

Hyperspectral Image Reconstruction using Deep External and Internal Learning

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Introduction and Motivation

In this paper, the authors attempt to solve the problem of reconstruction of Hyperspectral Image (HSI) from the corresponding colour coded image using the Convolution Neural Network (CNN) based method.

The authors' main contributions include : **1)** Design a CNN-based method for coded HSI reconstruction, using deep external and internal learning. **2)** Use external learning to exploit the spatial-spectral correlation of the HSI. **3)** Use internal learning for guaranteed generalisation ability and adaptation.

Approach

For CASSI model, define $X(m, n, \lambda)$ to be the intensity of incident light where $1 \leq m \leq M$ and $1 \leq n \leq N$ index the spatial coordinates and $1 \leq \lambda \leq \Lambda$ indexes the spectral coordinate.

$$y^c(m, n) = \sum_{\lambda=1}^{\Lambda} \varphi(m\psi(\lambda), n)x(m\psi(\lambda), n, \lambda)\omega(\lambda)$$

[where $\varphi(m, n)$ is the transmission function of the coded aperture, $\psi(\lambda)$ the wavelength-dependent dispersion function for the prism, x is the spectral distribution of the (m, n, λ) -th pixel of the HSI, $\omega(\lambda)$ represents the response function of the detector and LHS is the (m, n) -th pixel]

In matrix form this can be written as,

$$Y^c = \Phi^c X$$

[where c denotes the projection matrix of CASSI and jointly determined by $\varphi(m, n)$, $\psi(\lambda)$ and $\omega(\lambda)$, Y^c denotes the vectorized representation of the compressive image $y^c(m, n)$, and X the underlying HSI]

For DCD system, the representation takes the form of,

$$y^p(m, n) = \sum_{\lambda=1}^{\Lambda} x(m, n, \lambda)\omega(\lambda)$$

For reconstruction network, let C_{in}^c denote the first convolutional layer and C_{out}^c denote the last one in the reconstruction network. For the l -th Dense Block, the inputs are B_0^c to B_{l-1}^c and the output can be expressed as $B_l^c = D_l^c(B_0^c, \dots, B_{l-1}^c)$, where $B_0^c = C_{in}^c(Y^c)$ and D_l^c denotes the l -th Dense Block function in the CASSI reconstruction network, respectively.

The final output can be expressed as,

$$X_c^b = C_{out}^c(B_L^c + C_{in}^c(Y^c)) = f^c(Y^c, \Theta^c)$$

External learning : Here, we need to minimise the loss functions. For the CASSI system it is,

$$L_{ex}^c(\Theta_{ex}^c) = 1/T \sum_{t=1}^T \|f^c(Y_{ex,t}^c, \Theta_{ex}^c)X_{ex,t}\|^2$$

where $Y_{ex,t}^c$ is the t -th external compressive image, $X_{ex,t}$ the t -th corresponding ground truth from external dataset, and Θ_{ex}^c are the parameters of the external trained CASSI reconstruction network, and T is the number of training samples in the external dataset.

For DCD reconstruction, the function,

$$L_{ex}^d(\Phi_{ex}^d) = 1/T \sum_{t=1}^T (\|f^d(Y_{ex,t}^c, Y_{ex,t}^p, \Phi_{ex}^d)X_{ex,t}\|^2 + \eta \|f^c(Y_{ex,t}^c, \Phi_{ex}^c)X_{ex,t}\|^2)$$

Internal Learning : The details are similar to external learning except that the learning rate is 0.0001 and all learnable layer's weights are initialised by external learned model. For reducing the effect of distributed variation, the network can be updated with spatial-spectral constraint from input coded image for every scene,

$$L_{in}^c(\Theta_{in}^c) = \|\Phi^c f^c(Y_{in}^c, \Theta_{in}^c)Y_{in}^c\|^2$$

Hence, the characteristics are modeled in deep prior instead of hand crafted prior.

Experimental Observations

The method is evaluated on three public HSI datasets, including the CAVE dataset, the Harvard dataset, and ICVL dataset.

By comparing the CASSI reconstruction results and DCD reconstruction results, it can be concluded that the DCD outperforms CASSI with better vision quality.

Advantages

1) The architecture used effectively adapts to various scenes and variation in real world data. **2)** This method effectively exploits the spectral-spatial correlation and requires no handcrafted elements as priors which are not sufficient to represent various real world data. **3)** As shown by the experimental results, this method outperforms the current methods both on real and synthetic data and thus would be a better choice for hyperspectral image reconstruction.

Scope of Improvement

1) The scope of this method can be expanded to include systems other than CASSI and DCD. **2)** The method is powerful but has a very complex architecture. Efforts to simplify the architecture while preserving the performance and accuracy can be made.