Multiple Frame Splicing and Degradation Learning for Hyperspectral Imagery Super-Resolution

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Recent problem

Hyperspectral imagery (HSI) suffers from low spatial resolution due to hardware and imaging conditions, limiting object detection. Existing super resolution methods are either imprecise or require additional data, not addressing multiple degradation sources.

New Method

A novel framework employing a multiple frame splicing strategy and incorporating multiple HSI degradation models to enhance super resolution quality and reflect real-world scenarios.

Technical Innovations

An end-to-end super resolution network that simplifies processing by using same-size low-resolution inputs for high-resolution outputs, improving clarity, accelerating training, and handling various degradation types, outperforming existing methods.

Data set

Three public datasets: CAVE, Chikusei, and Pavia Centre.

Multiple Frame Splicing Strategy

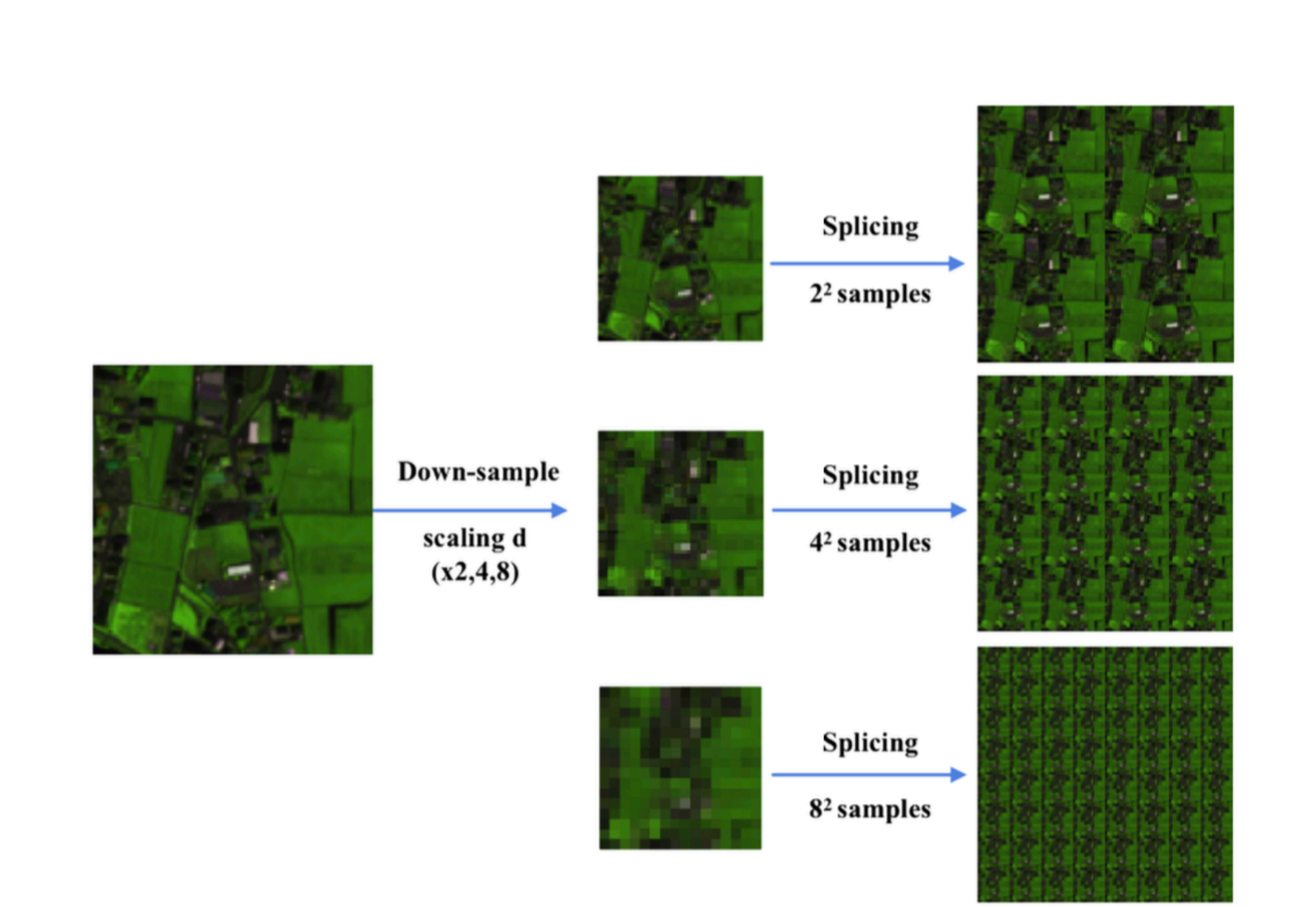
main method

- **Objective**: The multi-frame splicing strategy aims to increase the richness of the input information by combining multiple low-resolution images together

- **Implementation**: multiple low-resolution images are obtained by **downsampling** the high-resolution HSI. Then, these low-resolution images are spliced together in a certain manner to form a collection of low-resolution images

Multiple Frame Splicing Strategy

- For each different downsampling level (i.e. x2, x4, x8), a corresponding number of LR image samples are generated, and then these samples are spliced (or called combined) to form a larger LR image collection,



Multiple Degradation Learning Strategy

Main method

- **Objective**: a single degradation model may not be able to effectively simulate these complex degradation processes. Therefore, this strategy aims to better adapt and recover the real degraded HSI by learning multiple models of HSI degradation.

- **Implementation:** By introducing a variety of different degradation models (such as Gaussian blur, additive noise, PCA compression, etc.), different degradation processes are applied to each low-resolution image to form multiple degraded low-resolution images. These degraded images are used to train the MFSDM model

