Accelerating computed tomographic imaging spectrometer reconstruction using a parallel algorithm exploiting spatial shift-invariance

Larz White\textsuperscript{a}, W. Bryan Bell\textsuperscript{a}, Ryan Haygood\textsuperscript{a}
\textsuperscript{a}Lockheed Martin Aeronautics, Fort Worth, TX 76108

ABSTRACT

Computed Tomographic Imaging Spectrometers (CTIS) capture hyperspectral images in real-time. However, post processing the imagery can require enormous computational resources; thus, limiting its application to non-realtime scenarios. To overcome these challenges we developed a highly parallelizable algorithm that exploits spatial shift-invariance. To demonstrate the versatility of our new algorithm, we developed implementations on a desktop and an embedded graphics processing unit (GPU). To our knowledge, our results show the fastest image reconstruction times reported.

Keywords: GPU, CUDA, CTIS, computed tomography imaging spectrometer, parallel algorithm

1. INTRODUCTION

Hyperspectral imaging has widespread uses. From commercial applications such as mining, agriculture, and geology\textsuperscript{1–10} to defense applications, where it has been used for Intelligence Surveillance and Reconnaissance (ISR)\textsuperscript{1, 2, 4–7, 9, 11–16}

The goal of hyperspectral imaging is to obtain a datacube which is composed of images (the spatial component) of a scene at multiple wavelengths (the spectral component). For example, a datacube could be obtained by taking a picture with a filter placed over the lens, then repeating the process with different filters. However, this is a time consuming task that does not scale well for dynamic scenes. To overcome these challenges snapshot methods were developed to encode spatial and spectral information directly into the sensed image. A reconstruction algorithm is then used to form the hyperspectral datacube. One instrument for snapshot hyperspectral imaging is CTIS which is robust, simple, fast, and has military successes in missile defense, ISR and target/threat characterization/detection\textsuperscript{1, 2, 9, 16, 17}

Even though CTIS captures raw images in milliseconds\textsuperscript{1, 11, 13, 18–21} post processing the imagery requires enormous computational resources, typically taking minutes to hours\textsuperscript{18, 22}. Since potential applications for CTIS are embedded realtime or near-realtime systems, a better reconstruction algorithm is needed. Previous attempts at speeding up the reconstruction algorithm have been performed by Hagen\textsuperscript{18} and Vose-Horton\textsuperscript{1, 23} where they developed fast reconstruction algorithms exploiting spatial shift-invariance (hereafter referred to as shift-invariance). Additionally, hardware accelerations were performed by Thompson\textsuperscript{22} and Sethaphong\textsuperscript{24} using cell processors and supercomputers. Our approach is a combination where we developed a highly parallelizable algorithm that exploits shift-invariance and uses a GPU for hardware acceleration. GPUs are common in modern computers and provide hardware acceleration while still maintaining small form factors. To our knowledge researchers have not utilized GPUs for CTIS reconstruction, but a few hinted at the idea\textsuperscript{1, 22, 24}

Send correspondence to larz.g.white@lmco.com
2. CTIS OVERVIEW

Fig. 1 depicts a typical CTIS snapshot hyperspectral imaging sensor $H$ that encodes spatial $(x,y)$ and spectral $(\lambda)$ information about a scene into an image $g$ on a focal plane array (FPA). The image is then computationally decoded/reconstructed to produce a hyperspectral datacube $f(x,y,\lambda)$. To reconstruct the datacube $f$ from an image $g$ the linear imaging equation is assumed

$$g = Hf,$$  \hspace{1cm} (1)

where the system matrix $H$ is obtained via calibration. Calibration is performed by placing a monochromatic point source such as a small optical fiber illuminated via a monochromator at one pixel in an $\alpha \times \alpha$ field stop. Then a set of $w$ calibration images as shown in Fig. 2 are obtained on a $\gamma \times \xi$ FPA. After this, each calibration image is converted into a vector (via column major or row major order) of length $n = \gamma \xi$ and becomes one column of the system matrix. The remaining columns are obtained assuming shift-invariance where we assume for a given wavelength, shifting the optical fiber one pixel in the field stop or one voxel in the datacube will result in a calibration image that is shifted one pixel on the FPA. Doing so results in an $n \times m$ system matrix with $m = aaw$. The assumption of shift-invariance is widely used and it’s validity is explored by Hagen \cite{18,26}

Figure 1. (Color online) Diagram of a CTIS sensor along with an FPA image and reconstructed datacube.

