy, B. Li, J. Kossaifi, S. Otta, M. A. Nabian, M. Stadler, C. Hundt, K. Azizzadenesheli, et al. Geometry-informed neural operator for large-scale 3d pdes. Advances in Neural Information Processing Systems, 36, 2024.