Hyperspectral Image Denoising Using Features Extraction and Attention Mechanism

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Introduction

1. Hyperspectral images are obtained by airborne or satellite sensors imaging a target area.
2. That contains information on objects in tens to two hundred of continuous and segmented bands from visible light to the infrared (wavelength) spectral region.
3. Hyperspectral Images (HSIs), simultaneously acquire both spatial and spectral information.
4. The pixels are important features in hyperspectral data analysis. Therefore, the spatial and spectral information has been characterized into pixels.
5. Each pixel is a vector of values that specify the strength at a location **(x,y)** in **z** different bands.

Introduction (Continued)

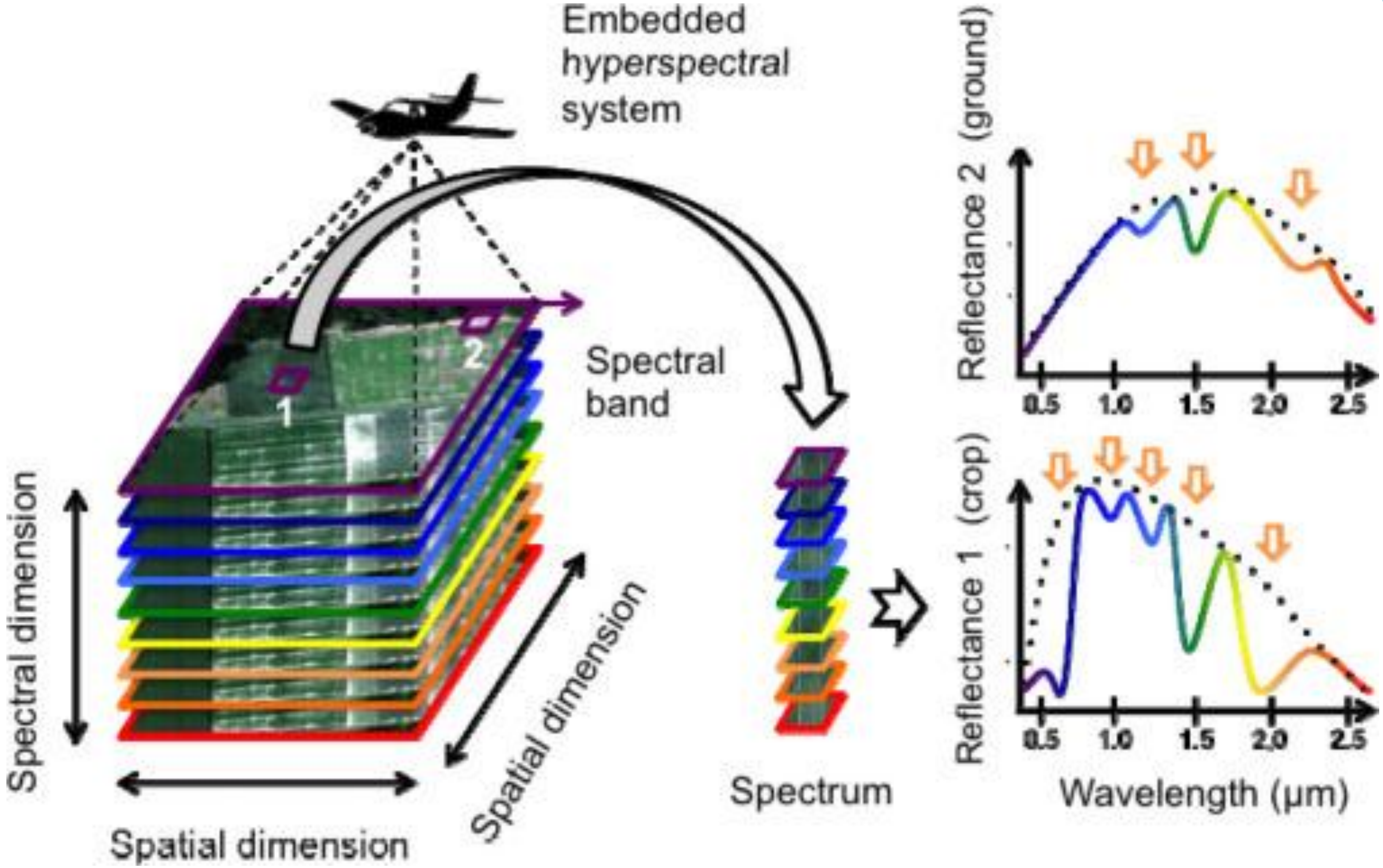


Figure-1: **Hyperspectral Image structure [1].**

Literature Review/ Related Work

Sr No	Year	Basic Idea	Methodologies	Results	Limitations
[3]	2023	Mixed Attention Network for Hyperspectral Image Denoising.	• Simultaneously considers the inter- and intra-spectral correlations • Interactions between low- and high-level spatial-spectral meaningful features.	• Simulated and real noise experiments outperform existing state-of-the-art methods. • Maintaining a low cost of parameters and running time.	• Efficiently integrates the inter-spectral features across all the spectral bands.
[4]	2022	Deep Spatial-Spectral Global Reasoning Network for Hyperspectral Image Denoising	• To address the issue of ignoring global contextual information. • That utilizes both local and global information for HSI noise removal.	• Efficiently considered both the spatial and spectral in synthetic and real HSIs data. • That outperforms other state-of-the-art HSI denoising methods.	• The global spatial relations between pixels in feature maps. • The global relations across the channels. • Tackle complex noise by exploiting multiple representations.
[5]	2022	Hyperspectral Image Denoising With Weighted Nonlocal Low-Rank Model and Adaptive Total Variation Regularization	That utilize some method for HSIs spatial-spectral data. • The non-independent and non-local similarity. • The edge-preserving total variation regularization. • The identically distributed.	• The ADMM network has extensive experiments on simulated data and real data. • That justifies the superiority of the proposed method beyond state-of-the-art.	• Exploit HSI's non-local similarity and spatial-spectral relation. • To characterize the non-local smooth property of HSI and complex noise.

