GPU TECHNOLOGY CONFERENCE 2019

Accelerating Magnetic Resonance Imaging (MRI) using GPUs

Presenter

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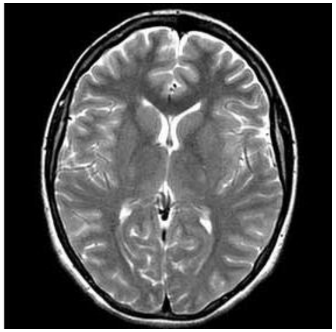
Outline

- **Overview of Magnetic Resonance Imaging (MRI)**
- **GPU based Advance MR Image Reconstruction**
  - GPU based GRAPPA Reconstruction using CUDA
  - GPU based SENSE Reconstruction using CUDA
  - GPU based Gridding using CUDA
- **Magnetic Resonance Finger Printing (MRF)**
  - GPU based MRF using CUDA
- **Acknowledgements**

Outline

What is MRI ?

- Safe and painless diagnostic procedure
- Excellent soft tissue contrast
- No need to change the position of the patient
- Non-invasive
- Diagnoses & monitors treatments such as
  - Heart problems
  - Blockage or enlargement of blood vessels
  - Lungs
  - Diseases of the liver such as cirrhosis
  - Tumors and other cancer related abnormalities



Human head (Coronal axis)

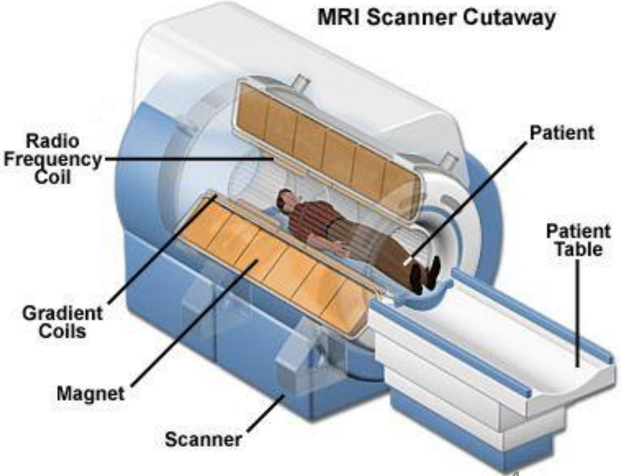
Human head (sagittal axis)

Outline

MRI Hardware

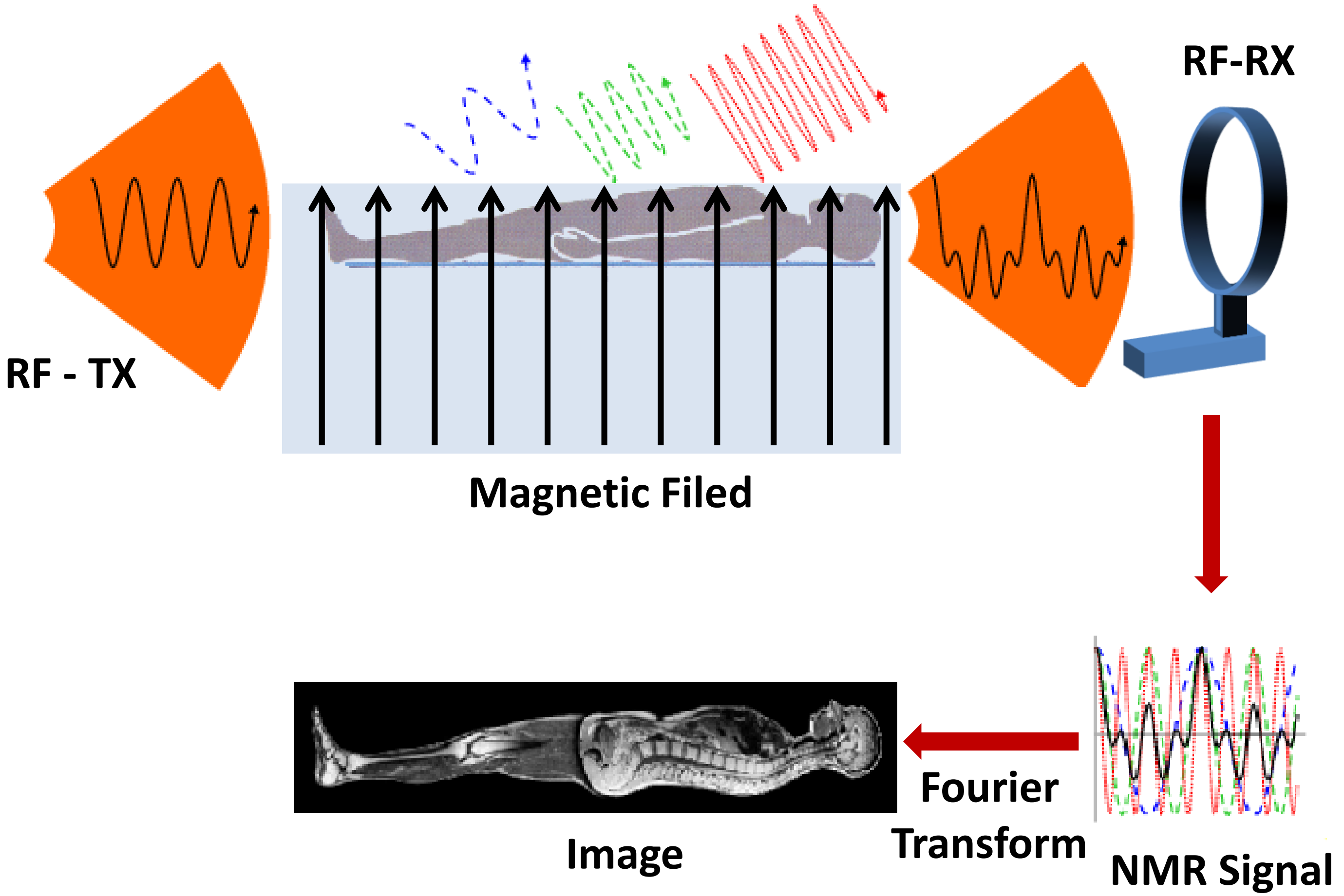
- **Magnets**
  - Permanent Magnets
  - Resistive Magnets
  - Super Conducting Magnets
- **RF Coils**
  - Surface coils
  - Body coils
  - Head coils
- **Gradient Coils**
  - Induce non-linear change in the magnetic field

