

# Content-Adaptive Non-Local Convolution for Remote Sensing Pansharpening

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## Abstract

Currently, machine learning-based methods for remote sensing pansharpening have progressed rapidly. However, existing pansharpening methods often do not fully exploit differentiating regional information in non-local spaces, thereby limiting the effectiveness of the methods and resulting in redundant learning parameters. In this paper, we introduce a so-called content-adaptive non-local convolution (CANConv), a novel method tailored for remote sensing image pansharpening. Specifically, CANConv employs adaptive convolution, ensuring spatial adaptability, and incorporates non-local self-similarity through the similarity relationship partition (SRP) and the partition-wise adaptive convolution (PWAC) sub-modules. Furthermore, we also propose a corresponding network architecture, called CANNet, which mainly utilizes the multi-scale self-similarity. Extensive experiments demonstrate the superior performance of CANConv, compared with recent promising fusion methods. Besides, we substantiate the method's effectiveness through visualization, ablation experiments, and comparison with existing methods on multiple test sets. The source code is publicly available at <https://github.com/duanyll/CANConv>.

## 1. Introduction

Due to technological constraints, existing remote sensing satellites can only capture low-resolution multispectral images (LRMS) and high-resolution panchromatic images (PAN). Wherein, LRMS images consist of four, eight, or more channels in different bands, but have low spatial resolution. PAN images usually have  $4\times$  higher spatial resolution, but they are monochromatic and grayscale. Especially, pansharpening in this work involves merging an LRMS image and a PAN image to produce a high-resolution multispectral (HRMS) image, see Fig. 1. Also shown in Fig. 1,

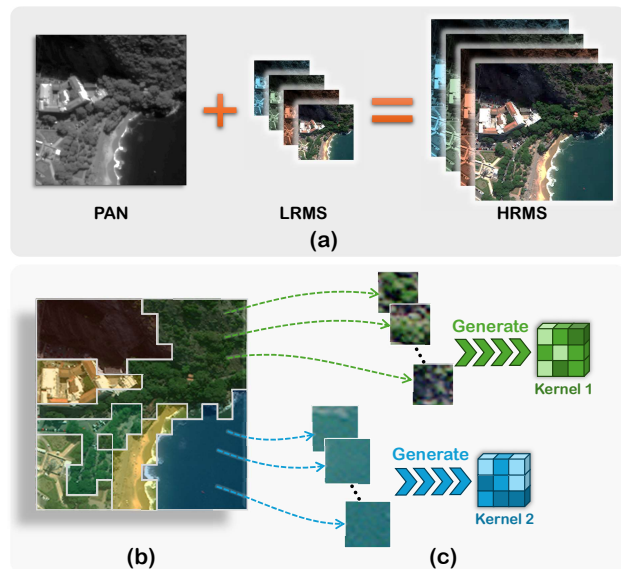


Figure 1. (a) Pansharpening involves fusing the PAN and LRMS images into an HRMS image. (b) A toy example of partitioned regions and (c) their corresponding content-adaptive convolution kernels, which is the motivation of this paper: 1) different content (regions) should be filtered by distinct kernels; 2) non-local information with the same content (regions) is extracted and represented only by the same convolution kernel.

remote sensing images possess unique characteristics compared to common natural images. Just as facial images are composed of fixed parts such as eyes, nose, and mouth, remote sensing images also consist of relatively stable elements, such as oceans, forests, buildings and streets, *etc.* These components exhibit distinct and easily distinguishable features in terms of color and texture. Within regions with similar semantics, there are numerous repetitive tiled textures, and even in distant locations, similar textures can be found. Given these characteristics of remote sensing images, an ideal pansharpening method should be able to adapt to different regions with varying features and should leverage information from non-local similar regions.

To obtain HRMS images, various prior arts have been

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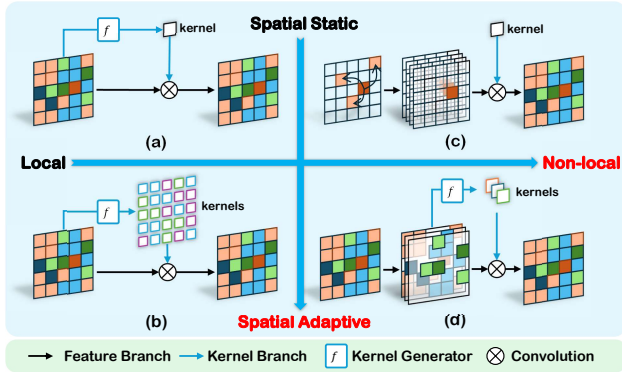


Figure 2. Overall workflow of four convolution methods related to adaptivity and non-locality. (a) Global adaptive/standard convolution [18]. (b) Spatial adaptive convolution [19, 31, 45]. (c) Graph convolution [23, 46]. (d) The proposed method.

proposed for the task of pansharpening. These methods include traditional methods and modern deep learning-based methods. Specifically, traditional pansharpening methods can be categorized into three types [26]: component substitution (CS) methods [8, 34], multi-resolution analysis (MRA) methods [35, 36], and variational optimization (VO)-based methods [14, 32]. In recent years, a plethora of methods based on convolutional neural networks (CNN) has also been employed for pansharpening, such as DiCNN [17], PanNet [44], and FusionNet [11], *etc.* Compared to traditional approaches, CNN-based methods have made significant progress in performance.