Literature Review/ Related Work (Continued)

[6]	2022	Fast Hyperspectral Image Denoising and Inpainting Based on Low-Rank and Sparse Representations	• Fast hyperspectral denoising: to handle Gaussian and Poissonian noise. • Fast hyperspectral inpainting: to restore HSIs where some observations from known pixels in some known bands are missing.	• In experiments with simulated and real data, FastHyDe and FastHyIn compete with the state-of-the-art methods. • Lower computational complexity	• Fully exploit extremely compact and sparse HSI representations. • Utilized to low-rank and self-similarity characteristics.
[7]	2021	LR-Net: Low-Rank Spatial-Spectral Network for Hyperspectral Image Denoising	• The low-rank features are utilized to capture the latent semantic relationships of the HSIs to recover clean HSIs.	• Extensive experiments on simulated and real-world. • That LR-Net outperforms other state-of-the-art denoising methods in terms of evaluation metrics and visual assessments.	• The atrous blocks exploit spatial-spectral features. • Forwarded to a multi-atrous block to aggregate the context fields. • The contextual and spatial-spectral features are concatenated to a low-rank module (LRM).
[8]	2021	Hyperspectral Image Denoising Using a 3-D Attention Denoising Network	• The parallel separate processes of the spatial and spectral information. • That managed the global dependence and correlation between spatial and spectral.	• Experimental results on simulated and real data support the better quality of our method. • When compared with state-of-the-art methods visually and quantitatively.	• The position attention module to spatial feature map. • The channel attention module to the spectral combined branches. • The multiscale features to extract and fusion.

Literature Review/ Related Work (Continued)

[9]	2021	Hyperspectral Image Denoising via Low-Rank Representation and CNN Denoiser	• The sparse-based low-rank representation explores the global correlations of spatial and spectral. • The CNN-based denoiser represents the deep prior restoration models.	• Simulated experiments the achieves better denoising results for both additive noise in quantitative evaluation • Real data experiments show that the proposed model yields the best performance.	• Denoising model with low-rank representation. • CNN denoiser prior in the flexible and extensible plug-and-play framework.
[10]	2020	Spatial-spectral weighted nuclear norm minimization for hyperspectral image denoising	• The weighted Nuclear Norm Minimization to recover the spectral LR structure. • The multi-channel Weighted Nuclear Norm Minimization to recover spatial LR matrix.	• Experiments implemented on simulated and real HSIs data sets. • That validates the denoising visual quality and efficiency of the proposed method.	• Spatial domain nonlocal similar cubic patches are found. • Stacked into an LR matrix contains the local detailed spatial texture information.
[11]	2020	Enhanced Non-Local Cascading Network with Attention Mechanism for Hyperspectral Image Denoising	• That (ENCAM) extracts the joint spatial-spectral feature more effectively for Hyperspectral Image Denoising.	• The theoretical analysis and the experiments indicate. • That method is superior to the other state-of-the-art methods of HSIs denoising.	• The non-local structure enlarges to extract spatial features. • The multi-scale convolutions and channel attention module extracted multi-scale features.

Literature Review/ Related Work (Continued)

[12]	2020	A Single Model CNN for Hyperspectral Image Denoising	For spectral-spatial HSI denoising. • Convolutional neural networks (HSISDeCNN)	• Efficiently utilized both spatial and spectral data. • Synthetic and Real experiment results outperform other methods.	• High spectral correlation between adjacent bands in HSIs
[13]	2020	A Tensor Subspace Representation-Based Method for Hyperspectral Image Denoising (TenSRDe)	• Subspace-based methods can reduce computational complexity. • Matrix subspaces-based can't represent unfolding operations that destroy the tensor structure.	• Experiments implemented on simulated and real data sets. • That validates the denoising effect and efficiency of the proposed method.	• The low-tubal rankness of the HSI tensor. • The nonlocal self-similarity of the coefficient tensor.
[14]	2018	Hyperspectral Image Denoising Employing a Spatial–Spectral Deep Residual Convolutional Neural Network	• Nonlinear end-to-end mapping between the noisy and clean HSIs data. • The spatial-spectral deep convolutional neural network (HSID-CNN)	• The simulated and real-data experiments (HSID-CNN) outperform many of the methods. • In the case of evaluation indexes, visual effect, and classification accuracy.	The multiscale feature extraction is employed to capture. • Multiscale spatial feature. • Multiscale spectral feature.