MAGNETOM Skyra 3T (Siemens)



Outline

How MRI works



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- MIPRG at Glance
- **Overview**
  - What is MRI?
  - MRI Hardware
  - How MRI works?
  - **MR Image Formation**
  - Limitations in conventional MRI
- Parallel MRI
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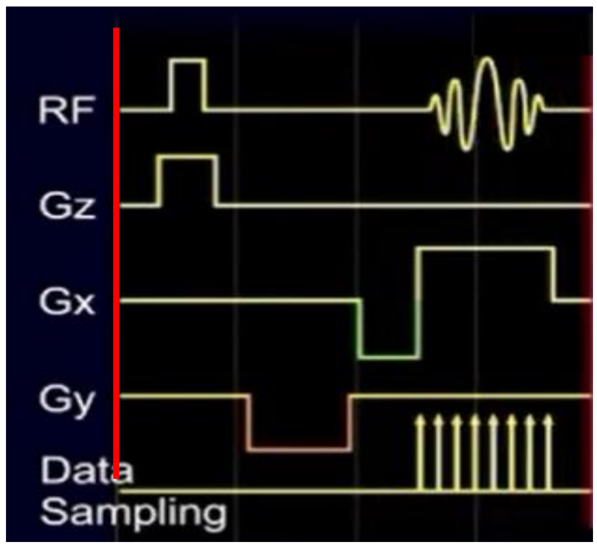
MR Image Formation

- **MRI Pulse Sequence and Data Acquisition**

Basic Gradient-Echo Pulse Sequence



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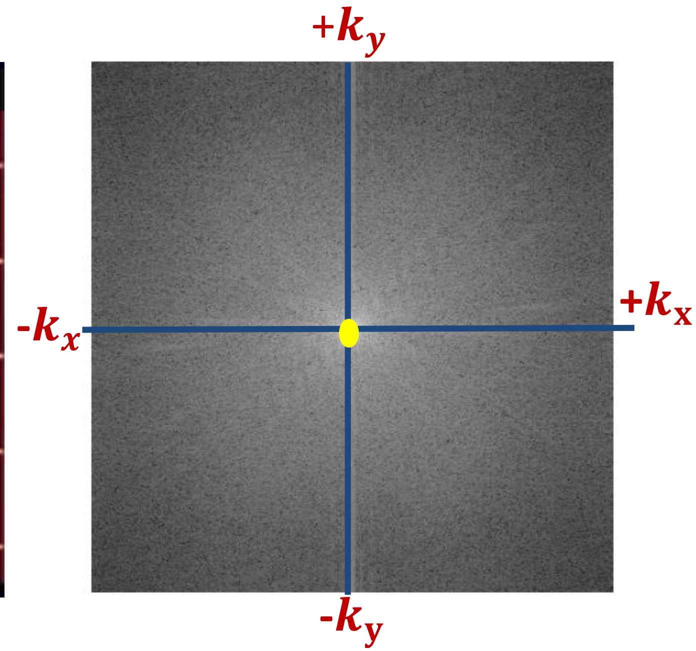

k_y = Phase encoding Direction

k_x = Frequency encoding Direction

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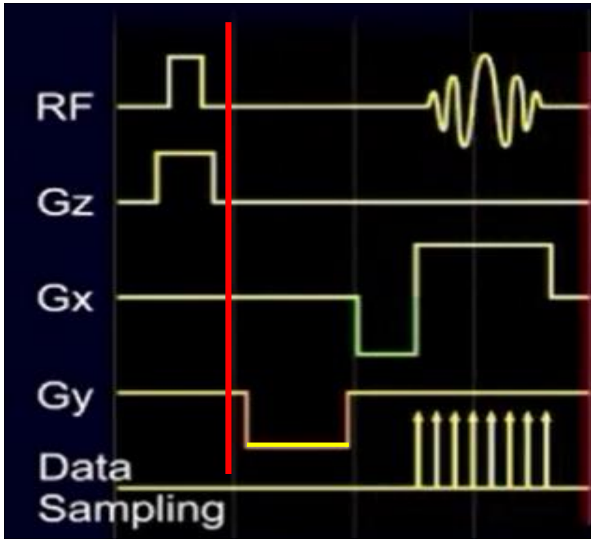

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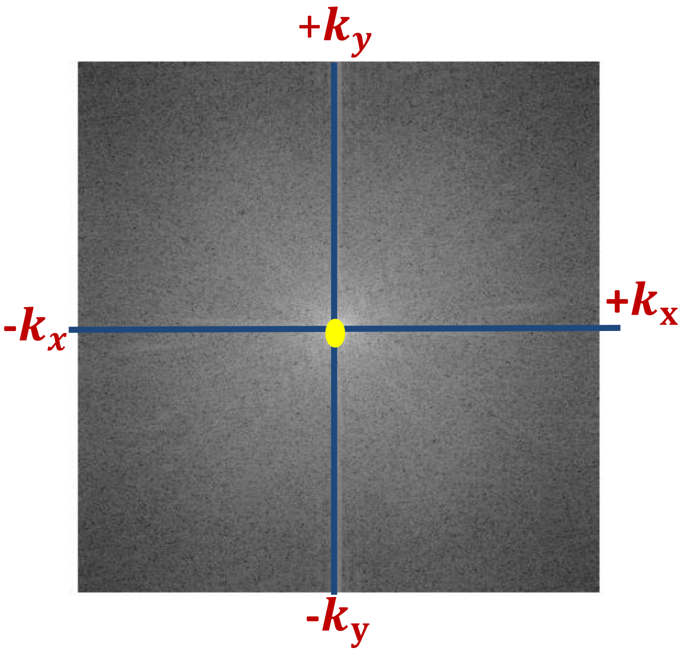