Among CNN-based pansharpening methods, in particular, local content-adaptive convolution techniques deserve special attention. As depicted in Fig. 2, an early adaptive convolution method, namely DFN [18], resembles standard convolution operators, employing spatially static convolution kernels that cannot adapt to differences in various parts of the space. However, DFN dynamically generates convolution kernels based on the input content through an extra network branch, enabling it to adapt to input variations and provide better feature extraction capabilities than standard convolution. Subsequently proposed spatial adaptive convolution methods, such as PAC [31], DDF [45], and LAG-Conv [19], *etc.*, generate different convolution kernels for each pixel based on the input, allowing them to adapt to differences in different spatial regions. However, these approaches have an obvious drawback: generating convolution kernels for each pixel consumes a considerable amount of redundant computation power and memory. Also, they generate convolution kernels based on local information and lack the ability to utilize non-local information. Graph convolution methods, such as CPNet [23] and IGNN [46], have the ability to leverage non-local information. IGNN models self-similarity relationships in the input using the k-NN algorithm, concatenating the most similar patches in

the global scope after each patch in the channel dimension. It then employs standard convolution layers to process this additional similarity information. This approach can utilize limited information from non-local similar regions, but lacks spatial adaptability. Deformable Convolution [10, 47] can dynamically change the offsets of sampling points, but their convolution kernel weights cannot be changed dynamically, and it cannot purposefully obtain long-range texture information from dispersed sampling points.

To overcome the limitations of previous methods, we designed the Content-Adaptive Non-Local Convolution (CANConv) method tailored to the characteristics of remote sensing images in pansharpening tasks. CANConv achieves spatial adaptability through content-adaptive convolution and utilizes non-local self-similarity information, incorporating two sub-modules: Similarity Relationship Partition (SRP) and Partition-Wise Adaptive Convolution (PWAC). The main contributions of this paper are as follows:

1. We propose the CANConv module, which utilizes adaptive convolution to simultaneously incorporate spatial adaptability and non-local self-similarity. Building upon the CANConv module, we design the CANNNet network, capable of leveraging multi-scale self-similarity information.
2. We analyze the prevalent non-local self-similarity relationships in remote sensing images. The theoretical effectiveness of the CANConv module is demonstrated through visualization and discussion experiments.
3. We validate the CANConv method on multiple pansharpening datasets by comparing it with various pansharpening methods. The results indicate that CANConv achieves state-of-the-art performance.

## 2. Related Works

### 2.1. Content-Adaptive Convolution

Compared to standard convolution operators that use global static convolution kernels, adaptive convolution operators employ different convolution kernels based on varying inputs, offering superior feature extraction capabilities and flexibility. Early adaptive convolution work, such as DFN [18], utilized a separate branch to generate convolution kernel filters. Subsequent efforts employed more intricate methods for convolution kernel generation. For instance, DYConv [7] aggregated multiple convolution kernels using attention. These methods use the same kernels to filter different spatial regions, lacking the ability to adapt to distinct areas. DRConv [6] considered spatial differences by selecting convolution kernels through independent convolution branches, yet it lacked adaptability. Spatial adaptive convolution methods apply a unique set of convolution kernels for each pixel, accommodating spatial differences in the input. PAC [31] fine-tuned convolution kernels us-

ing fixed Gaussian kernels for each pixel, but its flexibility was constrained. DDF [45] decoupled spatial adaptive convolution kernels in spatial and channel dimensions, somewhat reducing computational overhead but still faced redundancy due to generating a vast number of convolution kernels equal to the number of pixels. Involution [22] revealed the intrinsic connection between adaptive convolution and self-attention mechanisms.

Adaptive convolution methods designed specifically for remote sensing pansharpening tasks have already been developed. LAGConv [19] enhanced the ability of spatial adaptive convolution to gather information from local context, while ADKNet [28] tackled differences between PAN and LRMS images using distinct kernel generation branches. The success of these methods underscores the need to customize adaptive convolution techniques based on the characteristics of pansharpening tasks. Remote sensing images contain abundant non-local self-similarity information. However, in previous spatial adaptive convolution methods, the ability to utilize this information is absent.

## 2.2. Non-Local Methods

Many image restoration methods leverage information from non-local similar regions within images. Repeated patterns are prevalent in natural images, especially in remote sensing images. Traditional approaches like non-local means [5] and BM3D [9] directly aggregate similar parts within images to denoise the image. Methods proposed by Mairal *et al.* [24] and Lecouat *et al.* [21] exploit non-local self-similarity together with sparsity. The use of the  $k$ -nearest neighbors (kNN) algorithm is a vital technique for modeling non-local similarity relationships in images. Plötz and Roth [29] introduced a method to make the kNN algorithm differentiable in deep neural networks. Graph convolution networks based on the kNN algorithm, such as CPNet [23] and IGNN [46], have shown significant effectiveness in image denoising and super-resolution tasks. In these methods, for each patch,  $k$  most similar patches are identified to construct a similarity graph, and the found similar patches are concatenated with the original patch along the channel dimension. However, since increasing  $k$  will bring significant growth in the number of parameters, the value of  $k$  is usually small (less than 3), limiting the network’s access to a very limited set of similar patches and preventing it from capturing the complete context of similarity. This limitation hampers the network to fully utilize non-local information.

