

Fast Algorithms for Flash Hyperspectral Image Reconstruction

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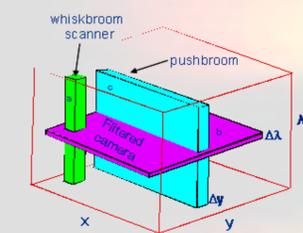
http://www.csm.ornl.gov/Internships/rams_06/abstracts/s_woods.pdf

Abstract

Missile defense requires flash radiometry for target kill assessment and spectral analysis of high impact scenarios. The Computed Tomography Imaging Spectrometer (CTIS) is a unique non-scanning sensor capable of simultaneously acquiring full spectral and spatial information that is being considered by the Missile Defense Agency (MDA) for such applications. Because of the considerable amount of information provided by CTIS, and the requirement for real-time performance, there is a critical need to accelerate the recovery time of the imaged hyperspectral object by orders of magnitude, both by designing new algorithms, and by considering implementation on emerging revolutionary hardware.

Background

Flash spectrometer produces **3D** data set: two spatial dimensions and one spectral dimension.



All **conventional** spectrometer data acquisition involves scanning and moving parts. Scene motion causes spatial artifacts.



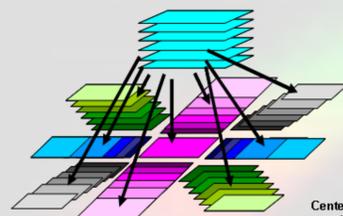
hyperspectral data cube

Computed tomographic imaging spectrometry (CTIS)



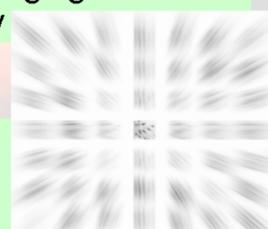
Scanning is eliminated by use of **dispersive optics**

Uses **computer generated hologram** to project to hyperspectral imaging on to focal plane array



Center image is not dispersed. Used to aim the CTIS

Each blurred image can be expressed as the **2D** recording of diffracted projections of the object cube for different dispersion angles.



Methodology

CTIS imaging involves the following general equation:

$$\mathbf{p} = H\mathbf{q} + \boldsymbol{\eta}$$

Given the optical system matrix, the focal plane image, and the noise statistical properties, an iterative algorithm estimates the object voxel contributions by minimizing E:

$$E = \|\mathbf{p} - H\mathbf{q}\|_2^2$$

H : optical system matrix (dimension: $M \times N$)

$\bar{\mathbf{q}}$: vector representation of hyperspectral object

$\bar{\boldsymbol{\eta}}$: noise including both Poisson noise and Gaussian post detection noise

$\bar{\mathbf{p}}$: vector representation of focal plane image

M : focal plane vector-image size ($M_x \cdot M_y$)

N : hyperspectral vector object-size ($N_x \cdot N_y \cdot N_\lambda$)

Three algorithms have been investigated:

I. MDA's current **mixed expectation maximization (MEM)** technique:

$$\mathbf{q}_n^{k+1} = \mathbf{q}_n^k \left\{ \frac{\sum_{m=1}^M \frac{(\mathbf{p}_m^2 + 2\mathbf{p}_m \sigma_s^2) H_{mn}}{[(H\mathbf{q}^k)_m + \sigma_s^2]^2}}{\sum_{m=1}^M \frac{[(H\mathbf{q}^k)_m^2 + (H\mathbf{q}^k)_m \sigma_s^2] H_{mn}}{[(H\mathbf{q}^k)_m + \sigma_s^2]^2}} \right\}$$

σ : standard deviation for Gaussian post detection noise

- Slow execution 40 min. per object reconstruction
- MDA new requirements
 - 5 milliseconds per object reconstruction
 - Faster algorithms
 - Implementation on faster hardware

II. **Asymptotic attractor dynamics (AAD)** algorithm derived from Lyapunov stability arguments

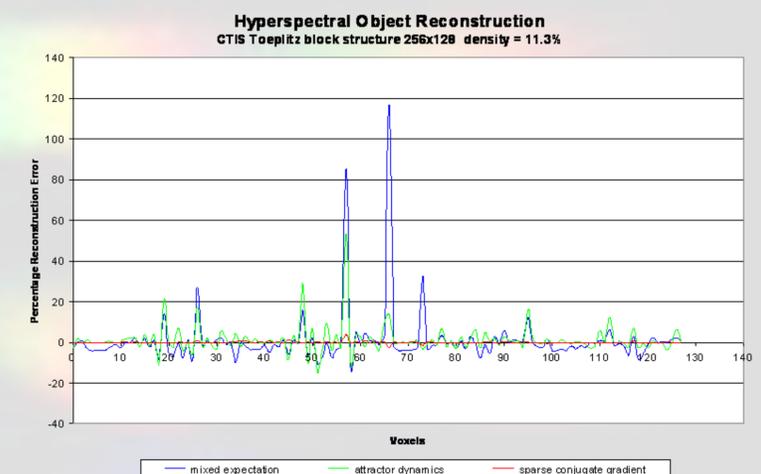
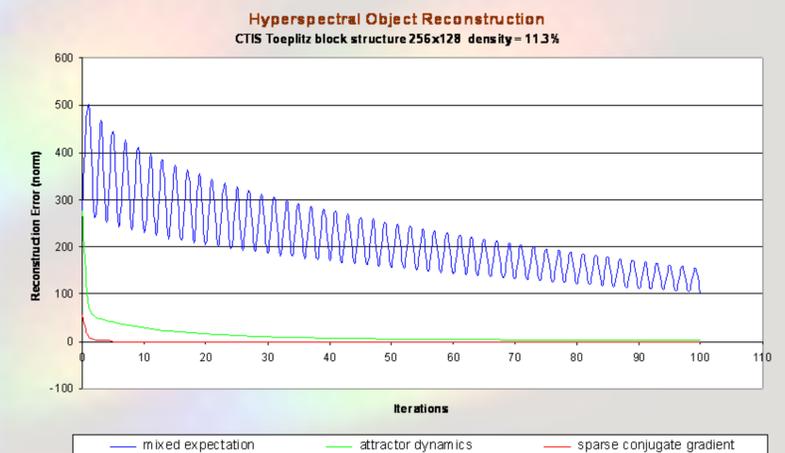
$$\mathbf{q}^{v+1} = \mathbf{q}^v + 2\alpha\Delta_t \left[\mathbf{p} - H\mathbf{q}^v \right]^T \cdot H$$

Advantages of Scheme

- no inversion of H is required
- no transpose of H is required
- Lyapunov stability: convergence to E=0

III. **Conjugate gradients** specialized for **sparse block Toeplitz** optical system matrix, (SCG). matrix.

Results



Conclusion

The newly developed algorithms (AAD and SCG) show substantial performance improvement over the current MDA technique (MEM):

- Over two orders of magnitude faster (SCG)
- Considerably more accurate in reconstructing target object

Future Research

- Implementation on the STI Cell
- Support ongoing work for the MDA
- Contribute to mission of the DOE Office of Science in high performance computing