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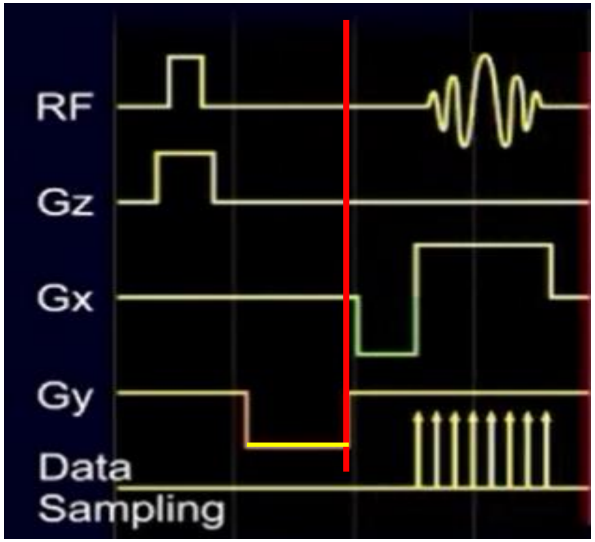
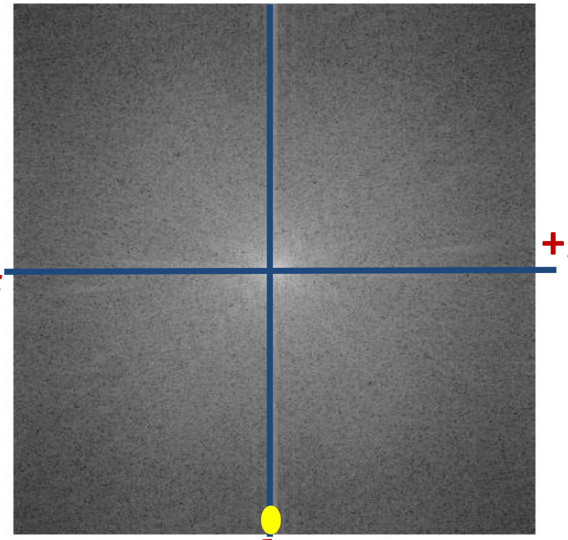


***k*-Space**

$+k_y$

$-k_x$



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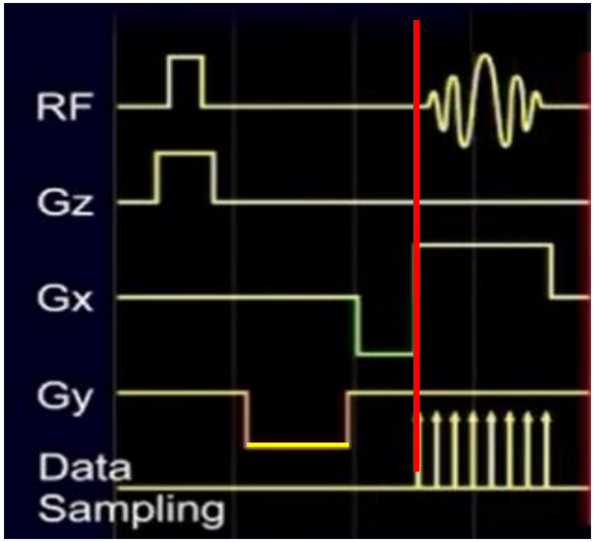

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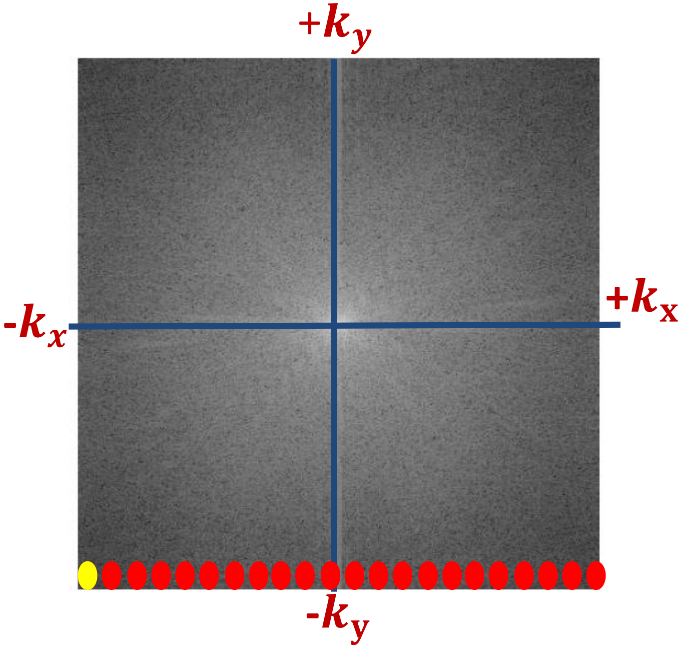

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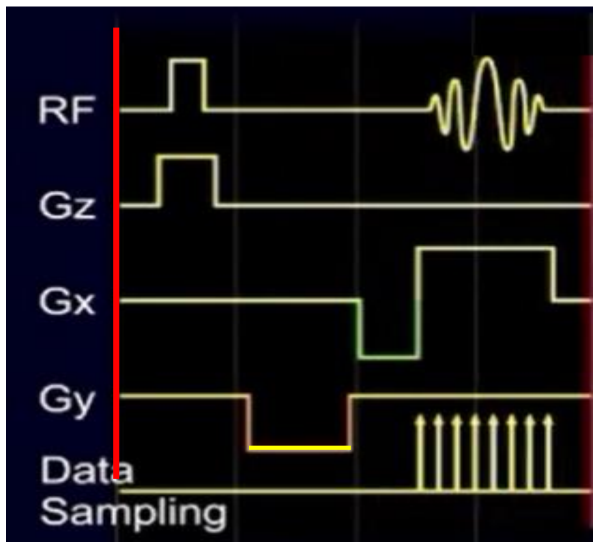