## 2.3. Motivation

Remote sensing images contain distinct regions with different semantics, each characterized by unique and fixed features. Using the same convolution kernel to filter regions with different contents is not the most rational approach. Spatial adaptive convolution methods achieve adaptability

to different regions by generating a large number of redundant convolution kernels. However, they cannot utilize information from similar patches that are spatially distant. To adapt to the distinct characteristics of different regions while comprehensively leveraging non-local self-similarity information in a global scope, we adopted a different approach from graph convolution. *We modeled the self-similarity relationships in the image by clustering, rather than using nearest neighbors.* Our method first clusters pixels on the image based on the features of their neighboring regions. Therefore, we may assign each pixel to one cluster and an unlimited amount of similar pixels from anywhere in the image may form a single cluster. Subsequently, we aggregate all contents belonging to the same cluster and generate a set of convolution kernels adaptively for each cluster based on its contents. Finally, the same adaptive convolution kernel is applied to all pixels within each cluster, allowing information from all similar patches to be propagated through convolutional kernels. Since the number of clusters is much smaller than the number of pixels, *our method significantly reduces the redundant computation required for generating convolution kernels* compared to common spatial adaptive convolution methods. Additionally, each cluster in our method contains a much larger number of pixels than the nearest neighbor patches aggregated by graph convolution methods, and the cluster number is not limited by the number of parameters, *enabling our approach to acquire self-similar information more comprehensively.*

## 3. Methods

This section introduces the design of the proposed CANConv module and CANNNet. The former, CANConv, can be divided into two sub-modules: Similarity Relationship Partition (SRP) and Partition-Wise Adaptive Convolution (PWAC). For the latter, we construct CANNNet by replacing standard convolution modules with CANConv, enabling the full utilization of non-local self-similarity in remote sensing pansharpening tasks. Fig. 3 shows the overall process of the CANConv module.

### 3.1. Content-Adaptive Non-Local Convolution

**Similarity Relationship Partition.** To effectively extract regional self-similarity relationships in remote sensing images, we first design the SRP module to cluster the input feature map. Let  $\mathbf{X} \in \mathbb{R}^{H \times W \times C_{in}}$  represent the input feature map, where  $H$  and  $W$  are the height and width of the feature map, and  $C_{in}$  is the number of input channels. Our goal is to compute a vector  $\mathbf{f}_{xy}$  for each pixel in the feature map as the observations for clustering, where  $(x, y)$  are the pixel coordinates (In subscripts, the comma and parenthesis are omitted to maintain conciseness). We define the unfold operation as extracting the neighborhood of each pixel with a  $k \times k$  sliding window. To reduce the dimension of the

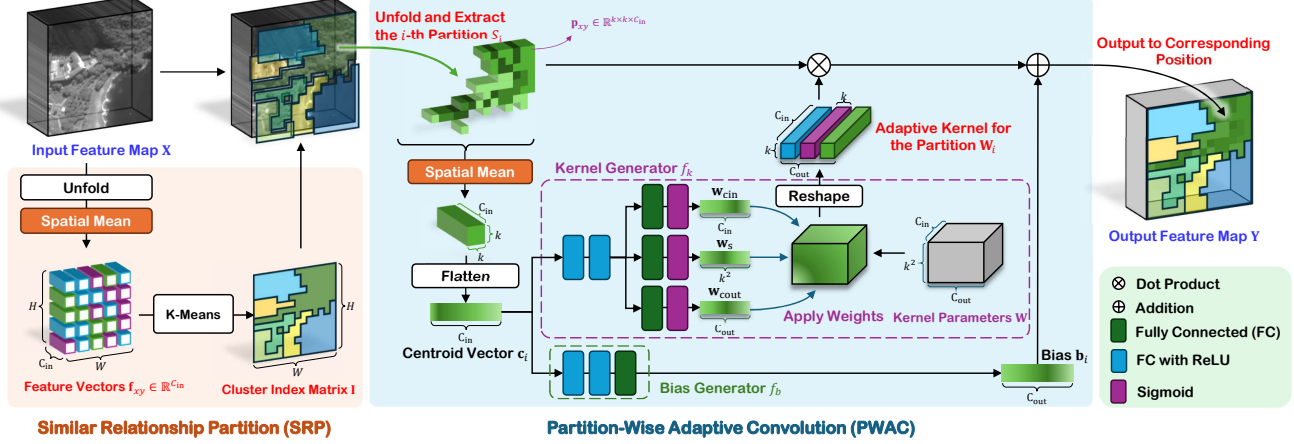


Figure 3. The overall workflow for a CANConv module. CANConv consists of two sub-modules: Similarity Relationship Partition (SRP) and Partition-Wise Adaptive Convolution (PWAC). In SRP, the input feature map is unfolded and reduced to obtain samples for clustering. PWAC is applied separately for each cluster distinguished by SRP. The figure demonstrates how PWAC adaptively generates convolution kernels and bias for a single cluster in the feature map.

neighborhood, a spatial mean pooling is performed on the neighborhoods to obtain  $\mathbf{f}_{xy}$ . The unfolding and pooling operation can be described as follows:

$$\mathbf{f}_{xy} = \frac{1}{k^2} \sum_{x'=-\lfloor k/2 \rfloor}^{\lfloor k/2 \rfloor} \sum_{y'=-\lfloor k/2 \rfloor}^{\lfloor k/2 \rfloor} \mathbf{X}_{x+x', y+y'}, \quad (1)$$

where the subscript of  $\mathbf{X}$  indicates the  $C_{in}$ -dimensional feature vector at the given position in the input feature map. Then we are able to cluster the obtained  $H \times W$  observation vectors. K-Means algorithm [13] is chosen for clustering because of its simplicity and high efficiency. The results of clustering are represented by a cluster index matrix  $\mathbf{I} \in \mathbb{N}^{H \times W}$ , where the elements  $\mathbf{I}_{xy}$  satisfy  $0 < \mathbf{I}_{xy} \leq K$ , indicating the cluster number to which the pixel at  $(x, y)$  belongs. Pixels with the same cluster index are in the same cluster, exhibiting non-local similarity.

