Research on Spectral Imaging Systems and Reconstruction Algorithms

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Presentation Outline

1. Introduction to Imaging Spectrometry
2. Compressvie Sensing
3. Reconstruction Algorithms

Definitions and Terminologies

Incorporating spectrometers and imaging techniques, **Spectral Imaging** can record light intensity data in multiple spectral bands for each pixel point, obtaining a 3-D data cube with both spatial and spectral information of the object, as demonstrated in Fig. 1.

- Multispectral Imaging: measures light in a small number (typically 3 to 15) of spectral bands with spectral resolution $\Delta\lambda/\lambda = 0.1$
- Hyperspectral Imaging: hundreds of contiguous spectral bands are available [1] with spectral resolution $\Delta\lambda/\lambda = 0.01$

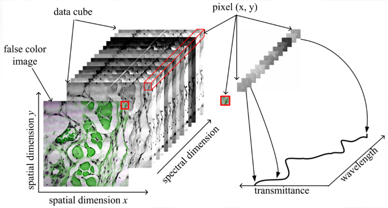

Figure 1: The concept of spectral data cube [2]

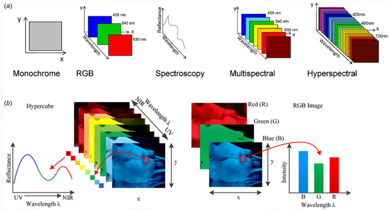

Figure 2: Comparison of different features [3]

Taxonomy

There are many ways to determine taxonomy. Below are two of them.

- Depending on the scanning method, they can be classified as whiskbroom, pushbroom, staring and snapshot, as illustrated in Fig. 3.
- Applying the spectroscopic principle as the criteria, shown in Fig. 4, there are dispersive, filter, interference and computational types. Among them, the computational imaging will be discussed in detail later.

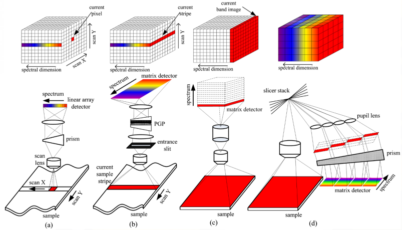

Figure 3: Taxonomy by the scanning method [2]

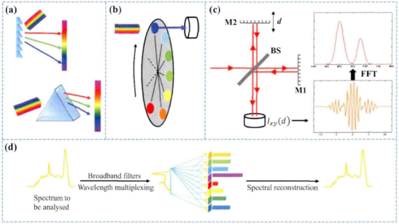

Figure 4: Taxonomy by the spectroscopic principle [4]

Application

- Remote sensing: Anomaly detection, background feature description
- Biomedical Science: Disease diagnosis
- Military: Hyperspectral imaging reconnaissance

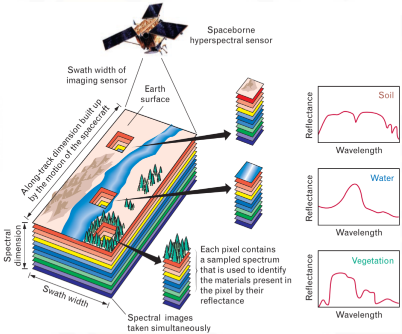

Figure 5: Spectral imaging for remote sensing [5]

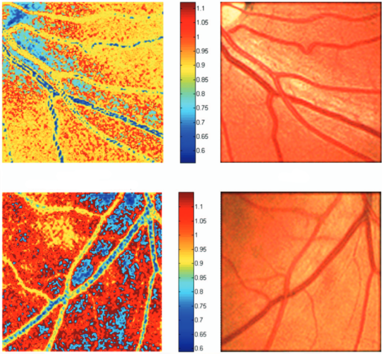

Figure 6: Hyperspectral imaging in ophthalmology [6]

Computational Imaging

By solving the inverse problem with a reconstruction algorithm, the target object can be recovered, illustrated below in Fig. 7.