The solution to Eq. (1) is formally the Moore-Penrose pseudoinverse $f = H^+g$, however, since the system matrix is large and sparse, iterative solvers such as: EM/MLEM, MART, MERT, ART, etc. are often employed\cite{1,18,24,27,31}. For our purposes we used the Expectation Maximization (EM) solver

$$f^{(k+1)} = \frac{f^{(k)}}{h} \left( H^T \frac{g}{Hf^{(k)}} \right) = \left( f^{(k)} \odot h \right) \odot \left( H^T \left( g \odot Hf^{(k)} \right) \right),$$  \hspace{1cm} (2)

where $k$ is the iteration number, $h$ in component notation is $h_j = \sum_{i=1}^{n} H_{ij}$ for $j = 1 \ldots m$, and $\odot$ ($\odiv$) denotes the Hadamard product (division). A typical initial guess for $f^{(1)}$ is either all ones\cite{24,32} or $H^Tg$\cite{2}. A typical total number of iterations $K$ is $10 - 30$\cite{24,29,32}. As Hagen pointed out, using a large number of iterations can result in increased reconstruction error and even unrealistic solutions recommending stopping the iterations early to avoid this effect.

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3. PARALLEL RECONSTRUCTION ALGORITHM

Our reconstruction algorithm utilizes the Vose-Horton decomposition. We start by assuming shift-invariance which means the system matrix can be partitioned as

$$ H = \begin{pmatrix} H_1 & H_2 & \cdots & H_w \end{pmatrix}, $$

(3)

where each block $H_i$ for $i = 1 \ldots w$ is partitioned further into rectangular circulant blocks

$$ H_i = \begin{pmatrix} T_{i,1} & T_{i,2} & \cdots & T_{i,\alpha} \end{pmatrix}, $$

(4)

and each block $T_{i,j}$ for $j = 1 \ldots \alpha$ is an $n \times a$ rectangular circulant matrix; hence, $H$ has $m = a\alpha w$ columns and $n = \gamma \xi$ rows. Next we define the $\gamma \times a$ matrix

$$ Q = \begin{pmatrix} I_a \end{pmatrix}, $$

(5)

and the $n \times a\alpha$ matrix

$$ E = \begin{pmatrix} I_\alpha \otimes Q \end{pmatrix}, $$

(6)

where $0$ is the zero matrix, $I_p$ is the $p \times p$ identity matrix, and $\otimes$ is the Kronecker product. We now decompose the system matrix as

$$ H_i = C_i E, $$

(7)

where $C_i$ is an $n \times n$ circulant matrix whose first column $c_i$ is $T_{i,1}$. By inserting our results from Eq. (7) into Eq. (3) and then into Eq. (1) we end up with

$$ g = Hf = \sum_{i=1}^{w} C_i E f_i = \begin{pmatrix} C_1 & C_2 & \cdots & C_w \end{pmatrix} \begin{pmatrix} I_w \otimes E \end{pmatrix} f, $$

(8)

where $f$ is a block vector composed of $w$ blocks each of length $\ell = a\alpha$

$$ f = \begin{pmatrix} f_1 \\vdots \\ f_w \end{pmatrix}; $$

(9)

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hence, \( f \) has length \( m = \ell w = a ow \).