**Partition-Wise Adaptive Convolution.** The PWAC sub-module first generates a set of convolution kernels for each self-similar partition based on its content, and then convolves all pixels within the partition using the generated kernel. During the convolution, we first unfold the feature map, and then group the neighborhoods by the cluster index matrix  $\mathbf{I}$  obtained in the SRP sub-module. Mathematically, let  $\mathbf{p}_{xy} \in \mathbb{R}^{k^2 C_{in}}$  denote the flat neighborhood of the input pixel at  $(x, y)$ , and pixel coordinates that belongs to the  $i$ -th cluster form a set

$$S_i = \{(x, y) | \mathbf{I}_{xy} = i\}, 0 < i \leq K. \quad (2)$$

The overall process of PWAC can be represented as

$$\mathbf{Y}_{xy} = \mathbf{p}_{xy} \otimes f(S_{\mathbf{I}_{xy}}), \quad (3)$$

where  $\mathbf{Y}_{xy}$  represents a  $C_{out}$ -dimensional vector at coordinates  $(x, y)$  in the output feature map,  $C_{out}$  is the number of

output channels,  $f$  is a mapping that transforms the content in  $S_i$  into a set of convolution kernels  $\mathbf{W}_i \in \mathbb{R}^{C_{in} k^2 \times C_{out}}$ , and  $\otimes$  denotes vector-matrix multiplication. To build  $f$ , we first compute the centroid vector of  $S_i$  with

$$\mathbf{c}_i = \frac{1}{|S_i|} \sum_{(x,y) \in S_i} \mathbf{p}_{xy}, \quad (4)$$

where  $|S_i|$  denotes the number of pixels belonging to the  $i$ -th partition. The centroid vector  $\mathbf{c}_i \in \mathbb{R}^{k^2 C_{in}}$  can represent the content of the self-similar partition  $S_i$ . Then, we design a mapping  $f_k$  to adaptively generate the unique convolution kernel  $\mathbf{W}_i \in \mathbb{R}^{k^2 C_{in} \times C_{out}}$  for the  $i$ -th partition from  $\mathbf{c}_i$ . The details about  $f_k$  will be discussed in the next part. Besides the convolution kernels, the biases  $\mathbf{b}_i \in \mathbb{R}^{C_{out}}$  of the convolution layer can also be adaptively generated. We directly utilize a multi-layer perceptron  $f_b$  to transform  $\mathbf{c}_i$  into  $\mathbf{b}_i$ . Thus, the complete partition-wise adaptive convolution with bias can be represented as

$$\mathbf{Y}_{xy} = \mathbf{p}_{xy} \otimes f_k(\mathbf{c}_{\mathbf{I}_{xy}}) + f_b(\mathbf{c}_{\mathbf{I}_{xy}}). \quad (5)$$

As illustrated in the cluster visualization in Sec. 4.3, there exist pixels with outlier features that fall into a few small clusters. Forcing the network to learn similarity information within such clusters may constrain its generalization ability. To address this issue, during training, the centroid vector of the cluster  $\mathbf{c}_i$  is replaced with the global centroid in clusters where the number of pixels is less than a given threshold, as follows:

$$\mathbf{c}_i = \frac{1}{HW} \sum_{0 < x \leq H, 0 < y \leq W} \mathbf{p}_{xy}. \quad (6)$$

Eq. (6) is utilized to substitute Eq. (4) if  $|S_i| < \eta HW$ , where  $\eta$  represents the specified threshold ratio.