- More information than conventional imaging systems
- Less time-consuming, less resource-consuming

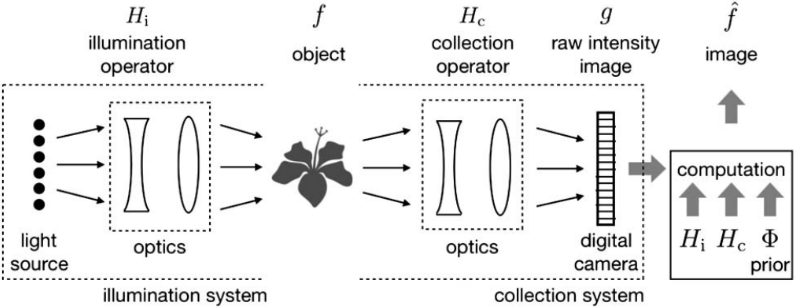

Figure 7: General computational imaging system [7]

Nyquist-Shannon Sampling Theorem vs. Compressvie Sensing

The compressive sensing achieves compression in the process of sampling the signal, improving the data acquisition efficiency remarkably.

Nyquist-Shannon Sampling Theorem [8]: For a given sample rate f_s, perfect reconstruction is guaranteed possible for a band limit $B < f_s/2$.

Compressvie Sensing [9]: Through optimization, the sparsity of a signal can be exploited to recover it from far fewer samples than required by the NyquistShannon sampling theorem. $\Rightarrow$ time-, money-saving!

Conditions: sparsity and incoherence

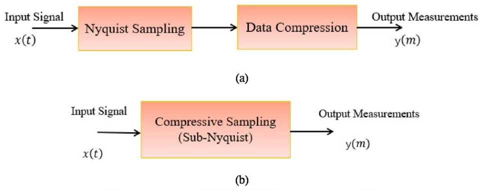

Figure 8: Nyquist Sampling vs. Compressvie Sampling

Sparsity

Assume that the 1-D signal $\mathbf{f} \in \mathbb{R}^n$ is sparse in the orthogonal basis $\mathbf{\Psi}$:

$$\mathbf{f} = \mathbf{\Psi}\boldsymbol{\theta}$$

Applying a matrix $\mathbf{\Phi}_{m \times n} (m \ll n)$ to measure $\mathbf{f}$, we can acquire $\mathbf{g} \in \mathbb{R}^m$:

$$\mathbf{g} = \mathbf{\Phi}\mathbf{f} = \mathbf{\Phi}\mathbf{\Psi}\boldsymbol{\theta} = \boldsymbol{A}\boldsymbol{\theta}$$

RIP (Restricted Isometry Property) [10]:

$$(1 - \delta_S)||\mathbf{f}||_2^2 \leq ||\mathbf{\Phi}\mathbf{f}||_2^2 \leq (1 + \delta_S)||\mathbf{f}||_2^2$$

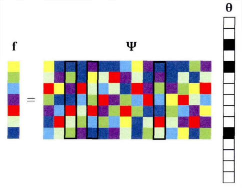

Figure 9: Sparse representation

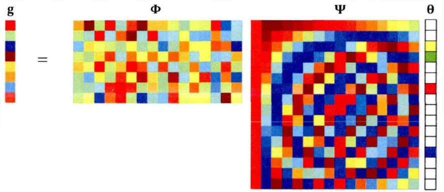

Figure 10: Compressvie sensing model

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Optimization Target and Reconstruction Algorithms

The compressive sensing signal reconstruction problem is the nonlinear optimization problem of the following equation [11]:

$$\hat{\mathbf{f}} = \mathbf{\Psi} \arg\min_{\theta} \left(||\mathbf{\Phi\Psi}\boldsymbol{\theta} - \mathbf{g}||_2^2 + \tau ||\boldsymbol{\theta}||_1 \right)$$

Reconstruction algorithms can be divided into five categories shown below in the big picture:

- Greedy algorithm: Create safe moves to approach the optimal solution
- Convex optimization: Optimize the cost function in the certain convex set
- Bayesian statistics: Search the maximum posteriori probability
- Non-convex optimization: Degenerate to a non-convex optimization problem and find the stationary point
- Brute force: Iterate through all possible solutions

★ Now let's focus on the Greedy Algorithm!

