

High-Performance Compressive Sensing

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Herschel Space Telescope



- Sensitive to the far infrared and submillimeter wavebands
- Capable of seeing the coldest and most obscure objects in space
- Projects approximate cost over 450 million (4 yr mission)

Taking measurements

- Why go through all the effort of aquiring data that will be lost anyway?
- Why can we not just measure the parts that are not thrown away?
- Is there a way to take advantage of structure and redundancy?

Compressive Sensing (CS)

- CS encodes a signal into a relatively small number of linear measurements.
- Exploits structure and redundancy in the majority of interested signal.
- Recovers sparse compressible signals using $k < \text{Shannon-Nyquist}$ sample rate.
 - No information loss if we sample at 2x the bandwidth

Applications of *Compressive Sensing*

Advantages:

- faster sampling
- higher-dimensional data
- lower energy consumption



Real-World applications:

- MRI images
- Image reconstruction
- Face recognition
- Infared spectroscopy

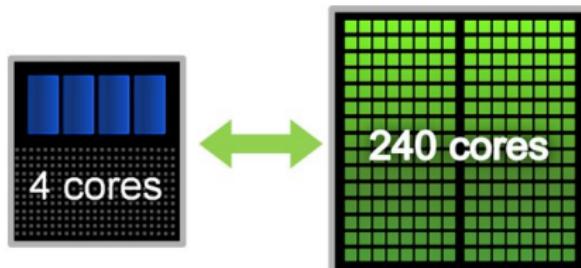
$$\begin{matrix} \text{Test image} \\ y \in \mathbb{R}^m \end{matrix} = \begin{matrix} \text{Combined training dictionary} \\ [A_1 \mid A_2 \mid \dots \mid A_k] \end{matrix} \times \begin{matrix} \text{coefficients} \\ x \in \mathbb{R}^n \end{matrix}$$

The diagram illustrates the mathematical model for compressive sensing. It shows a test image y (a 1D vector in \mathbb{R}^m) being equal to the product of a combined training dictionary $[A_1 \mid A_2 \mid \dots \mid A_k]$ (a matrix where each column A_i represents a basis function) and a vector of coefficients x (a 1D vector in \mathbb{R}^n). The diagram uses a grid of faces to represent the dictionary columns and a horizontal bar to represent the coefficient vector.

GPU computation



- Use of a GPU (graphics processing unit) to do general purpose computing.
- Use a CPU and GPU together in a heterogeneous computing model.
- Major difference:



- Brings speed and visual computing capability of GPUs to MATLAB programs.
- NOT a collection of GPU functions.
- Allows the use of multiple GPUs simultaneously.

Disadvantages of the GPU

- Recursion is not allowed.
- Double precision computation CANNOT reach card peak performance (78 v. 933).
- The bus bandwidth and latency between the CPU and the GPU becomes a **bottleneck**.
- Branching may impact performance *significantly*.

Reconstruction from Partial Fourier data (RecPF)

$$\min_u TV(u) + \lambda \|\Psi u\| + \mu \|\mathcal{F}_p(u) - f_p\|^2$$

where we have

- u is the signal/image to be reconstructed
- $TV(u)$ is the total variation regularization term
- Ψ is a sparsifying basis
- \mathcal{F}_p is a partial Fourier matrix
- f_p is a vector of partial Fourier coefficients

RecPF using circulant matrices (RecPC)