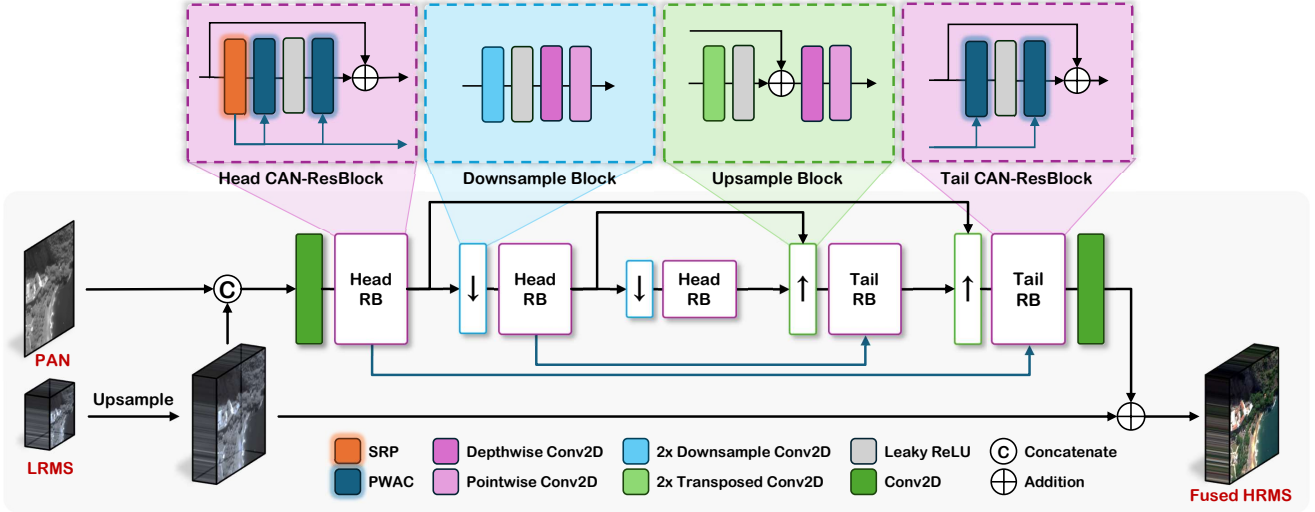


Figure 4. The overall architecture of CANNNet. CANNNet follows the classic U-Net design and features CAN-ResBlocks. Black arrows indicate the flow of feature maps, while blue arrows indicate the flow of cluster index matrices. The downsampling module halves the spatial resolution while doubling the number of channels, and the upsampling module does the opposite. Tail CAN-ResBlocks reuse cluster index matrices obtained in the Head CAN-ResBlock at the same level.

**Lightweight Adaptive Kernel Generation.** In this paragraph we will introduce the design of the kernel generator  $f_k$ . It is possible to use a simple multi-layer perceptron with  $k^2 C_{in}$  input features and  $k^2 C_{in} C_{out}$  output features to directly map  $c_i$  to  $W_i$ . However, this approach includes too much amount of learnable parameters and makes the network harder to train. To reduce the parameter number, we utilize a global kernel parameter  $W \in \mathbb{R}^{C_{in} \times k^2 \times C_{out}}$  and apply attention weight on it to obtain the unique convolution kernels  $W_i$  for each partition. We first use a multi-layer perceptron with three heads to generate three weight vectors corresponding to input channel dimension ( $w_{cin} \in \mathbb{R}^{C_{in}}$ ), spatial dimension ( $w_s \in \mathbb{R}^{k^2}$ ), and output channel dimension ( $w_{cout} \in \mathbb{R}^{C_{out}}$ ). These three vectors are then used to weight the corresponding dimensions of the global convolution kernel parameters  $W$ , and then the result is reshaped into  $W_i$ . The weighting process can be formulated as

$$f_k(c_i) = W_i = w_{cin} \otimes w_s \otimes w_{cout} \odot W, \quad (7)$$

where  $\otimes$  represents the Kronecker product, and  $\odot$  represents element-wise multiplication.

### 3.2. Network Architecture

This section describes how to construct the network architecture of CANNNet with non-local information utilization capabilities using the CANConv module. Similarity relationship partitioning and partition-wise adaptive convolution together form a complete CANConv module, which can directly replace standard convolution layers in existing convolutional networks. CAN-ResBlocks can replace the original ResBlocks [16]. First, it extracts similarity relationships from input features with an SRP module, and

then both PWACs use the same cluster index matrix. This design choice is made because the similarity relationships in CAN-ResBlock do not change significantly. Sharing the same index matrix helps save computational expenses. As illustrated in Fig. 4, CANNNet follows the U-Net [30, 40] design, incorporating both skip connections for feature maps and skip connections for index matrices. PAN images and upsampled LRMS images are concatenated along the channel dimension to form the input feature map. Subsequently, through a series of down-sampling operations, CANConv can analyze and utilize similarity across different spatial scales and semantic levels. Then in upsampling, tail CAN-ResBlocks reuse cluster index matrices from downsampling to maintain and enhance the self-similar relationships. Finally, following the common detail-injection pattern in pansharpening CNNs[11, 17], upsampled LRMS input is added to the output of the network to form the final HRMS image.

## 4. Experiment

### 4.1. Datasets, Metrics and Training Details

To validate our approach, we construct datasets following Wald’s protocol [11, 39] on data collected from the WorldView-3 (WV3), QuickBird (QB) and GaoFen-2 (GF2) satellites. Our datasets and data processing methods are downloaded from the PanCollection repository<sup>1</sup> [12]. Besides, we evaluated our method on three commonly used metrics in the field of pansharpening, including SAM [4], ERGAS [38] and Q4/Q8 [15] for reduced-resolution dataset, and HQNR [2],  $D_s$ , and  $D_\lambda$  for full-

<sup>1</sup><https://github.com/liangjiandeng/PanCollection>

Table 1. Result benchmark on the WV3 dataset, evaluated with 20 reduced-resolution samples and 20 full-resolution samples. Best results are marked with bold font, and second-best results are marked with underline.