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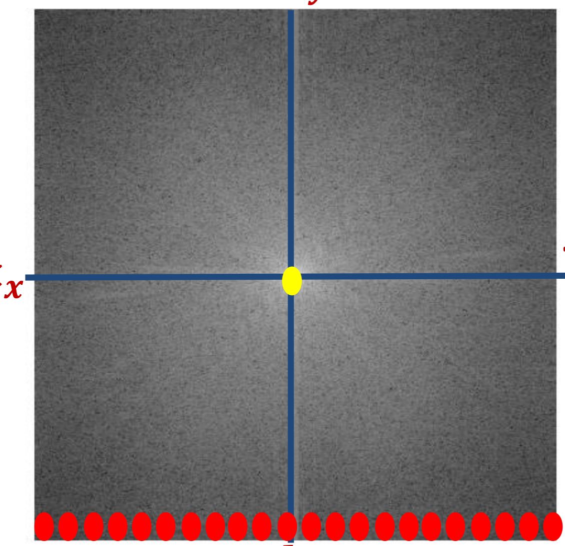

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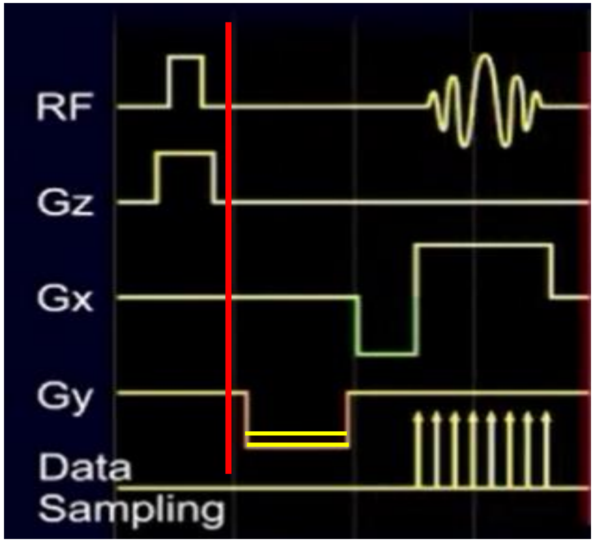

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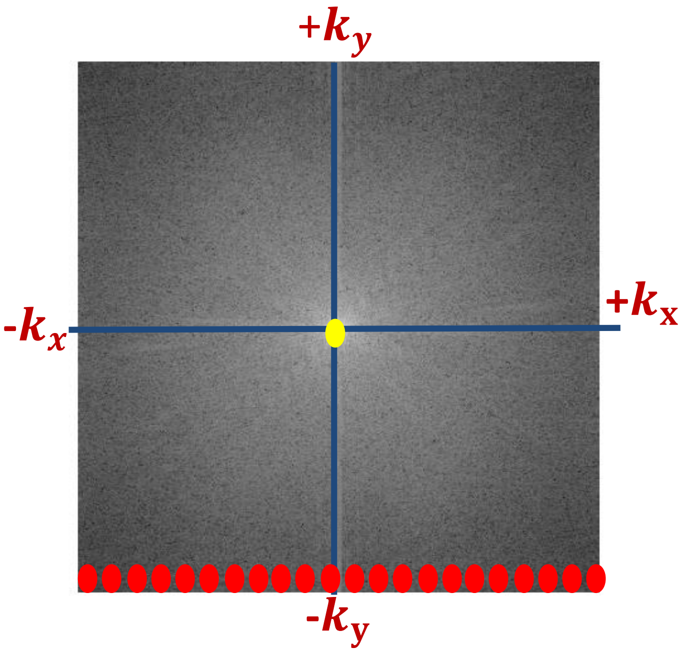

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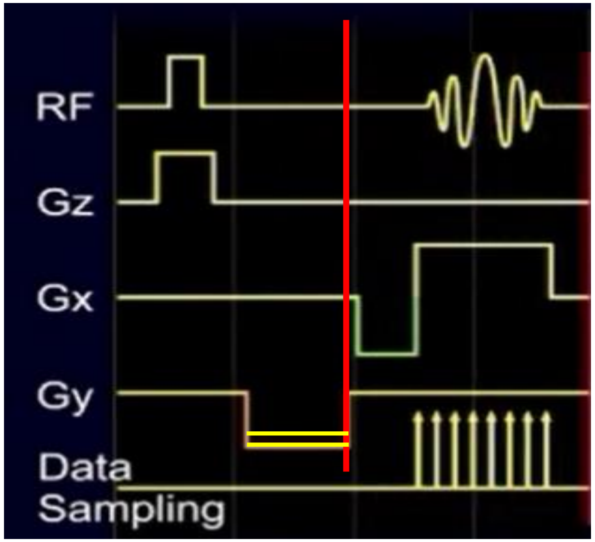
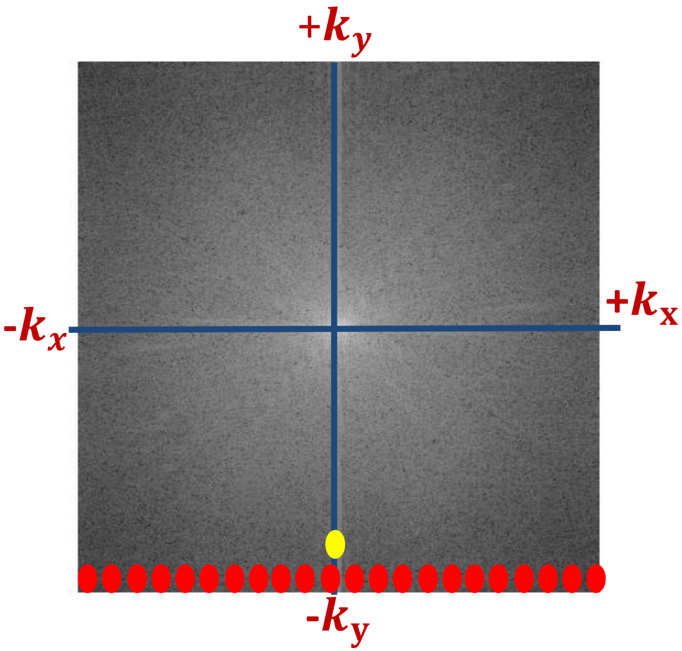


k-Space



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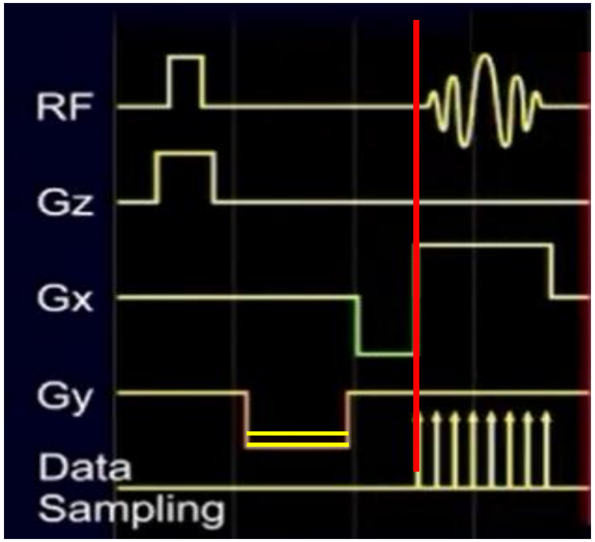