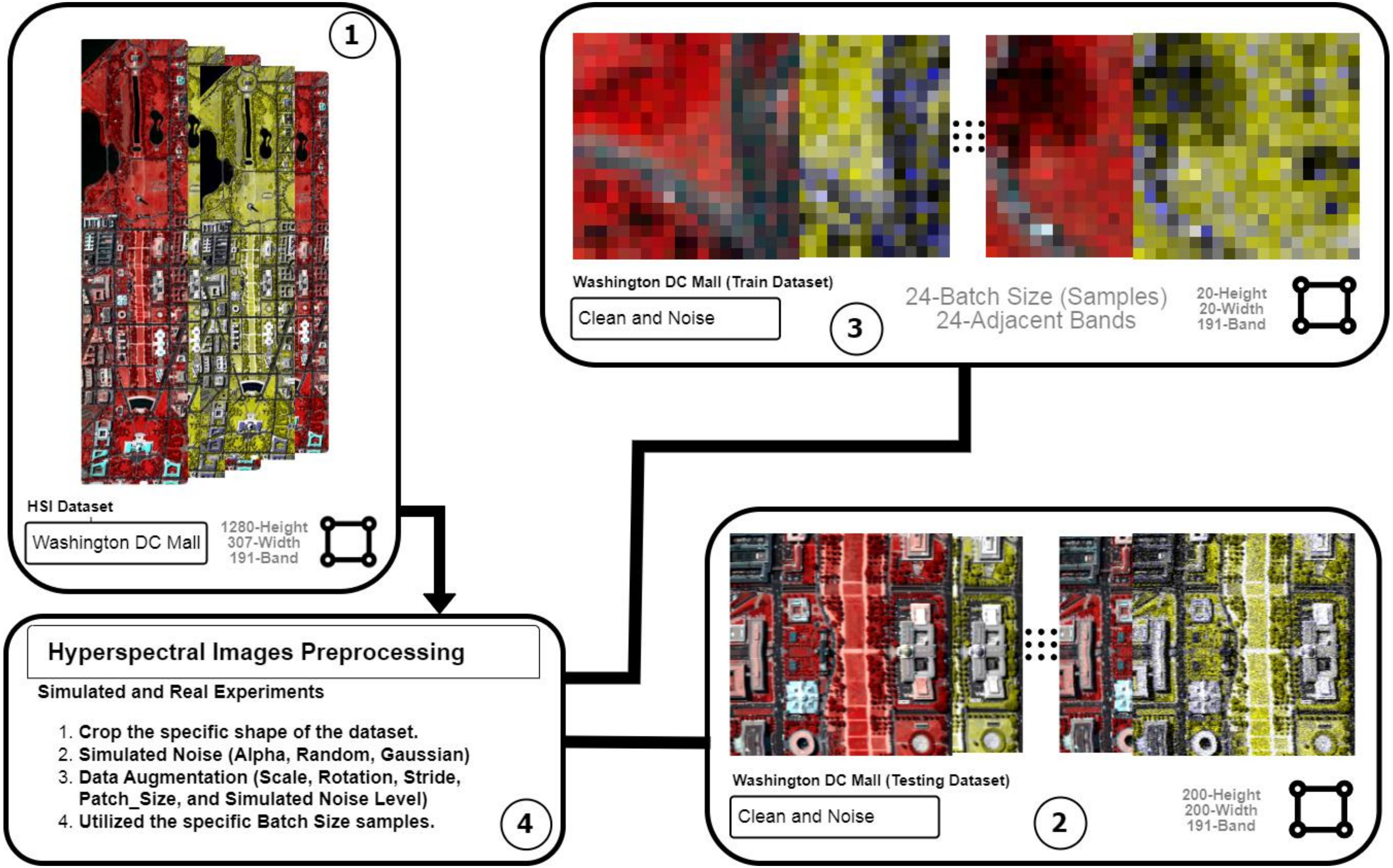
Problem Statement

“State-of-the-art models for Hyperspectral Images (HSIs) can't utilize the features of spectral band correlation, geometrical characteristics, and eventually decompose high-frequency features. This inability degrades further processing of Target Detection and Classification.”

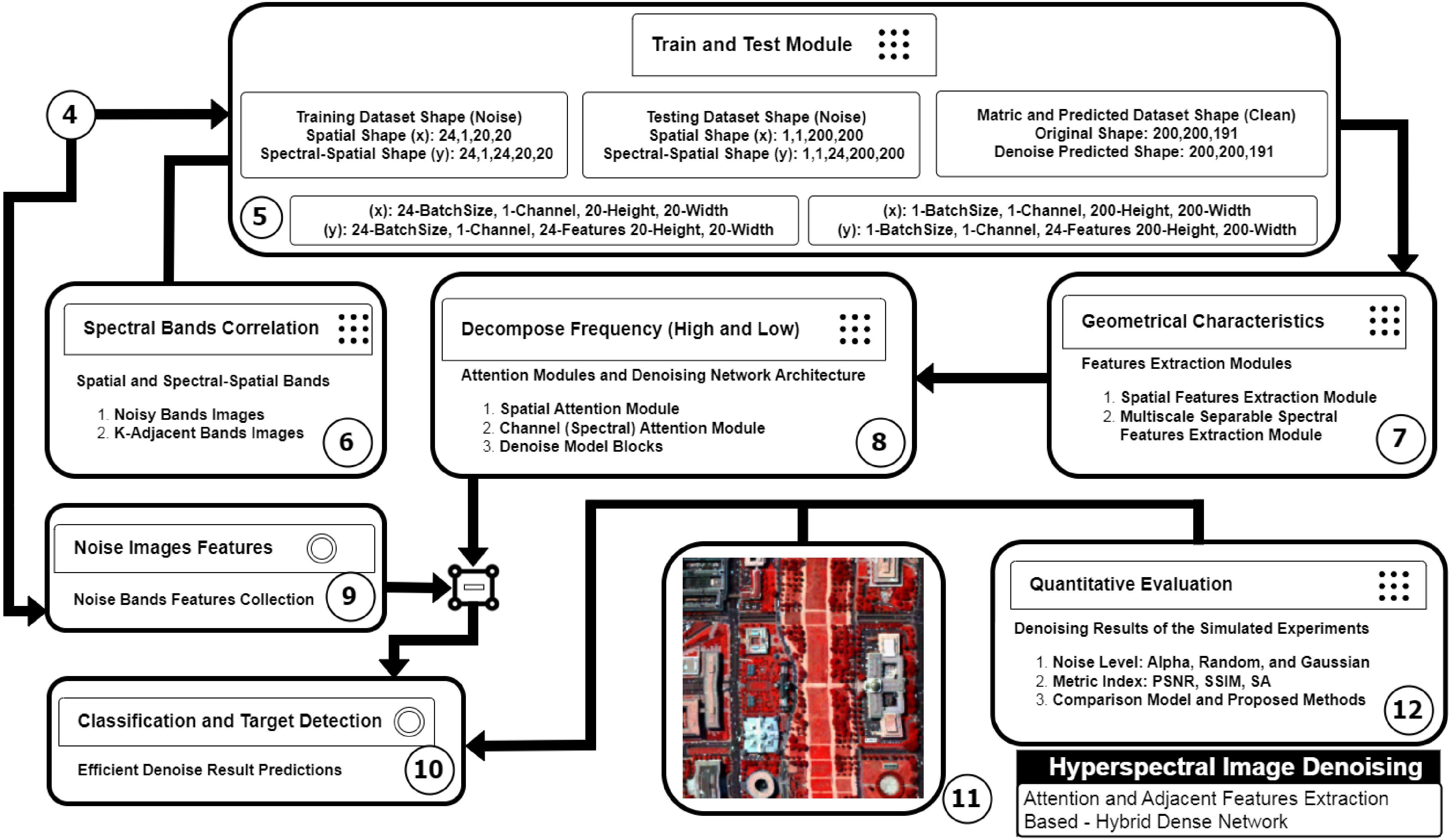
System Design [1/4]