Methods	Reduced-Resolution Metrics			Full-Resolution Metrics		
	SAM↓	ERGAS↓	Q8↑	$D_\lambda$ ↓	$D_s$ ↓	HQNR↑
EXP [1]	5.800±1.881	7.155±1.878	0.627±0.092	0.0232±0.0066	0.0813±0.0318	0.897±0.036
MTF-GLP-FS [36]	5.316±1.766	4.700±1.597	0.833±0.092	0.0197±0.0078	0.0630±0.0289	0.919±0.035
TV [27]	5.692±1.808	4.856±1.434	0.795±0.120	0.0234±0.0061	0.0393±0.0227	0.938±0.027
BDS-PC [34]	5.429±1.823	4.698±1.617	0.829±0.097	0.0625±0.0235	0.0730±0.0356	0.870±0.053
CVPR2019 [14]	5.207±1.574	5.484±1.505	0.764±0.088	0.0297±0.0059	0.0410±0.0136	0.931±0.0183
LRTCFFPan [42]	4.737±1.412	4.315±1.442	0.846±0.091	<u>0.0176±0.0066</u>	0.0528±0.0258	0.931±0.031
PNN [25]	3.680±0.763	2.682±0.648	0.893±0.092	0.0213±0.0080	0.0428±0.0147	0.937±0.021
PanNet [44]	3.616±0.766	2.666±0.689	0.891±0.093	<b>0.0165±0.0074</b>	0.0470±0.0213	0.937±0.027
DiCNN [17]	3.593±0.762	2.673±0.663	0.900±0.087	0.0362±0.0111	0.0462±0.0175	0.920±0.026
FusionNet [11]	3.325±0.698	2.467±0.645	0.904±0.090	0.0239±0.0090	0.0364±0.0137	0.941±0.020
DCFNet [41]	<u>3.038±0.585</u>	<u>2.165±0.499</u>	0.913±0.087	0.0187±0.0072	0.0337±0.0054	<u>0.948±0.012</u>
MMNet [43]	3.084±0.640	2.343±0.626	<u>0.916±0.086</u>	0.0540±0.0232	<u>0.0336±0.0115</u>	0.914±0.028
LAGConv [19]	3.104±0.559	2.300±0.613	0.910±0.091	0.0368±0.0148	0.0418±0.0152	0.923±0.025
HMPNet [33]	3.063±0.577	2.229±0.545	0.916±0.087	0.0184±0.0073	0.0530±0.0055	0.930±0.011
<b>Proposed</b>	<b>2.930±0.593</b>	<b>2.158±0.515</b>	<b>0.920±0.084</b>	0.0196±0.0083	<b>0.0301±0.0074</b>	<b>0.951±0.013</b>

Table 2. Result benchmark on the QB dataset with 20 reduced-resolution samples. **Bold**: best, underline: second best.

Methods	SAM↓	ERGAS↓	Q4↑
EXP [1]	8.435±1.925	11.819±1.905	0.584±0.075
TV [27]	7.565±1.535	7.781±0.699	0.820±0.090
MTF-GLP-FS [36]	7.793±1.816	7.374±0.724	0.835±0.088
BDS-PC [34]	8.089±1.980	7.515±0.800	0.831±0.090
CVPR19 [14]	7.998±1.820	9.359±1.268	0.737±0.087
LRTCFFPan [42]	7.187±1.711	6.928±0.812	0.855±0.087
PNN [25]	5.205±0.963	4.472±0.373	0.918±0.094
PanNet [44]	5.791±1.184	5.863±0.888	0.885±0.092
DiCNN [17]	5.380±1.027	5.135±0.488	0.904±0.094
FusionNet [11]	4.923±0.908	4.159±0.321	0.925±0.090
DCFNet [41]	<u>4.512±0.773</u>	3.809±0.336	0.934±0.087
MMNet [43]	4.557±0.729	3.667±0.304	0.934±0.094
LAGConv [19]	4.547±0.830	3.826±0.420	0.934±0.088
HMPNet [33]	4.617±0.404	<b>3.404±0.478</b>	<u>0.936±0.102</u>
<b>Proposed</b>	<b>4.507±0.835</b>	<u>3.652±0.327</u>	<b>0.937±0.083</b>

Table 3. Result benchmark on the GF2 dataset with 20 reduced-resolution samples. **Bold**: best, underline: second best.

Method	SAM↓	ERGAS↓	Q4↑
EXP [1]	1.820±0.403	2.366±0.554	0.812±0.051
TV [27]	1.918±0.398	1.745±0.405	0.905±0.027
MTF-GLP-FS [36]	1.655±0.385	1.589±0.395	0.897±0.035
BDS-PC [34]	1.681±0.360	1.667±0.445	0.892±0.035
CVPR19 [14]	1.598±0.353	1.877±0.448	0.886±0.028
LRTCFFPan [42]	1.315±0.283	1.301±0.313	0.932±0.033
PNN [25]	1.048±0.226	1.057±0.236	0.960±0.010
PanNet [44]	0.997±0.212	0.919±0.191	0.967±0.010
DiCNN [17]	1.053±0.231	1.081±0.254	0.959±0.010
FusionNet [11]	0.974±0.212	0.988±0.222	0.964±0.009
DCFNet [41]	0.872±0.169	0.784±0.146	0.974±0.009
MMNet [43]	0.993±0.141	0.812±0.119	0.969±0.020
LAGConv [19]	<u>0.786±0.148</u>	0.687±0.113	0.980±0.009
HMPNet [33]	0.803±0.141	<b>0.564±0.099</b>	<u>0.981±0.030</u>
<b>Proposed</b>	<b>0.707±0.148</b>	<u>0.630±0.128</u>	<b>0.983±0.006</b>

resolution dataset. In addition, we utilize the  $\ell_1$  loss function and Adam optimizer[20] with a batch size of 32 in training. *More details on datasets, metrics, and training can be found in supplementary materials Sec. 8.*

## 4.2. Results

The performance of the proposed CANNNet method is showcased through extensive evaluations on three benchmark

datasets: WV3, QB, and GF2. Tabs. 1 to 3 present a comprehensive comparison of CANNNet with various state-of-the-art methods, including both traditional and deep learning approaches. These results confirm the robustness of CANNNet in handling different datasets and its consistent ability to produce high-quality pan-sharpened images. Furthermore, visual comparisons in Fig. 5 illustrate that CANNNet generates results closer to the ground truth. This