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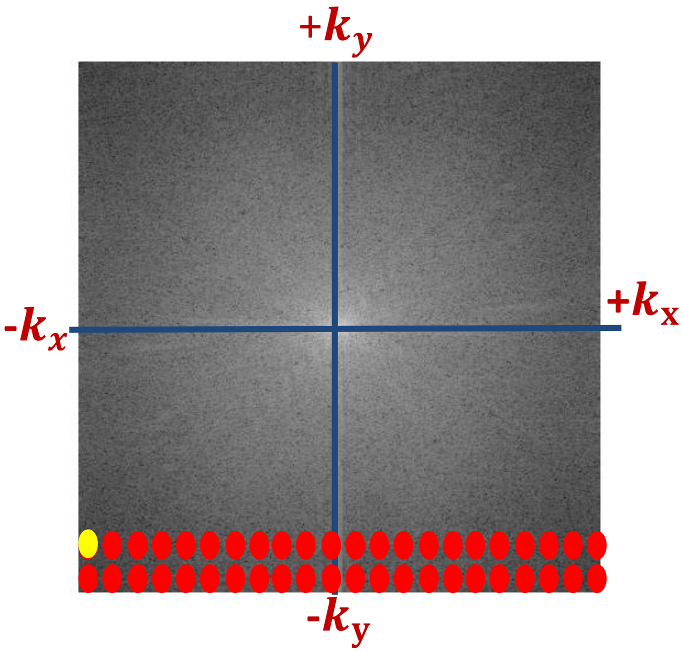

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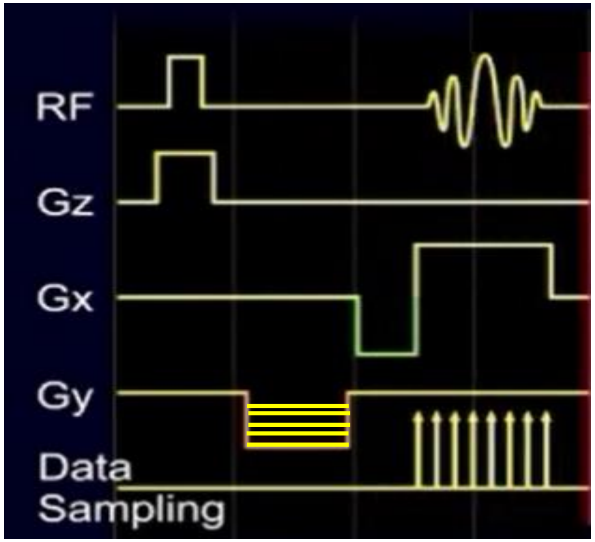

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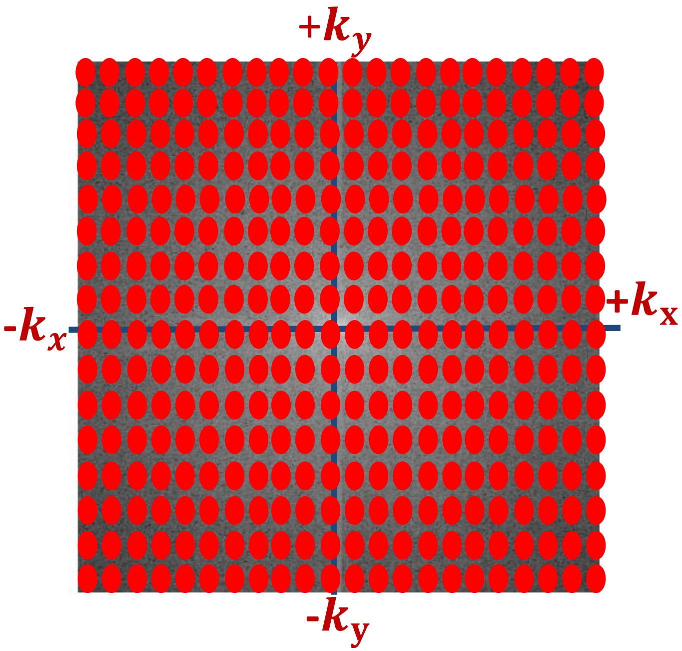

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Outline

MR Image Formation

- **MR Pulse Sequence and Data Acquisition**

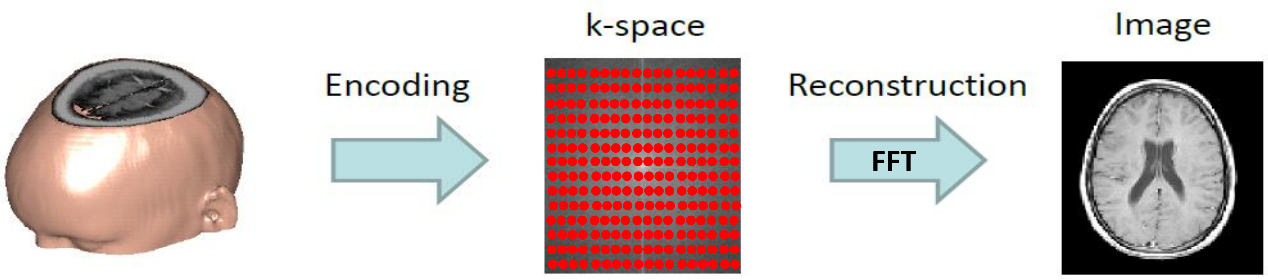
The Total acquisition time (T_A) (fully sampled *k*-space)