1. **Hyperspectral Images (HSI) Data:** The filtered dataset is given after applying some preprocess techniques such as Cropping, Simulated Noise, Data Augmentation, and Specified Batch Size Samples. The provided shape of the dataset is Training, Testing, and Matric.
2. **Spectral Band Correlation:** The utilization of spectral bands in which correlation through K-Adjacent noisy bands.
3. **Geometrical Characteristics:** The utilization of feature extraction modules on both case of spatial and spectral to preserve geometrical characteristics in structured prior information.
4. **Decompose Frequency (High & Low):** The hybrid dense network based on attention modules (spatial and channel) is used to decompose frequency of higher and lower noisy features.
5. **Classification and Target Detection:** The predicted denoise results (loss) are substituted by noisy band features.

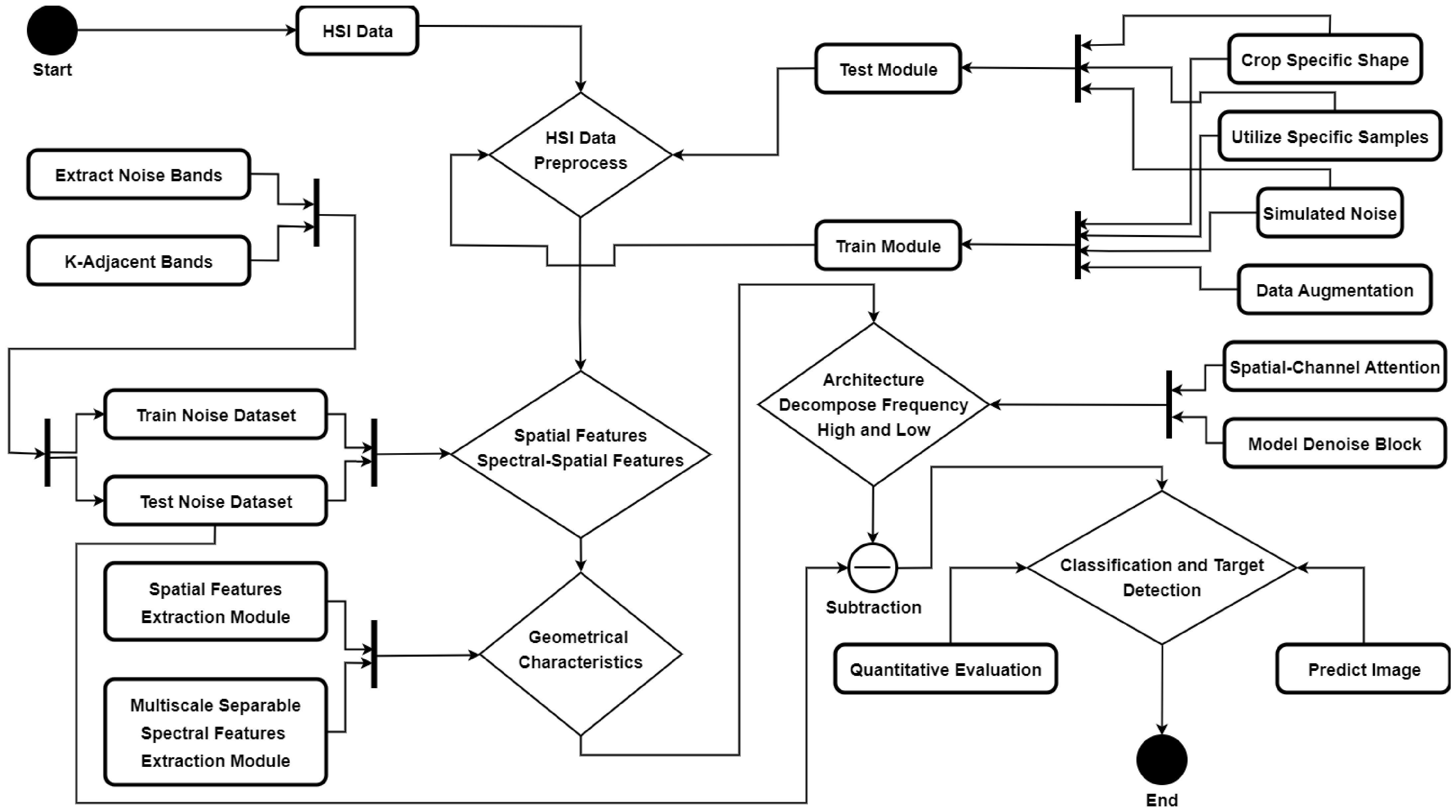
System Design (Component Diagram) [2/4]