Greedy algorithm: Create safe moves

Matching Pursuit (MP) [12] is one of the most basic greedy algorithms, which can find the best matching projection of a signal in an over-complete dictionary $\mathbf{D} = [d_1, d_2, d_3, \cdots, d_d] \in \mathbb{R}^{n \times d}$.

Algorithm 3.1: Matching Pursuit (MP)

Input: $\mathbf{g}, \mathbf{\Phi}$, dict $\mathbf{D}$
Output: $(\boldsymbol{\theta}_q)_{q=1}^{Q}$, iteration number Q

Init: Residue $r_1 \leftarrow \mathbf{g}$, $q \leftarrow 1$;
while $r_q \geq$ *threshold* **do**
  $\gamma_q \leftarrow \arg\max_{\gamma} |\langle r_q, d_\gamma \rangle|$;
  $\boldsymbol{\theta}_q \leftarrow \langle r_q, d_{\gamma_q} \rangle$;
  $r_{q+1} \leftarrow r_q - \mathbf{\Phi} d_{\gamma_q} \boldsymbol{\theta}_q$
End

Proposal & One More Thing

Basic Proposal

To understand more reconstruction algorithms based on compressive sensing.

★ One More Thing: Future?

Thanks to the remarkable development of deep learning, end-to-end mapping mechanism for efficient spectral reconstruction can be developed [13]–[15].

I am impressed by the idea that Feature Map ⇄ HSI Channels!

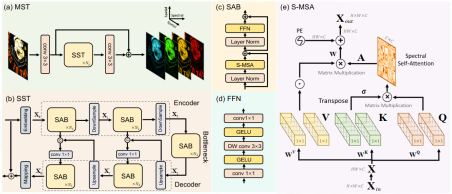

Figure 11: The overall pipeline of the proposed solution MST++

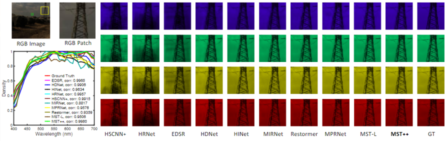

Figure 12: Reconstructed hyperspectral image (HSI) comparisons

Typical CNNs Method

CNNs has been successfully applied in the field of image classification and detection, because of the *special structure of the convolutional network*, it has a good effect on two-dimensional images.

The hyperspectral data cube can be regarded as a multi-channel image, the number of channels is the number of bands of the hyperspectral data, and the size of the image is the window size of the spatial information.

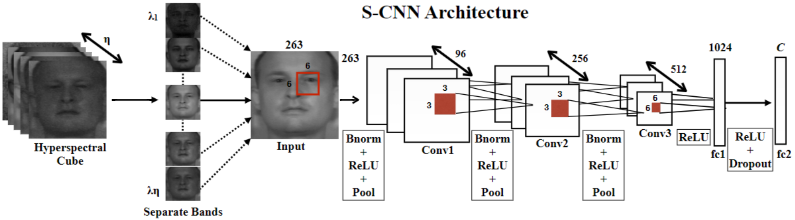

Figure 13: Example of CNNs on Hyperspectral Imaging [16]

Drawbacks of CNNs

Drawbacks: the reconstruction accuracy of pixels at the target edges in the image.