$$T_A = T_R \times N_y$$

Where,

T_R = Time required to collect a single line of *k*-space

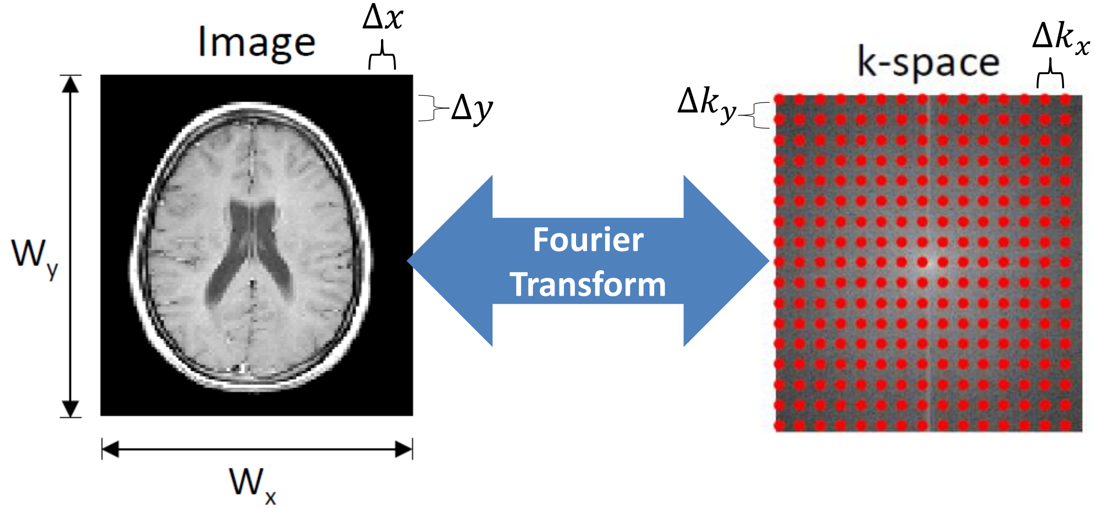
N_y = Total number of PE lines that must be acquired

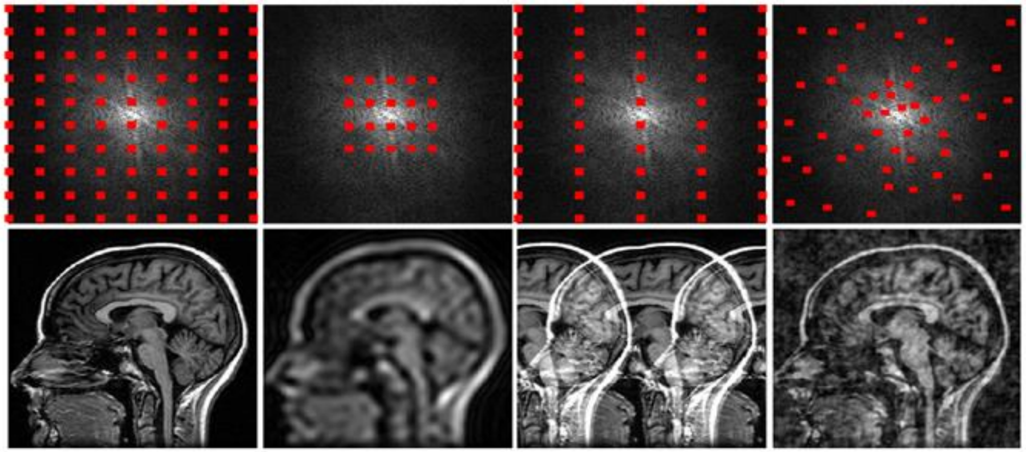


Outline

MR Image Formation

- **Image Resolution and Contrast**





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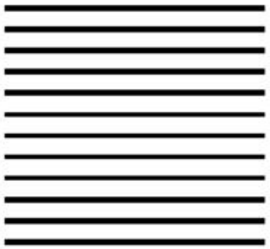
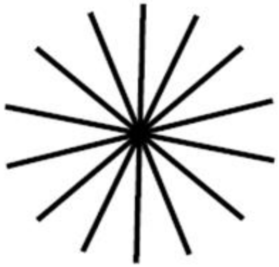
MR Image Formation