System Design (Component Diagram) [3/4]

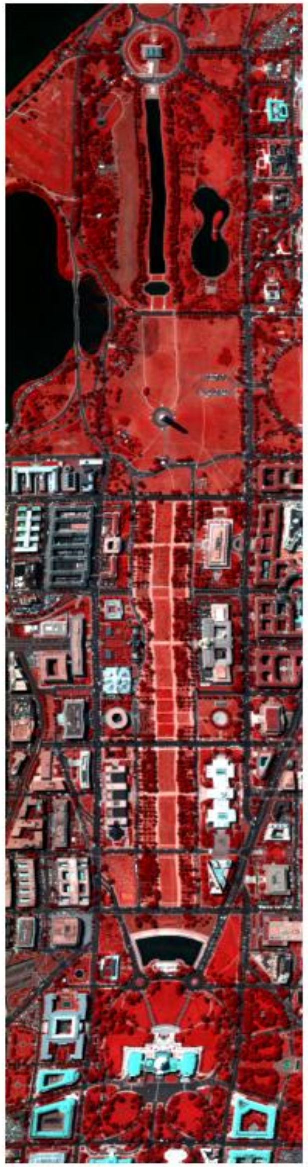


System Design (Activity Diagram) [4/4]



Hyperspectral Image Preprocessing (Simulated and Real Experiment) [1/6]

Cropped Specific Shape (Data): Train and Test

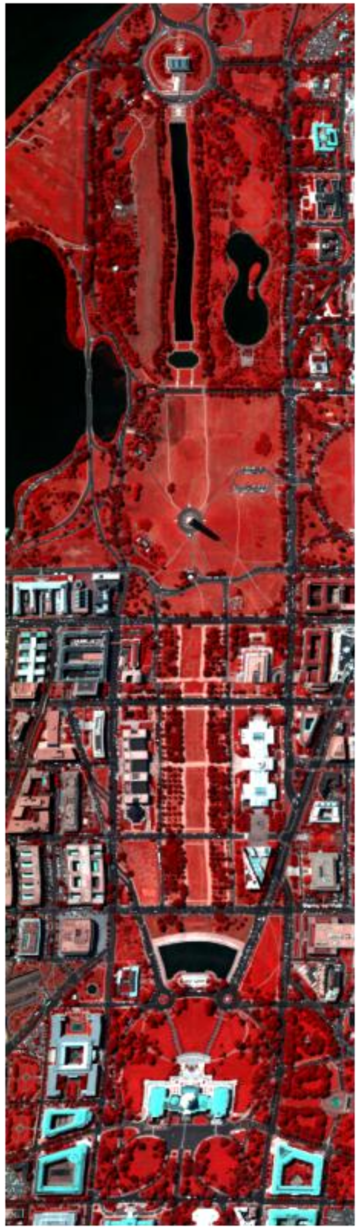


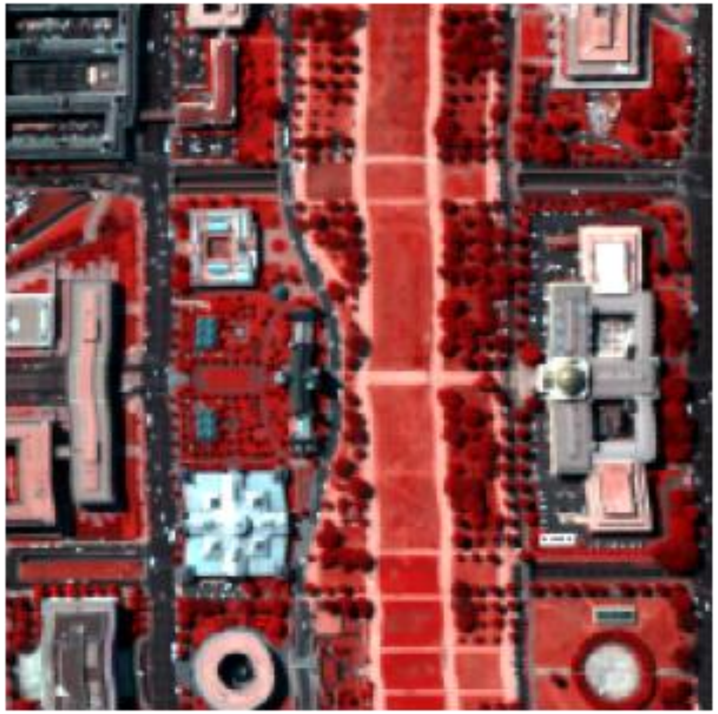
Washington DC Mall

Shape: (1280, 307, 191)

Training Dataset

Height and Width: 0 to 600 and 800 to 1280 scale, with total width and band 191.
Concatenation: (0,600) with (800,1280) scale.
Height and Width: (1080, 307, 191)