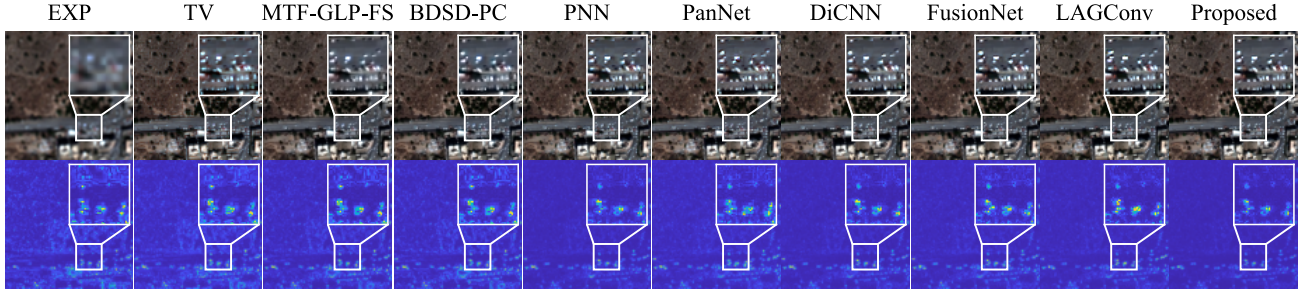


Figure 5. Qualitative result comparison between representative methods on the WV3 reduced-resolution dataset. The first row presents RGB outputs, while the second row shows the residual compared to the ground truth. Refer to supplementary material for more comparison.

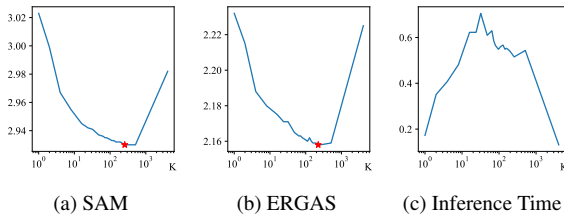


Figure 6. Variations of SAM, ERGAS and inference time on the WV3 reduced-resolution dataset with changing cluster number  $K$ . The optimal metrics are obtained around  $K = 256$ .

Table 4. Result of replacing convolution modules in other backbones with CANConv on WV3 reduced-resolution dataset.

Method	SAM↓	ERGAS↓	Q8↑
DiCNN	3.593±0.762	2.673±0.663	0.900±0.087
CAN-DiCNN	3.371±0.694	2.492±0.609	0.906±0.086
FusionNet	3.325±0.698	2.467±0.645	0.904±0.090
CAN-FusionNet	3.293±0.703	2.407±0.591	0.907±0.086
LAGConv	3.104±0.559	2.300±0.613	0.910±0.091
CAN-LAGConv	3.051±0.617	2.251±0.564	0.914±0.086

is a testament to CANNet’s utilization of non-local self-similarity information, endowing it with outstanding spatial fidelity capabilities. For more benchmarks and visualizations, please refer to the supplementary material Sec. 8.5.

### 4.3. Discussions

**Cluster Count of CANNet:** We explored the effectiveness of CANNet by varying the number of clusters  $K$  in the K-Means algorithm. We trained the network with  $K = 32$  and then inferred on the test set with different values of  $K$ . In Figs. 6a and 6b, we found that performance improves as  $K$  increases when small, but deteriorates when too large. Small  $K$  yields results close to no clustering, as dissimilar pixels are grouped together, hindering effective kernel adaptation. Excessively large  $K$  results in too few pixels per

cluster, impeding information gathering. The leftmost and rightmost points on the curves correspond to the cases of using a global convolutional kernel and a fully spatial adaptive convolutional kernel, respectively. The experiments show the effectiveness of clustering in transferring information between similar pixels. It is worth noting that the optimal value of  $K$  on the test set is about four times that of the training set. This is because the images in the test set cover a larger spatial range and more diverse features.

**Analysis on Complexity:** Compared to other adaptive convolutions, additional computation complexity of CANConv mainly attributes to K-Means, which has a theoretical complexity of  $O(tKnd)$ , where  $t$ ,  $K$  and  $n$  are the number of iterations, clusters and samples, and  $d$  is the dimension of samples. The adaption from [13] is used to reduce  $t$  by observing the change in cluster centers. Fig. 6c presents the observed inference time on an RTX3090 with changing  $K$ . It is noticeable that the time decreases when  $K$  is high, because the decline in  $t$  counteracts the increase in  $K$ .

**Replacing Standard Convolution:** To verify the performance of CANConv as a standalone convolution module, we try to replace convolution modules in various pansharp-ening backbones with CANConv. The results are presented in Tab. 4. For DiCNN [17], a three-layer convolutional neural network, replacing one convolutional layer with CANConv significantly improves network performance. In FusionNet [11], which consists of four standard ResBlocks, replacing some with CAN-ResBlocks also yields noticeable improvements. Even for LAGNet [19], which already incorporates spatial adaptive convolution, substituting some spatial adaptive ResBlocks with CAN-ResBlocks using CANConv further enhances performance by leveraging additional self-similarity information. The supplementary material Sec. 8.4 contains details of this experiment.

