

# Accurate Spectral Super-resolution from Single RGB Image Using Multi-scale CNN

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### Introduction

- Single image spectral super-resolution aims at producing a high-resolution hyperspectral image directly from the RGB observation. The main challenge is to accurately reconstruct a high-dimensional continuous spectrum from three discrete intensity values at each pixel.
- Multi-scale deep convolutional neural network jointly encodes the local and non-local image information through symmetrically downsampling and upsampling the intermediate feature maps in a cascading paradigm, and improves the reconstruction accuracy.
- Experimental results on the latest and largest hyperspectral dataset demonstrate the effectiveness of the proposed method.



## **Comparison experiments**

**Competing Methods** Spline interpolation (serves as baseline), dictionary learning and sparse coding [2, 1], and another deep learning method [3].



#### **Basic Building Blocks**

• Double convolution (Double Conv) **block** consists of two  $3 \times 3$  convolutions. Each of them is followed by batch normalization, leaky ReLU and dropout.

**Dataset** The NTIRE2018 challenge on spectral reconstruction from RGB images (in conjunction with CVPR2018) provides 256 high-resolution hyperspectral images  $(1392 \times 1300)$  and 5 independent images for testing. During training, patches of size  $64 \times 64$  are extracted. During testing, we directly feed the whole image to the network and get the estimated hyperspectral image in one single forward pass.

**Evaluation** For evaluating **pixel-level reconstruction error**, we follow [1] to use absolute and relative root-mean-square error (RMSE and rRMSE). Note that There are two formulas for RMSE and rRMSE respectively. Besides, we also use use spectral angle mapper (SAM) to measure the spectral similarity.

#### Quantitative Results

The table shows the average evaluation results on the test set. For the complete table, please refer to Table.2 in our paper.

	$RMSE_1$	$RMSE_2$	$rRMSE_1$	$rRMSE_2$	SAM (degree)
Interpolation	1.9454	3.2500	0.0610	0.1038	3.6813
[2]	1.6154	2.6061	0.0656	0.0844	3.6457
[1]	1.2988	1.8936	0.0570	0.0610	3.2985
[3]	0.7584	1.2445	0.0262	0.0407	1.5523
Out method	0.7177	1.2899	0.0233	0.0414	1.4673

- Downsample block contains a regular max-pooling layer. It reduces the spatial size of the feature map and enlarges the receptive field of the network.
- Upsample block We use the pixel shuffle operation (subpixel convolution), which is good at alleviating the checkboard artifacts.

Network Architecture Our method is inspired by the well known U-Net architecture for image segmentation. The network follows the encoder-decoder pattern.

- Encoder Each downsampling step consists of a "Double Conv" with a downsample block. The spatial size is progressively reduced, and the number of features is doubled at each step.
- **Dncoder** Every step consists of an upsampling operation followed by a "Double" Conv" block, recovering the spatial size while halving the number of features.

#### Visual Results

Absolute reconstruction error From left to right: RGB rendition, [1], [3], and our method. More images are available in our paper.



**Spectral reconstruction** Sample results of spectral reconstruction by our method. The corresponding pixel locations are indicated by different colors. More images are available in our paper.









• Skip connections The corresponding feature maps of the encoder and decoder are concatenated.

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