Multiple Degradation Learning Strategy

- The original high-resolution image first undergoes different degradation processes, such as blur, noise, and their combinations (such as blur+noise (B+N) and blur+noise+compression (B+N+C))). These degradation processes simulate the degradation of image quality that occurs in the real world due to a variety of factors.
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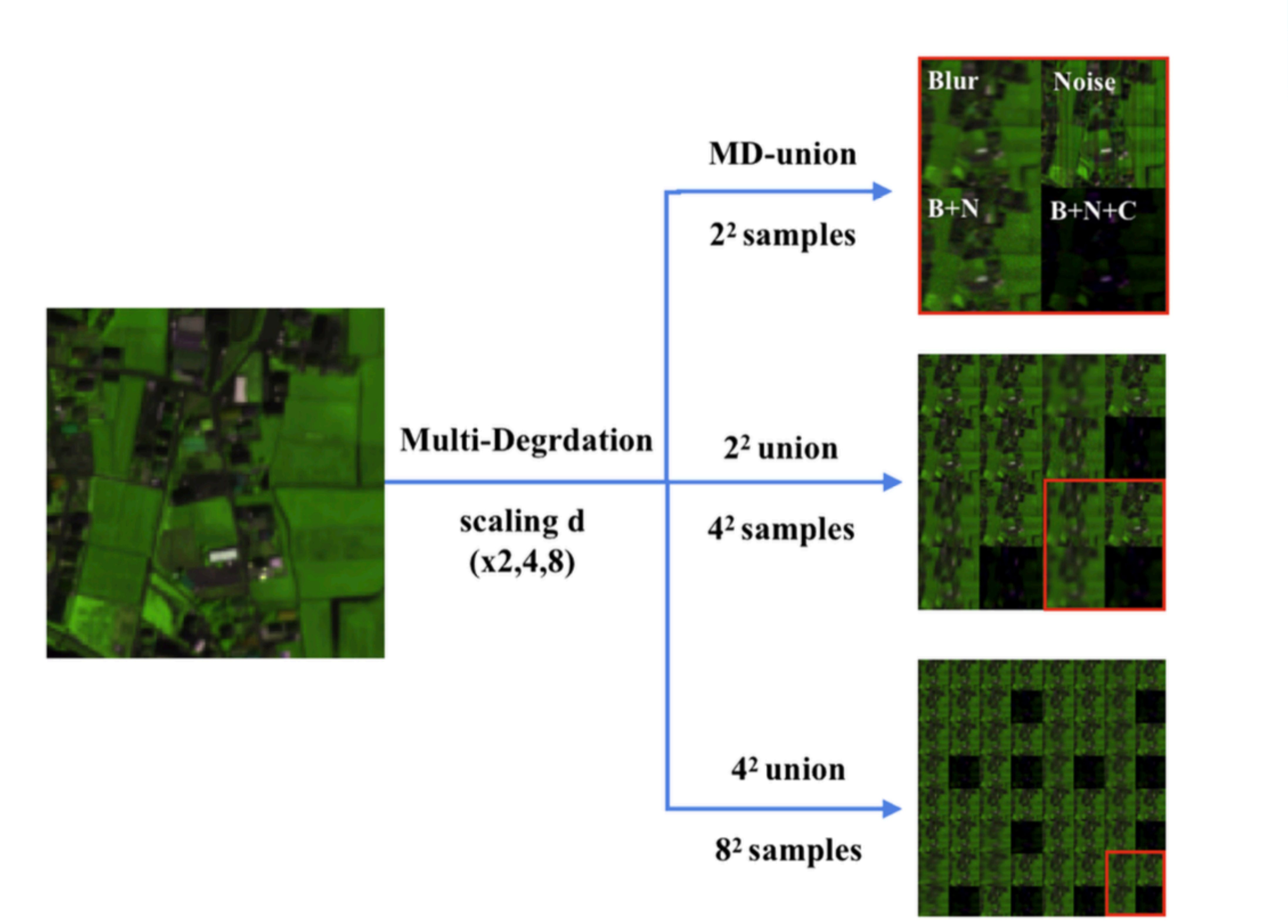
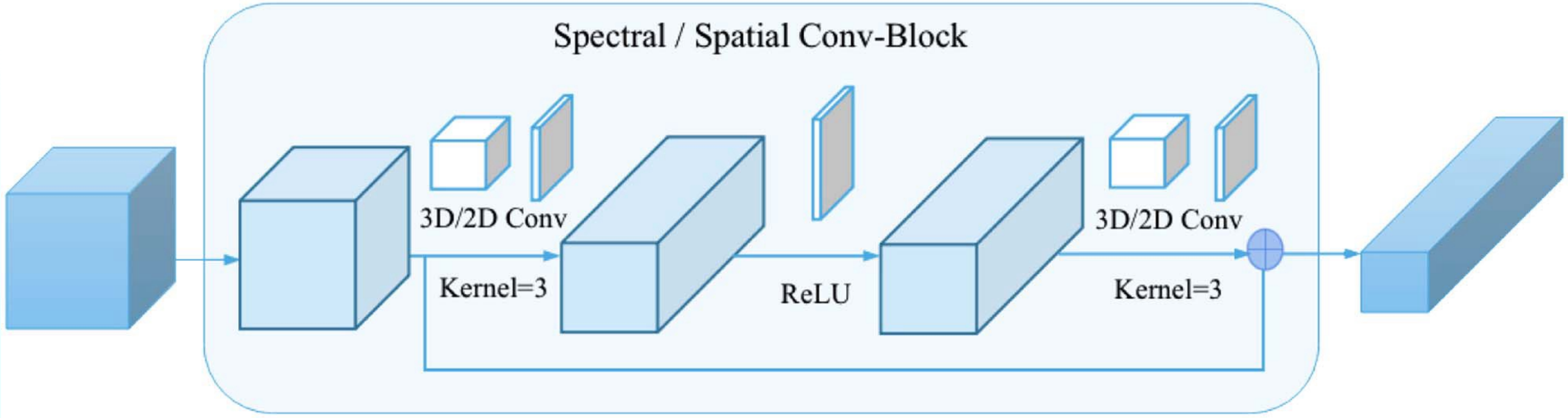


SR network

- The MFSDM algorithm is implemented through an end-to-end super-resolution network. This network not only integrates the above-mentioned multi-frame splicing and multiple degradation learning strategies, but also optimizes the network structure, removes the complex attention residual model, and simplifies the upsampling process. The input of the network is a collection of multi-frame spliced low-resolution images, and the output is the restored high-resolution HSI.



Result

- Demonstrated superior SHSR index and clearer visualization SR outputs on three public hyperspectral datasets, matching Full High Spatial Resolution (FHSR) performance, validating the effectiveness of the strategies.