Compared with the reconstruction algorithm based on compressive sensing, the reconstruction accuracy of the CNNs-based algorithm still *needs further improvements.*

- CNNs ⇒ Small Receptive Field ⇒ *Deeper Networks? Limited!*

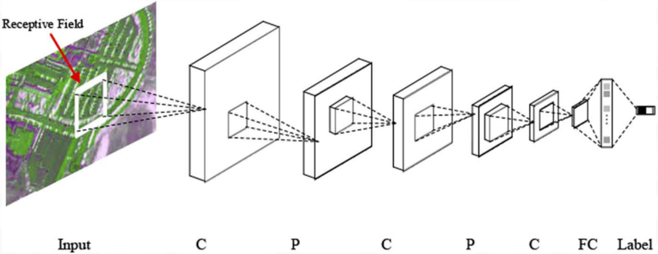

Figure 14: Receptive Field

Attention Is All You Need: Transformer

These CNN-based methods achieve impressive performance while showing limitations in capturing the long-range dependencies and self-similarity prior.

Transformer-based method [17] for efficient spectral reconstruction is presented recently.

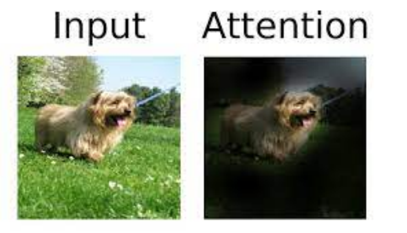

Figure 15: Example of Attention Mechanism

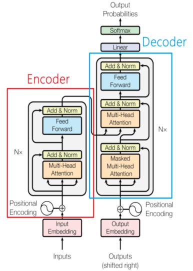

Figure 16: Transformer

Self-Attention Mechanism

Self-Attention is a mechanism that can consider global information

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{D_k}}\right)V$$

- Convolution Process ⇒ Self-Attention
- Feature Map ⇒ Multi-Head Attention
- CNNs ⇒ Transformer

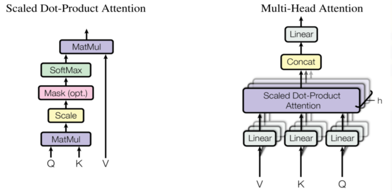

Figure 17: Multi-Head Attention

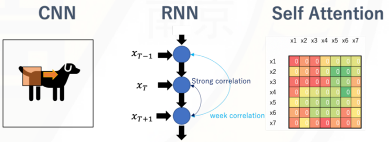

Figure 18: CNN vs. Transformer

Drawbacks of Transformer

Vision Transformer, entirely provides the convolutional inductive bias by performing self attention across of patches of pixels. The drawback is that, they require *large amount data to learn everything* from scratch. ⇒ Back to traditional methods?

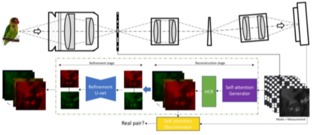

Fig. 11. Imaging process of snapshot compressive-spectral imaging (SCI)

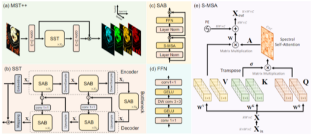

Fig. 13. Multi-stage Spectral-wise Transformer for Efficient Spectral Reconstruction (MST++)

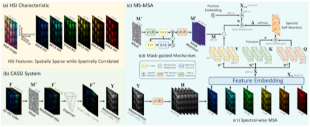

Fig. 12. Mask-guided Spectral-wise Transformer for Efficient Hyperspectral Image Reconstruction

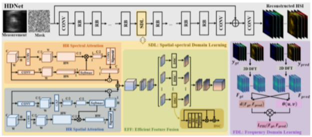

Fig. 14. High-resolution Dual-domain Learning for Spectral Compressive Imaging (HDNet)

Figure 19: Transformer Models for HSI

Conclusion

CNNs-based or Transformer-based methods have the disadvantages which are discussed in detail. Therefore, traditional methods are irreplaceable by deep learning methods, and we can only say that each has its own advantages and disadvantages.

Deep learning based approach is a very hot direction recently, and I hope it will get better and better in the future research.

Thanks to the community for their contribution.

Figure 20: GitHub

Figure 21: PyTorch

Figure 22: CUDA

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Thank You.