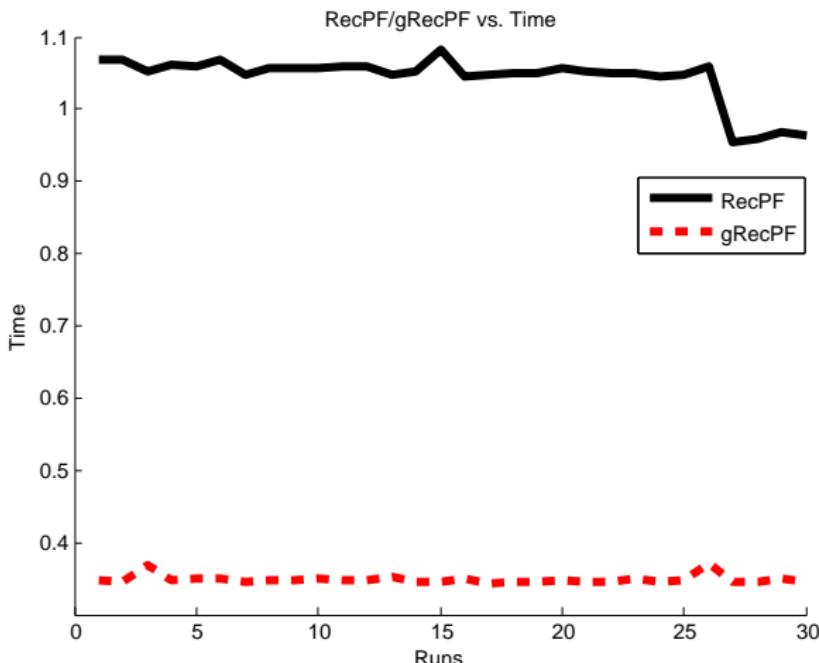
$$\min_u TV(u) + \lambda \|\Psi u\| + \frac{\mu}{2} \|PCu - b\|^2$$

where we have

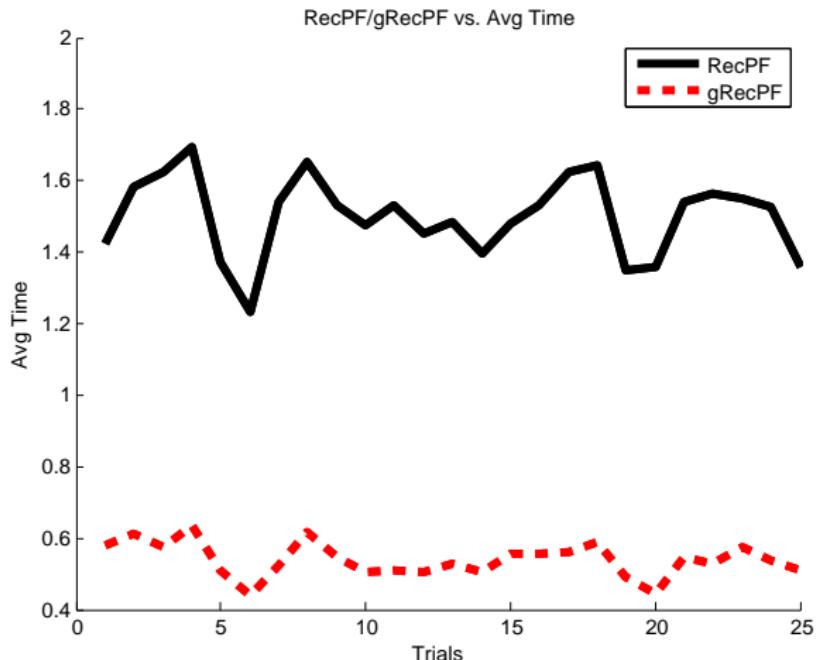
- u is the signal/image to be reconstructed
- $TV(u)$ is the total variation regularization term
- Ψ is a sparsifying basis
- P is a selection operator
- C is a block-circulant matrix

RecPF \Rightarrow gRecPF (using Jacket)

- RecPF uses an alternating minimization scheme where the main computation involves shrinkage and fast Fourier transforms (FFTs)