It turns out, the matrix vector multiplication \((I_w \otimes E)f\), is a parallel \( 1 - 1 \) index mapping. This mapping can be done quickly on a GPU with \( m \) threads. To see this, we define the vector of length \( nw \) that results from the matrix vector multiplication \( v = (I_w \otimes E)f \) as

\[
v = \begin{pmatrix} v_1 \\ \vdots \\ v_w \end{pmatrix},
\]

(10)

where each \( v_i = Ef_i \) for \( i = 1 \ldots w \) is a vector of length \( n \). Next we denote the \( i^{th} \) element of \( v \) as \((v)_i\) (and similarly for the \( j^{th} \) element of \( f \)). Then the zero based indexing mapping algorithm is

1. Initialize \( v = 0 \).
2. \((v)_i = (f)_j\) for \( j = 0 \ldots m - 1 \) and \( i \) is defined completely in terms of \( j \) and constants as

\[
i = j - s \ell + (\gamma - a) \left\lfloor \frac{j - s \ell}{a} \right\rfloor + sn \text{ where } s = \left\lfloor \frac{j}{w} \right\rfloor.
\]

(11)

Rewriting Eq. (8) in terms of \( v \), we arrive at

\[
g = Hf = \sum_{i=1}^{w} C_i v_i.
\]

(12)

It is well known that circulant matrix vector multiplication can be performed via Fourier transforms in \( \mathcal{O}(n \log n) \) time. This is because a circulant matrix \( C \) can be written in terms of a diagonal matrix \( D \) as \( D = F_1 C F_1^{-1} \). In our notation, we denoted the 1D Fourier transform and its inverse as \( F_1 \) and \( F_1^{-1} \). It follows that Eq. (12) can be written as

\[
g = Hf = \sum_{i=1}^{w} F_1^{-1} F_1 C_i F_1^{-1} F_1 v_i = F_1^{-1} \sum_{i=1}^{w} D_i F_1 v_i = F_1^{-1} \sum_{i=1}^{w} d_i \odot (F_1 v_i),
\]

(13)

where \( d_i = F_1 c_i \) is precomputed. Thus, we reduced the expensive matrix vector multiplication \( Hf \) down to three trivial parallel operations. The processing bottleneck then becomes the Fourier transform which can be computed using cuFFT on a GPU.

We now need the backward projection \( H^T u \) which is found by taking the transpose of the system matrix defined by Eq. (8) \( H^T = ((C_1 \quad C_2 \quad \ldots \quad C_w) (I_w \otimes E))^T = (I_w \otimes E)^T (C_1 \quad C_2 \quad \ldots \quad C_w)^T \). This results in

\[
H^T u = (I_w \otimes E)^T \begin{pmatrix} C_1^T u \\ C_2^T u \\ \vdots \\ C_w^T u \end{pmatrix},
\]

(14)

which is also composed of a trivial index mapping \((I_w \otimes E)^T\) that can be performed on a GPU with \( m \) threads. If we again denote the resulting vectors \( z = (C_1 \quad C_2 \quad \ldots \quad C_w)^T u \) and \( \zeta = (I_w \otimes E)^T z \) the zero based indexing mapping algorithm is

1. \( \zeta_i = z_j \) for \( i = 0 \ldots m - 1 \) and \( j \) is defined completely in terms of \( i \) and constants as

\[
j = i - s \ell + (\gamma - a) \left\lfloor \frac{i - s \ell}{a} \right\rfloor + sn \text{ where } s = \left\lfloor \frac{i}{w} \right\rfloor.
\]

(15)

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Since the transpose of a circulant matrix is also circulant, and because Fourier transforms along with diagonal matrices are symmetric, we can simplify Eq. (14) as

$$
C_i^T u = F_1 (F_1 C_i F_1^{-1})^T F_1^{-1} u = F_1 D_i F_1^{-1} u \quad \text{for } i = 1 \ldots w.
$$  \hfill (16)