Testing Dataset

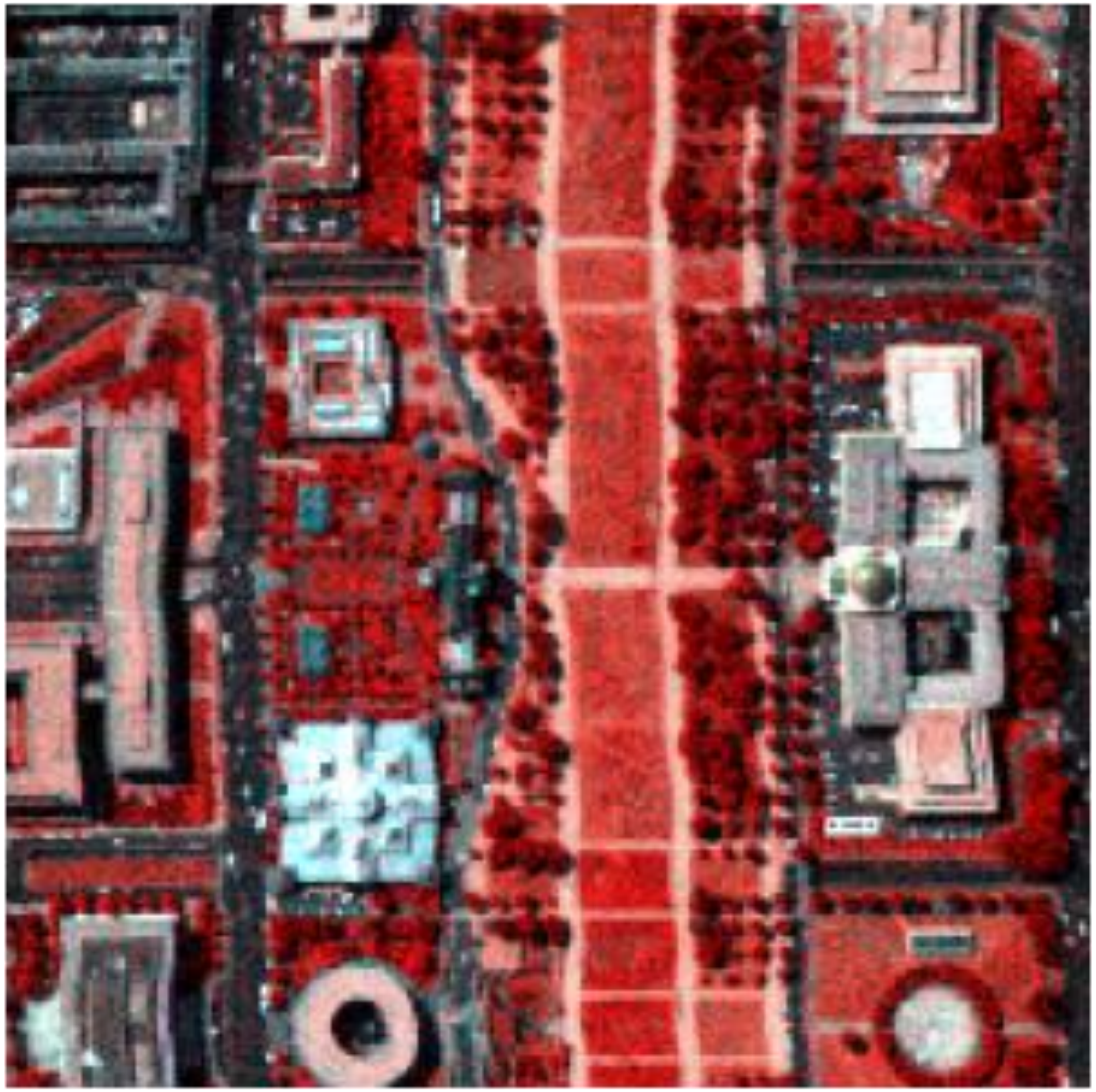
Height: 600 to 800 scale and 191-B.
Width: 50 to 250 scale and 191-B.
Height and Width: (200, 200, 191).

Hyperspectral Image Preprocessing (Simulated and Real Experiment) [2/6]

Simulated Experiments for Testing

- Alpha Noise
- Random Noise
- Gaussian Noise

Here for example, I’ve used the Alpha Sigma = 50.



Testing Dataset

Height: 600 to 800 scale and 191-B.

Width: 50 to 250 scale and 191-B.

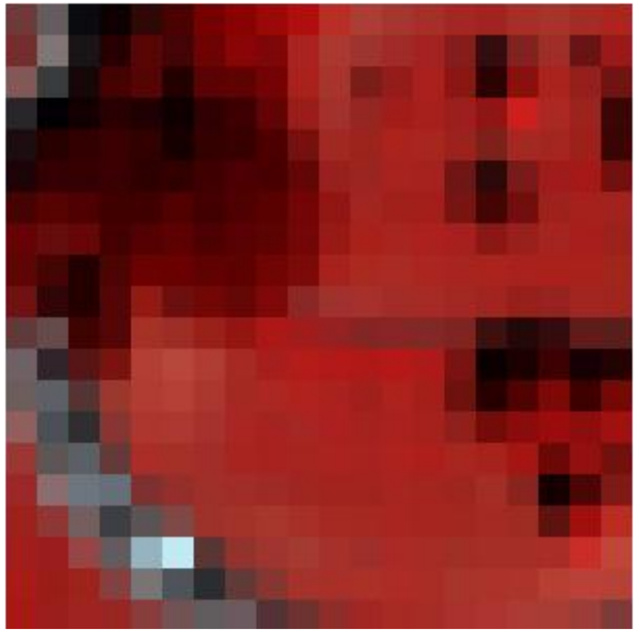
Height and Width: (200, 200, 191).

Hyperspectral Image Preprocessing (Simulated and Real Experiment) [3/6]

Simulated Experiments for Training

- Alpha Noise, Random Noise, and Gaussian Noise

Here for example, I've used the Alpha Sigma = 50.