- *k*-space sampling trajectories

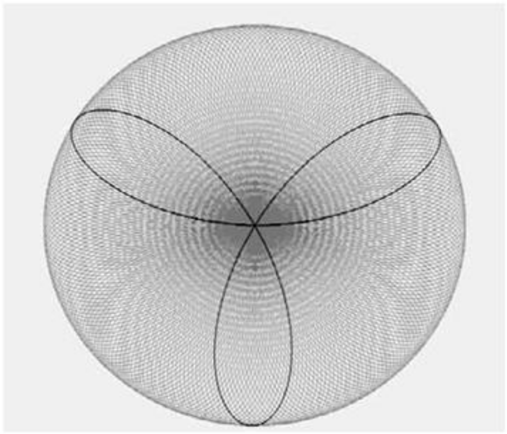


(a) Cartesian

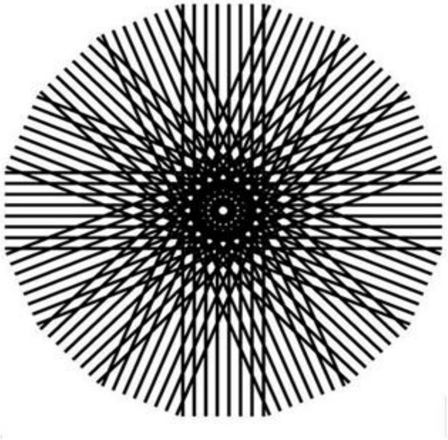


(b) Radial

(c) Spiral



(d) Rosette



(e) Propeller

Outline

Limitations in Conventional MRI

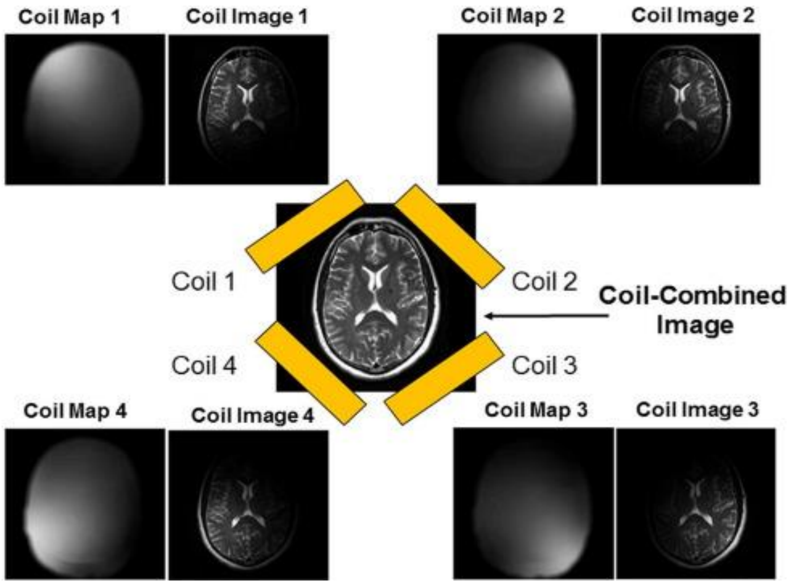
- **Major Limitations**
  - Scan duration of conventional MRI (30 to 40 mins)
  - Too expensive (typically £350-£500 per hour)
  - Long Breath hold (abdominal imaging)
  - Moving structures (e.g. heart)
  - Contrast changes(Flowing blood)

Outline

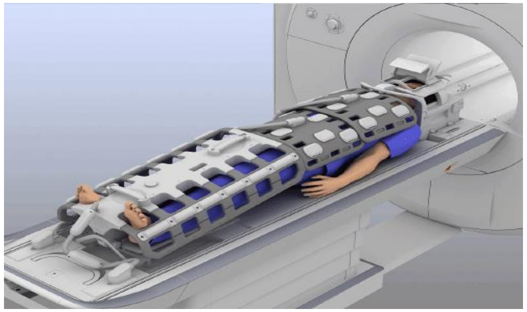
Parallel MRI

- Multichannel receiver coils
- Reduce acquisition time
- Advanced pMRI Techniques (GRAPPA, SENSE etc.)

- Key properties of pMRI techniques
  1. Acceleration factors
  2. Reconstruction accuracy
  3. Reconstruction time



