Research on Spectral Imaging Systems and Reconstruction Algorithms

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May 26, 2022

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Presentation Outline

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

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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 $\Delta\lambda/\lambda = 0.01$

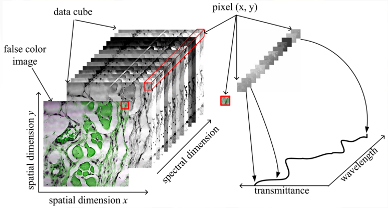

Figure 1: The concept of spectral data cube [2]

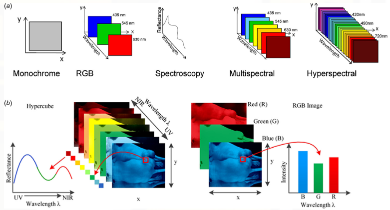

Figure 2: Comparison of different features [3]

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.

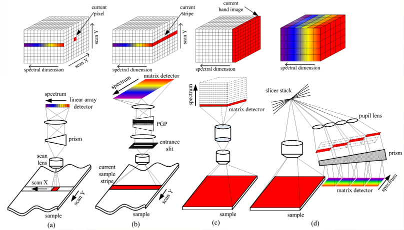

Figure 3: Taxonomy by the scanning method [2]

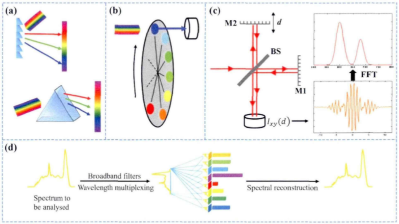

Figure 4: Taxonomy by the spectroscopic principle [4]

Application

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

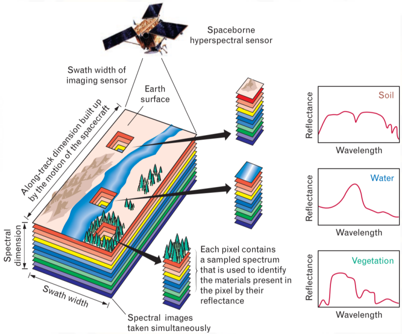

Figure 5: Spectral imaging for remote sensing [5]

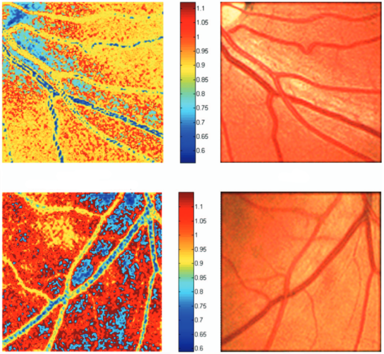

Figure 6: Hyperspectral imaging in ophthalmology [6]

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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

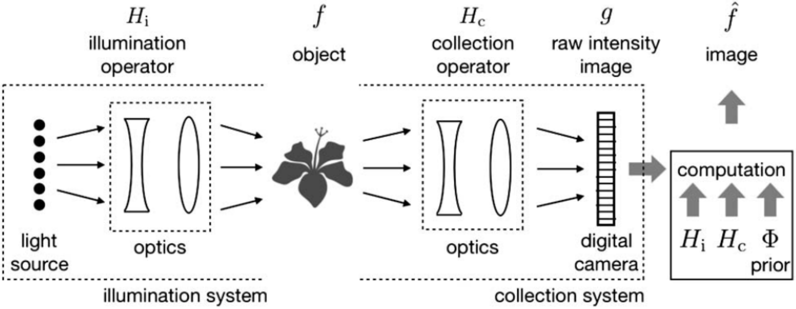

Figure 7: General computational imaging system [7]

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 Nyquist–Shannon sampling theorem. ⇒ time-, money-saving!

Conditions: sparsity and incoherence

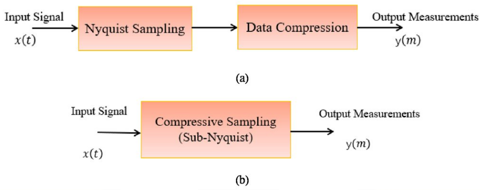

Figure 8: Nyquist Sampling vs. Compressvie Sampling

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]:

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

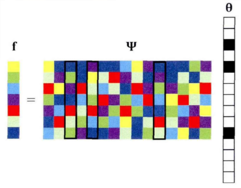

Figure 9: Sparse representation

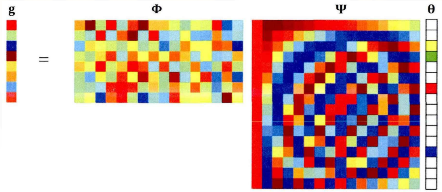

Figure 10: Compressvie sensing model

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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!

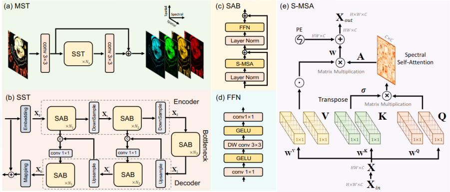

Figure 11: The overall pipeline of the proposed solution MST++

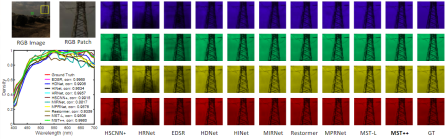

Figure 12: Reconstructed hyperspectral image (HSI) comparisons

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Fin.

Thank You.