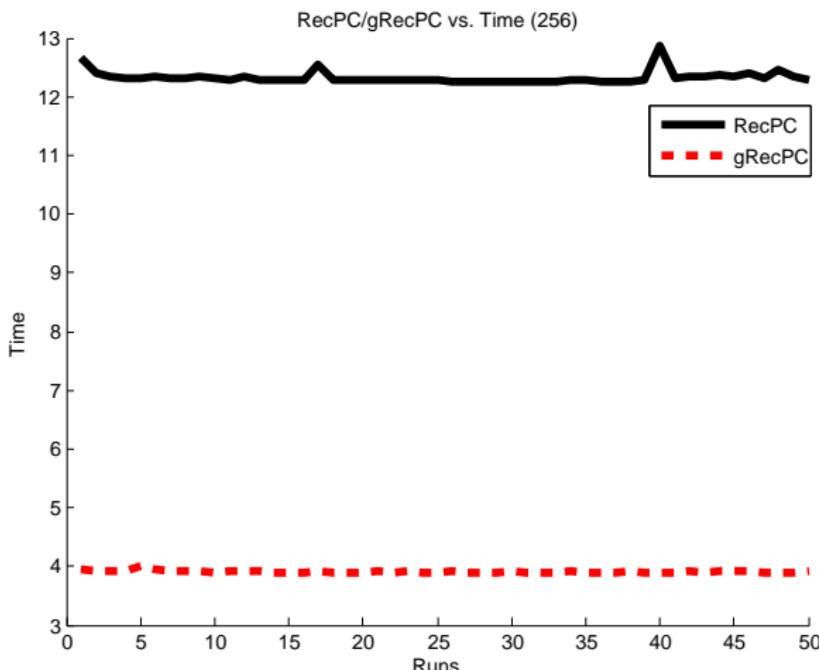


With avg. time taken before instantiation



RecPC \Rightarrow gRecPC (using Jacket)

- However, hardware realizations make it difficult and costly to implement random matrices.
- Sol'n: use circulant matrices as basis matrix

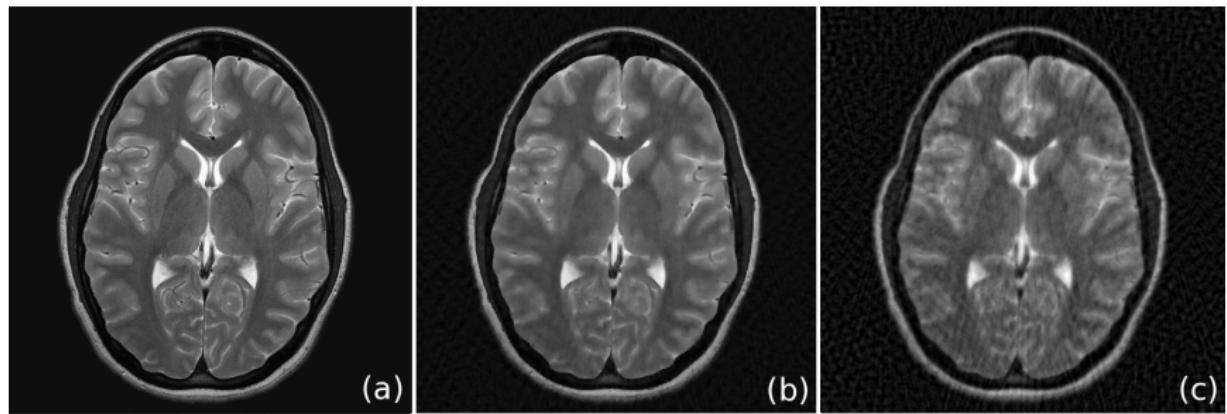


- Need to finish the anisotropic cases for both gRecPF & gRecPC.
- Try and make new algorithms (Median formula).
- Make CUDA prototypes.

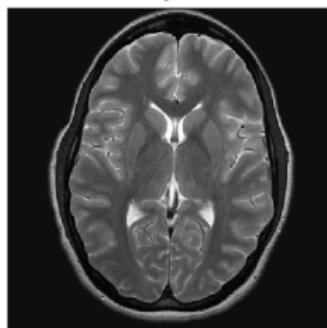
Acknowledgements

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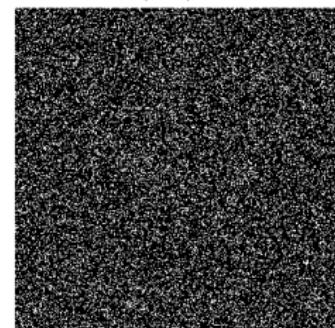
Using only 22% of measurements we can reconstruct images to single precision.



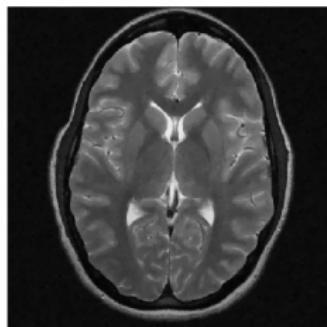
original



sample mask, 20.0%



recovery, SNR 19.1



error