An additional optimization using Hermitian symmetry can also be exploited. Hermitian symmetry implies that when we compute the forward Fourier transform of a real vector of length $n$, we only need the resulting complex vector of length $\beta = \left\lfloor \frac{n}{2} \right\rfloor + 1$. Likewise, the inverse Fourier transform of a complex vector results in a real vector of length $n$, so the complex input only needs a length of $\beta$. In order to leverage Hermitian symmetry we need to write Eq. (16) with the Fourier terms flipped. This is accomplished by noticing that, $F_1 = F_1^{-1}$, $F_1^{-1} = F_1$ (bar denotes complex conjugate), while $u$ and $C_i^T u$ are real

$$
C_i^T u = C_i^T u = C_i^T \bar{u} = C_i^T u = F_1 D_i F_1^{-1} u = F_1^{-1} D_i F_1 u = F_1^{-1} (\bar{d}_i \circ (F_1 u)) \quad \text{for } i = 1 \ldots w.
$$  \hfill (17)

This substantially reduces the spacetime complexity since

1. $d_i = F_1 c_i$ with $c_i$ real implies we only need the first $\beta$ elements of $d_i$ instead of $n$ elements.

2. $F_1 v$ ($F_1 u$) result in vectors of length $\beta$ which means the Hadamard product between them and $d_i \circ (\bar{d}_i)$ is performed on $\beta$ elements instead of $n$ elements.

Just like the forward projection, we reduced the expensive matrix vector multiplication $H^T u$ down to two simple parallel operations leaving the bottleneck as the Fourier transform since the remaining Hadamard operations $g \circ (\ldots)$ and $(f \circ h) \circ (\ldots)$ are trivially parallelizable.

For convenience we provided pseudocode for our parallel algorithm (hereafter referred to as WBH) implemented for the EM solver in Alg. 1. Note that, even though we applied our algorithm to the EM solver, the WBH algorithm is solver agnostic. Finally, the complexity analysis of the WBH algorithm is driven by the Fourier transform. Since cuFFTs\textsuperscript{33} has a guaranteed runtime of $O(n \log n)$, we conclude our complexity is $O(knw \log n)$. This is in contrast to the $O(knw^2)$ runtime using a brute-force (hereafter referred to as BF) matrix vector multiplication algorithm. In addition, the space complexity of WBH is $O(nw)$ which is also better than the $O(nw^2)$ BF method.

**Algorithm 1: WBH algorithm implemented in the EM solver. Each line in the for loop is a kernel call.**

1. Read and copy $d_1, d_2, \ldots, d_w$ to the GPU
2. Read and copy $g$ to the GPU
3. $K = $ some value between 10 – 30
4. Initialize $f^{(1)}$ to all ones
5. for $k = 1 \text{ to } K$ do
6. \quad $v = (I_w \otimes E) f^{(k)}$
7. \quad $g^{(k)} = F_1^{-1} (d_1 \circ (F_1 v_1) + d_2 \circ (F_1 v_2) + \cdots + d_w \circ (F_1 v_w))$
8. \quad $u = g \circ g^{(k)}$
9. \quad $U = F_1 u$
10. \quad $z = F_1^{-1} \left( \bar{d}_1 \circ U \quad \bar{d}_2 \circ U \quad \cdots \quad \bar{d}_w \circ U \right)^T$
11. \quad $\zeta = (I_w \otimes E)^T z$
12. \quad $f^{(k+1)} = (f^{(k)} \circ \zeta) \circ h$
13. end
14. Copy $f^{(k+1)}$ from the GPU to the CPU
15. Save: $f^{(k+1)}$

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4. RESULTS AND DISCUSSION

Using a system matrix provided by Sethaphong which spans 421 nm up to 495 nm in steps of 1 nm we synthetically generated an image using a fully illuminated \( f(x, y, \lambda) = 100 \) \( 89 \times 80 \) field stop \((a = 89 \text{ and } \alpha = 80)\) on a \( 2048 \times 2048 \) FPA \((\gamma = \xi = 2048)\). The FPA image is shown in Fig. 3.