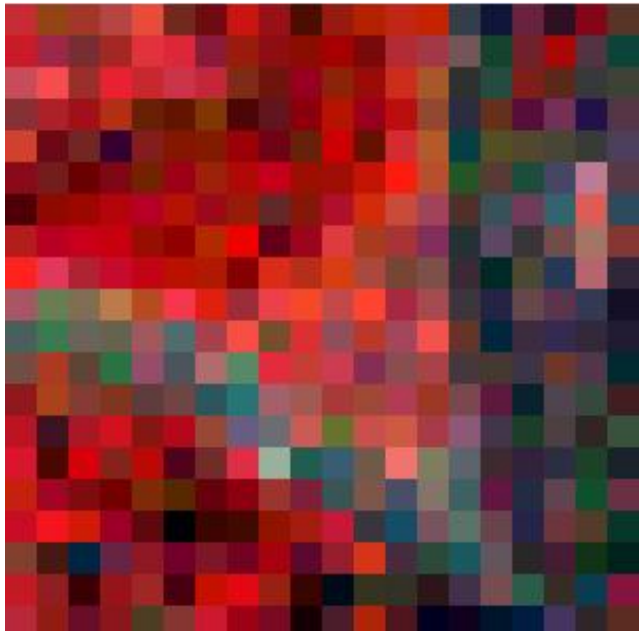


Utilized Specific Dataset

Before: (810, 20, 20, 191). Then we used 24 Batch Size. After: (24, 20, 20, 191)

Data Augmentation for Training

These are techniques used in the data augmentation procedure. After (810, 20, 20, 191) with 810 samples. With Scale (1) data is (1080, 307, 191).



- Scale: The data dimension point of scale have 1.
- Stride and Patch Size : The size of stride have 20.
- Rotation: The angle of rotation have 90 degree.
- Simulated Noise: Used the different types of Noise functionalities for denoise features, such have these (Random, Gaussian, and Alpha) noise.

Note: If scale is 2, then 3240 samples with data augmentation (2160, 614, 191) of WD Mall dataset.

Simulated Noise Methods

Gaussian Noise:

For different bands, the noise intensity is also different, where the noise level σn is added along the spectral axis and is varied like a Gaussian curve.

- β intensity of the noise,
- η standard deviation for Gaussian curve.
- $\sigma n = \text{Gau}(\beta, \eta)$, where $\beta = 200$ and $\eta = 30$.

$$\sigma_n = \beta \sqrt{\frac{\exp\{-(n - B/2)^2/2\eta^2\}}{\sum_{i=1}^{B} \exp\{-(i - B/2)^2/2\eta^2\}}}$$

[Link: Gaussian Noise Curve]

Normal Gaussian Distribution:

The probability density for the Gaussian distribution is

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}},$$

where μ is the mean and σ the standard deviation. The square of the standard deviation, σ^2, is called the variance.

Parameters:

loc : *float or array_like of floats*

Mean ("centre") of the distribution.

scale : *float or array_like of floats*

Standard deviation (spread or "width") of the distribution. Must be non-negative.

size : *int or tuple of ints, optional*

Output shape. If the given shape is, e.g., `(m, n, k)`, then `m * n * k` samples are drawn. If size is `None` (default), a single value is returned if `loc` and `scale` are both scalars. Otherwise, `np.broadcast(loc, scale).size` samples are drawn.

[Link: Numpy Random Normal]

Hyperspectral Image Preprocessing (Simulated and Real Experiment) [5/6]

Washington DC Mall (HSI) Data Processing (Truncate Image In Linear Stretch**)**

- Used to adjust the dynamic range of an image by cutting off the extreme values at both ends and then rescaling the remaining values to cover the full range of the display.
- To enhance the contrast of the image and bring out more detail.

```
def trim_image_in_linear_stretch(image, q_sequence_of_percentiles=2, maxout=1, min_out=0):

    def image_ojbect_process(image_ojbect, maxout=maxout, minout=min_out):
        # Truncate the HSI Image. # 2% of pixels to be truncated from both ends
        trim_down = np.percentile(a=image_ojbect, q=q_sequence_of_percentiles)
        trim_up = np.percentile(a=image_ojbect, q=100 - q_sequence_of_percentiles)
        # q = between 0 and 100 inclusive. If q is a single percentile and axis=None,
        # then the result is a scalar. The return output is specified in array.

        # Rescale the pixel values. Just like Numpy Clip image function. In ranage of b/w 0 and 1.
        image_ojbect_new = (image_ojbect - trim_down) / ((trim_up - trim_down) / (maxout - minout))
        # Formula: ((Old Image - Low Percentile) / ((Max Percentile - Low Percentile) / (Max Edge - Min Edge))
        image_ojbect_new[image_ojbect_new < minout] = minout # Replace 0.
        image_ojbect_new[image_ojbect_new > maxout] = maxout # Replace 1a.

        return np.float32(image_ojbect_new)

    image = np.float32(image)
    height, width, band = image.shape
    new_image = np.zeros((height, width, band))

    for b in range(band):
        new_image[:, :, b] = image_ojbect_process(image[:, :, b])
    return new_image
```

Hyperspectral Image Preprocessing (Simulated and Real Experiment) [6/6]