**Cluster Visualization:** Fig. 7 displays the similarity partition distribution by the SRP sub-module at various CANNet levels, suggesting CANConv effectively classifies different region types on the feature map. Moreover, considering the edge morphology of the regions, shallow layers emphasize



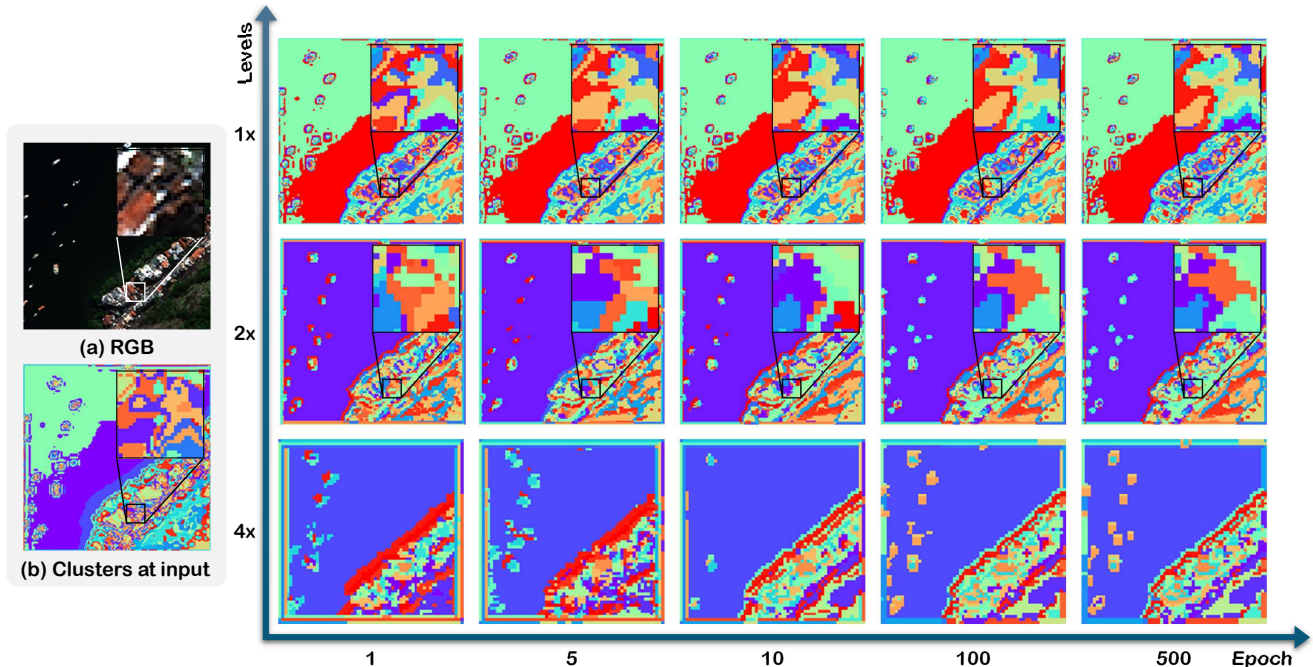


Figure 7. Visual representations of cluster index matrices in CANNNet at different downsample levels and training epochs. (a) RGB appearance for the sample image from the WV3 reduced-resolution test dataset. (b) Clustering results on concatenated raw PAN and LRMS input images without being transformed by convolution layers. The color indicates the cluster to which the pixel belongs.

Table 5. Ablation experiment on WV3 reduced-resolution dataset.

Ablation	SAM↓	ERGAS↓	Q8↑
None	2.930±0.593	2.158±0.515	0.920±0.084
No SRP, $K = 1$	3.023±0.606	2.232±0.567	0.919±0.083
No SRP, $K = \infty$	2.982±0.608	2.225±0.546	0.918±0.084

Table 6. Ablation experiment on WV3 full-resolution dataset.

Ablation	$D_l$ ↓	$D_s$ ↓	HQNR↑
None	0.0196±0.0083	0.0301±0.0074	0.951±0.013
Replace $f_k$ with MLP	Not Converged		
$\eta = 0$	0.0169±0.0064	0.0400±0.0053	0.944±0.009

color and texture similarity, whereas in the deeper layers the clustering results encompass more semantic information. The cluster index matrix stabilizes and incorporates more semantics during network training. Although most pixels form large, similar clusters, some outliers fall into smaller, less similar clusters. Border clusters exhibit straight-line shapes due to zero padding when unfolding.

**Ablation Study:** We ablated different parts in our method to prove their effectiveness, and the results are shown in Tabs. 5 and 6. To ablate the SRP sub-module, the results in Fig. 6 and Tab. 5 reveal cases where SRP is disabled, including treating the whole input feature map as a single cluster

( $K = 1$ , leftmost) or considering each pixel as a separate cluster ( $K = \infty$ , rightmost). The network’s performance experiences a sharp decline when SRP is disabled, underscoring the effectiveness of the SRP. Regarding the ablation of the PWAC process, we attempted to replace  $f_k$  with a direct multi-layer perceptron comprising the same number of layers and inner features. However, this replacement increased the learnable parameters to about  $10\times$ , causing the network fail to converge. To demonstrate the impact of replacing centroid vectors in small clusters, we sought to mitigate this behavior by setting  $\eta = 0$  in training.

## 5. Conclusion

In conclusion, our paper introduces CANConv, a novel non-local adaptive convolution module that addresses the limitations of conventional spatial adaptive convolution methods by simultaneously incorporating spatial adaptability and non-local self-similarity. Integrated into the CANNNet network, CANConv leverages multi-scale self-similarity information, offering a comprehensive solution for the remote sensing pansharpening task. Our contributions include the analysis of non-local self-similarity relationships in remote sensing images, validating the CANConv method on multiple datasets, and demonstrating its state-of-the-art performance compared to existing pansharpening methods.

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