Figure 3. (Color online) FPA image generated using a fully illuminated field stop \( f(x, y, \lambda) = 100 \).

Our benchmarks in seconds are shown in Table 1 and were obtained using the following hardware:

1. Desktop computer with a modest Quadro P4000 GPU and 8 GB of GPU memory. We implemented the WBH + EM + P4000 (WBH implementation of the EM algorithm and running on a P4000 GPU) algorithm using CUDA C/C++ 10.1.

2. Nvidia Jetson AGX Xavier (hereafter referred to as Xavier) with an embedded 512-core Volta GPU and 16 GB of GPU memory. We will refer to this benchmark as WBH + EM + Xavier (WBH implementation of the EM algorithm running on an Xavier GPU).

3. Desktop computer with two 2.30 GHz Intel(R) Xeon(R) E5-2699 v3 CPUs and 256 GB of RAM. We implemented the BF + EM + CPU (BF implementation of the EM algorithm running on a CPU) algorithm using Matlab.
| BF + EM + CPU (s) | WBH + EM + Xavier (s) | WBH + EM + P4000 (s) | \( K \) | \( w \) |
|-------------------|------------------------|-----------------------|-------|------|
| 2159.7            | 853.0                  | 467.2                 | 3100  | 75   |
| 438.5             | 13.9                   | 7.5                   | 50    |      |
| 315.7             | 9.2                    | 5.0                   | 33    |      |
| 265.3             | 7.0                    | 3.8                   | 25    |      |
| 161.0             | 2.8                    | 1.5                   | 10    |      |
| 7537.2            | 281.1                  | 153.2                 | 3100  | 24   |
| 149.1             | 4.6                    | 2.5                   | 50    |      |
| 109.7             | 3.0                    | 1.6                   | 33    |      |
| 91.9              | 2.3                    | 1.2                   | 25    |      |
| 53.6              | 0.9                    | 0.5                   | 10    |      |
| 1039.3            | 41.3                   | 24.0                  | 3100  | 3    |
| 20.2              | 0.7                    | 0.4                   | 50    |      |
| 13.9              | 0.5                    | 0.3                   | 33    |      |
| 11.8              | 0.4                    | 0.2                   | 25    |      |
| 6.8               | 0.1                    | 0.08                  | 10    |      |

Table 1. Runtime comparisons in seconds for BF + EM + CPU, WBH + EM + Xavier, WBH + EM + P4000 with a given total number of iterations \( K \) and total number of wavelengths \( w \).

As can be seen from Table 1 the WBH algorithm performs well. For example, in the case \( w = 75, K = 25 \) the runtime is 3.8 s using a desktop GPU and 7.0 s using an embedded GPU. Furthermore, the relative error was 0.02. In comparison, the BF algorithm took 265 s and had a relative error of \( 1.4 \times 10^{-16} \). One explanation for the higher error is the use of single precision to save space when running WBH as opposed to double precision when running the BF method.

We can also compare our results to Vose-Horton. They used a CTIS system similar to ours but with 24 wavelengths and ran their novel heuristic reconstruction algorithm on a CPU. Their reconstruction quality/error was excellent and it took 423.0 s. They mentioned that choosing \( K = 33 \) for the BF MART solver did a fair job at reconstructing the image but the solver needed to be run for \( K = 3100 \) in order to get as good of results as them. Notice that, in both cases \( K = 33 \) and \( K = 3100 \), our algorithm ran faster. Furthermore, as discussed in Sec. 2, 10 – 30 is a typical total number of iterations. For these reasons, we conclude the WBH algorithm when applied to the EM solver runs in a few seconds.

In addition to Vose-Horton, Sethaphong, using the same CTIS system as us ran a BF parallel EM reconstruction algorithm on a dedicated set of 10 processors that was part of a larger 1500 core supercomputer. For his benchmarks he used \( w = 280, K = 50 \) and obtained a time of 37.08 s. Unfortunately, due to memory limitations, we only processed 75 wavelengths. However, we have table entries at \((w = 24, K = 50), (w = 75, K = 50)\) and our runtime is linear in the total number of wavelengths. If we linearly extrapolate for \( w = 280 \) we obtain 27.6 s. This is, theoretically, faster than Sethaphong.