Washington DC Mall (HSI) Data Augmentation

```
def data_aug(img, rot_time, filp_mode):
    if filp_mode == -1:
        return np.rot90(img, k=rot_time)
        # Rotate an array by 90 degrees in the plane specified by axes.
        # Output same as the given input, in case of k = -1
    else:
        return np.flip(np.rot90(img, k=rot_time), axis=filp_mode)
        # Reverse the order of elements in an array along the given axis.
        # filp_mode: vertically (axis=0), horizontally (axis=1).
```

```
augmentation(data_train_DC, count = 0)
```

```
Per number of total: 1/[1]
data scaled shape of per number ( 1 ) :  (1080, 307, 191)
Total number of augmention :  810
```

```
original = np.array(clean)
noise = np.array(noise)
print("Original Dataset Shape : ", original.shape, noise.shape)
```

```
Original Dataset Shape :  (810, 20, 20, 191) (810, 20, 20, 191)
```

```
# Used specific batch_size = 24 = K
batch_size = 24  # K = 24

original_ = original[:batch_size]
noise_ = noise[:batch_size]

print("Batch-Size Dataset Shape : ", original_.shape, noise_.shape)
```

```
Batch-Size Dataset Shape :  (24, 20, 20, 191) (24, 20, 20, 191)
```

```
clean = []
noise = []
aug_times = 1
scales = [1]
patch_size, stride = 20, 20

def augmentation(data_train, count = 0):
    for s in scales:
        print(f"Per number of total: {s}/{scales}")
        data_scaled = scipy.ndimage.zoom(data_train, (s, s, 1)).astype(np.float32)
        data_scaled[data_scaled < 0] = 0
        data_scaled[data_scaled > 1] = 1

        print("data scaled shape of per number (",s,") : ", data_scaled.shape)
        h_scaled, w_scaled, band_scaled = data_scaled.shape
        for i in range(0, h_scaled - patch_size + 1, stride):
            for j in range(0, w_scaled - patch_size + 1, stride):
                for k in range(0, aug_times):
                    count += 1
                    x = data_scaled[i:i + patch_size, j:j + patch_size, :]

                    rot_time = np.random.randint(0, 4) # Generate: 0, 1, 2, 3
                    filp_mode = np.random.randint(-1, 2) # Generate: -1, 0, 1
                    x_aug = data_aug(x, rot_time, filp_mode) # Data Augmented

                    y_aug = noise_add_by_bands(x_aug) # Add the Simulated Noise
                    x_np = np.array(x_aug, dtype='float32')
                    y_np = np.array(y_aug, dtype='float32')
                    clean.append(x_np)
                    noise.append(y_np)
    print("Total number of augmention : ",count)
```

Data Representation

Hyperspectral Dataset

The analysis would be conducted on two widely recognized hyperspectral data sets namely Indian Pines (IP) and Washington DC Mall (WDCM).

1. **IP:** Obtained using the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) **[16]** sensor in the year 1992. Collected from the Northwestern region of Indiana. The area comprised several agricultural fields, organized geometric structures, and irregular forests. The scene covers 145 × 145 pixels with 224 spectral bands with 400 to 2500 nm wavelength and a spatial resolution of 20 meters per pixel. Due to atmospheric water absorption the four null bands and 20 other bands effect. The remaining 200 bands were employed for experimentation.

2. **WDCM:** Washington DC Mall obtained using the Spectral Information Technology Application Center of Virginia **[17]** which was responsible for its collection. The sensor pixel system in 210 bands with the 0.4 to 2.4 µm region of the visible and infrared spectrum. Bands in the 0.9 and 1.4 µm regions where the atmosphere is non-transparently dropped from the data set, leaving 191 bands. The data set contains 1208 scan lines with 307 pixels in each scan line such as a (1208-W x 307-H) shape.

Excepted Results & Industry

Excepted Results

1. Simulated Experiments: The quantitative evaluation of the denoising results.
2. Real-World Experiments: The classification accuracy of the denoising results.
3. GUI Interface: We would design the Application Interface (Website or Desktop).

Industry

1. The global hyperspectral imaging systems market [15] is projected to reach USD 35.8 billion by 2026 from USD 15.4 billion in 2021, at a CAGR (Compound Annual Growth Rate) of 18.4% during the forecast period.
2. NASA (National Aeronautics and Space Administration), IEEE (Institute of Electrical and Electronics Engineers), and etc.

Team Work

Weeks Plain

1. From 4 to 7 weeks: The working on Research Papers and Literatures Review.
2. From 7 to 8 weeks: The creating of System Analysis (Use Case Diagram) and System Design (Component and Activity Diagrams).
3. From 8 to 16 weeks: The creation of Prototype (Hyperspectral Image Preprocessing) and Report (Documentation).

Teamwork Participation

1. Muhammad Allah Rakha (P19-0006): Review of Research Papers and Literature, System Design (Component and Activity Diagrams), Prototype (Hyperspectral Image Preprocessing), and Report (Introduction, Literature Review, Project Vision, Software Requirements Specifications).
2. Farkhanda Saleem (P19-0004): Review of Research Papers and Literature, and Introduction of Report.
3. Mina Riaz (P19-0099): Review of Research Papers and Literature, System Design (Activity Diagram), and Literature Review of Report.

Timeline Prototype

FYP - 1 (Spring 2023)

WEEK 1	WEEK 2-3	WEEK 4-8	WEEK 8-12	WEEK 12-16	WEEK 1-16
Project Proposal	Project Defence	Research Papers Review and Literatures Review	Problem-solving strategies and Project Outlines	First Prototype of our project.	Documentation

FYP - 2 (Fall 2023)

WEEK 1-2	WEEK 2-6	WEEK 6-9	WEEK 9-12	WEEK 12-16	WEEK 1-16
Build the structure and functionality of components	Development of core components and GUI interface	Testing and Validation	Research finalize	Write-up research/report	Documentation

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The End

THANK YOU FOR LISTENING