We validated our reconstruction quality using a method similar to Vose-Horton. Using an RGB image that corresponds to a datacube with three wavelengths, we multiplied the vectorized RGB image by our system matrix which produced an FPA image that was fed into both the EM and WBH algorithms. The reconstructed results using 33 iterations in the aforementioned algorithms are shown in the left and right of Fig. 4 respectively. As can be seen from Fig. 4 the reconstructed datacube using the WBH algorithm looks the same as the one using the EM method. Quantitatively, the average relative pixel error defined as \( \frac{1}{m} \sum_{j=1}^{m} \frac{|f_{wbh}^j - f_{em}^j|}{f_{em}^j} \) where \( f_{em}(f_{wbh}) \) denotes the vectorized left(right) RGB image in Fig. 4 was found to be \( 0.5 \times 10^{-3} \). Thus, we obtained excellent reconstruction quality.
It would be interesting as Horton suggested in his thesis\textsuperscript{1} to implement the Vose-Horton algorithm on a GPU. One benefit besides a potential processing gain, is the possibility to use a hybrid approach that utilizes both algorithms. This is feasible because the WBH and Vose-Horton algorithm share the same matrix decomposition. In fact, Thompson implemented hardware acceleration for the Vose-Horton algorithm on a cell processor (running on a Playstation 3). Unfortunately, due to memory limitations he was only able to process three wavelengths but, the results are still interesting. Thompson showed, with hardware acceleration the Vose-Horton algorithm could run in 4.14 s. In comparison, the WBH algorithm for $w = 3$, $K = 3100$ was slower. However, in the more common case $w = 3$, $K = 33$ the WBH algorithm was faster. Given that cell processors are less popular than GPUs today, we believe a GPU implementation is a better approach. Finally, Thompson’s issues with memory bring up a good point. For embedded systems and GPUs, memory is a commodity. The fact that we were able to run 75 wavelengths on a modest 8 GB GPU is an excellent result. If we were to use a high end desktop with better and more GPUs, we think it is possible to run as many wavelengths as Sethaphong while still maintaining a few second reconstruction time. Overall, we developed a simple, fast, and solver agnostic algorithm that is practical for near-realtime and/or embedded systems.

5. CONCLUSIONS

We have developed a parallel algorithm that accelerated CTIS reconstruction times and exploited spatial shift invariance. The new algorithm, WBH, was applied to the EM solver and implemented on a desktop and embedded GPU. After validating that our new algorithm maintained reconstruction quality on par with traditional methods we went on to benchmark the new WBH algorithm which was shown to preform well; achieving reconstruction times of a few seconds where traditional brute-force methods required minutes to hours. We also demonstrated the feasibility of GPUs for CTIS reconstruction.

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**BIOGRAPHIES**

**Larz White** received his BS in mathematics/physics from Western Washington University and his PhD in physics from the University of Idaho. He has been with Lockheed Martin Advanced Development Programs in Fort Worth since 2017 developing image and radar algorithms. He is also a professor of computer science and engineering at the University of Texas at Arlington.

**W. Bryan Bell** received his BSEE and MSEE from Texas A&M University and PhD in EE from the University of Texas at Arlington. He is currently a Senior Fellow with Lockheed Martin Advanced Development Programs in Fort Worth and a professor with TCU and UTEP. He is currently developing algorithms in targeting, geodesy, navigation fusion, combat ID, multi-sensor fusion, data exploitation, image fusion and image system development for tactical fighter aircraft.

**Ryan Haygood** received his BS in astrophysics from Texas Christian University. He has been with Lockheed Martin Aeronautics in Fort Worth, TX since 2005 performing optical design, testing, and analysis.

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