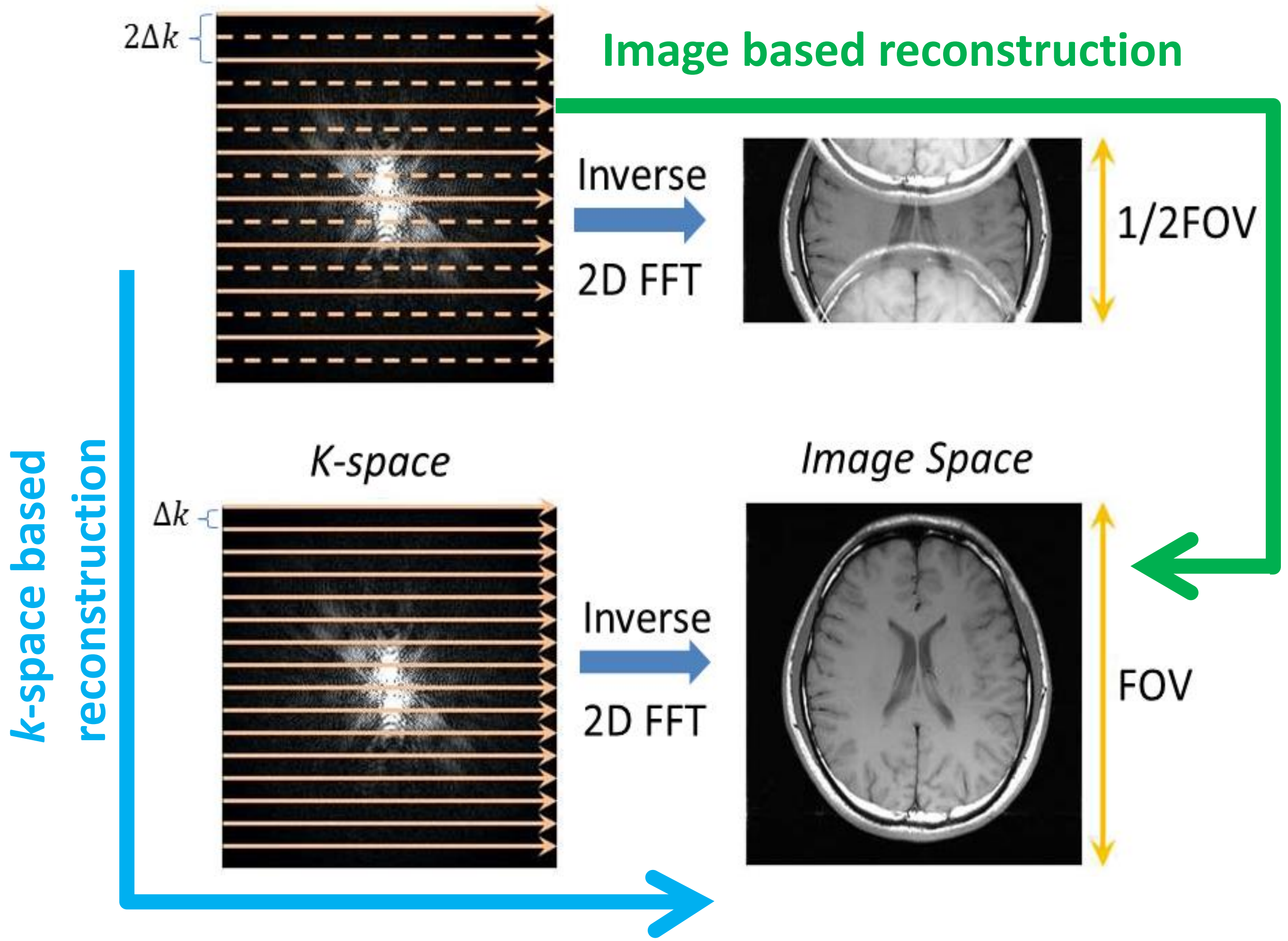
Example of 4-channe receiver coil



Parallel Imaging using multi-channel receiver coils

Outline

Parallel MRI



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- MPIRG at Glance
- Overview
- **Parallel MRI**
- Magnetic Resonance Finger printing
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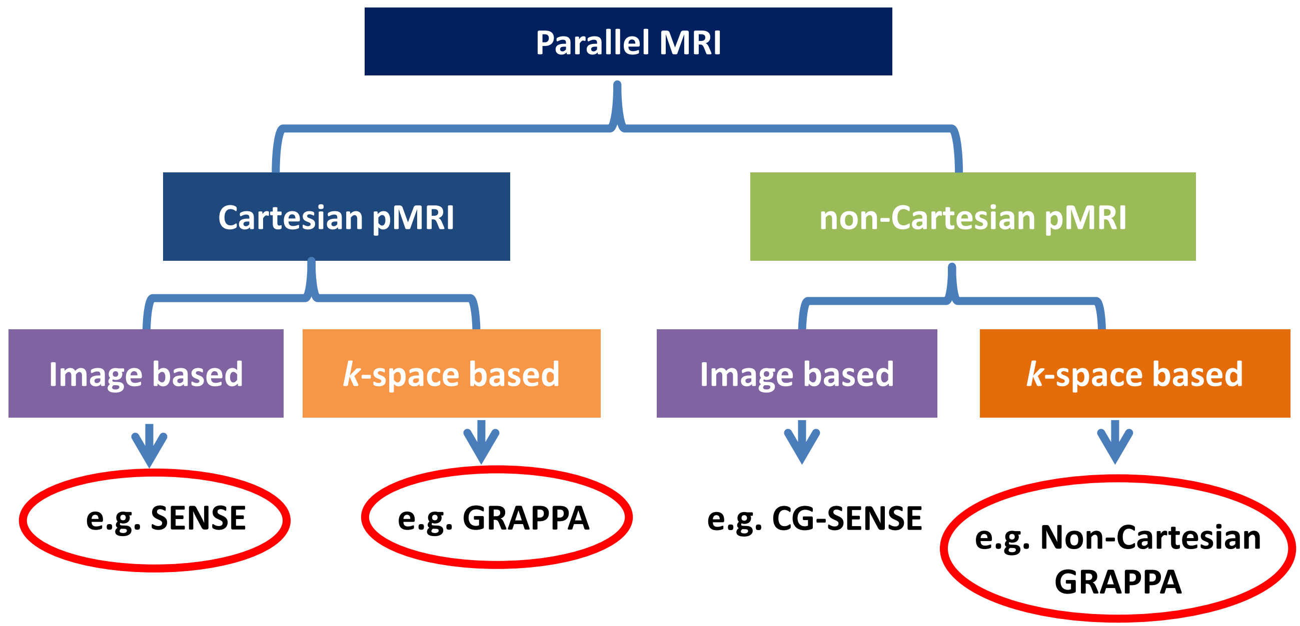
Parallel MRI



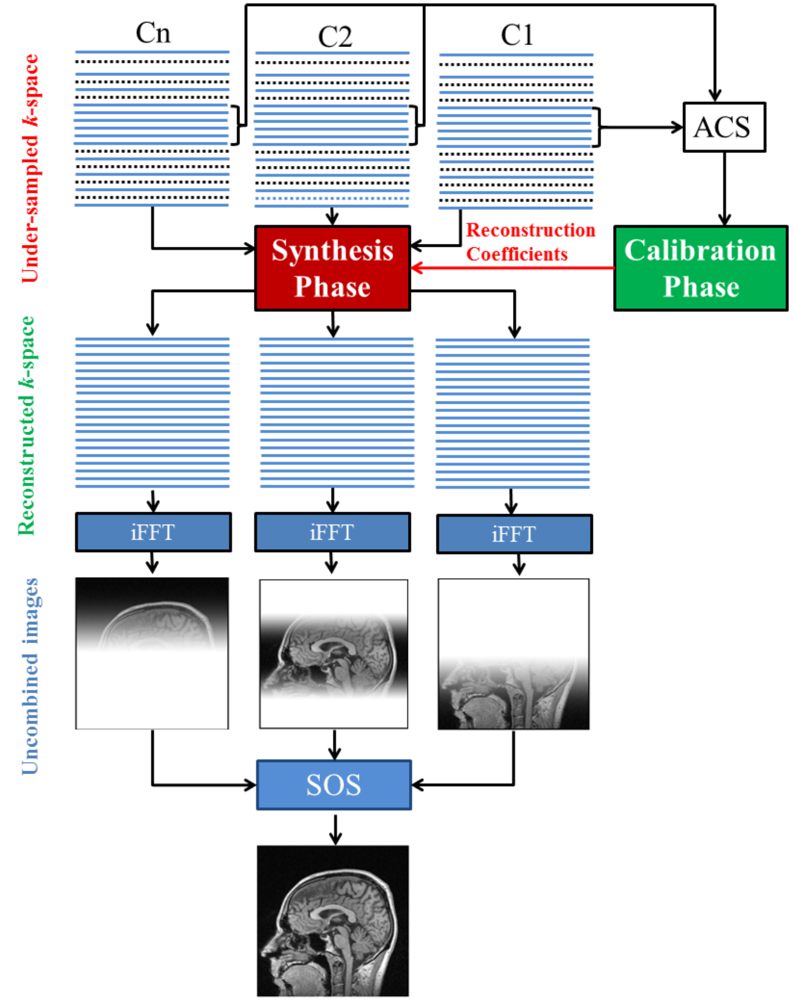
Outline

GRAPPA Reconstruction Method

Outline

GRAPPA Reconstruction

- *k*-space based pMRI
- Inspired by VD-Auto-SMASH technique
- Siemen's Health Care
- Abdominal and lung imaging
- **Calibration** Phase
- **Synthesis** Phase



GRAPPA reconstruction process

**M. A. Griswold, *et al.*, "Generalized autocalibrating partially parallel acquisitions (GRAPPA)," *Magnetic Resonance in Medicine*, vol. 47, pp. 1202-1210, 2002.

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- MPIRG at Glance
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- **Parallel MRI**
  - **GRAPPA**
  - GPU based GRAPPA
  - SENSE
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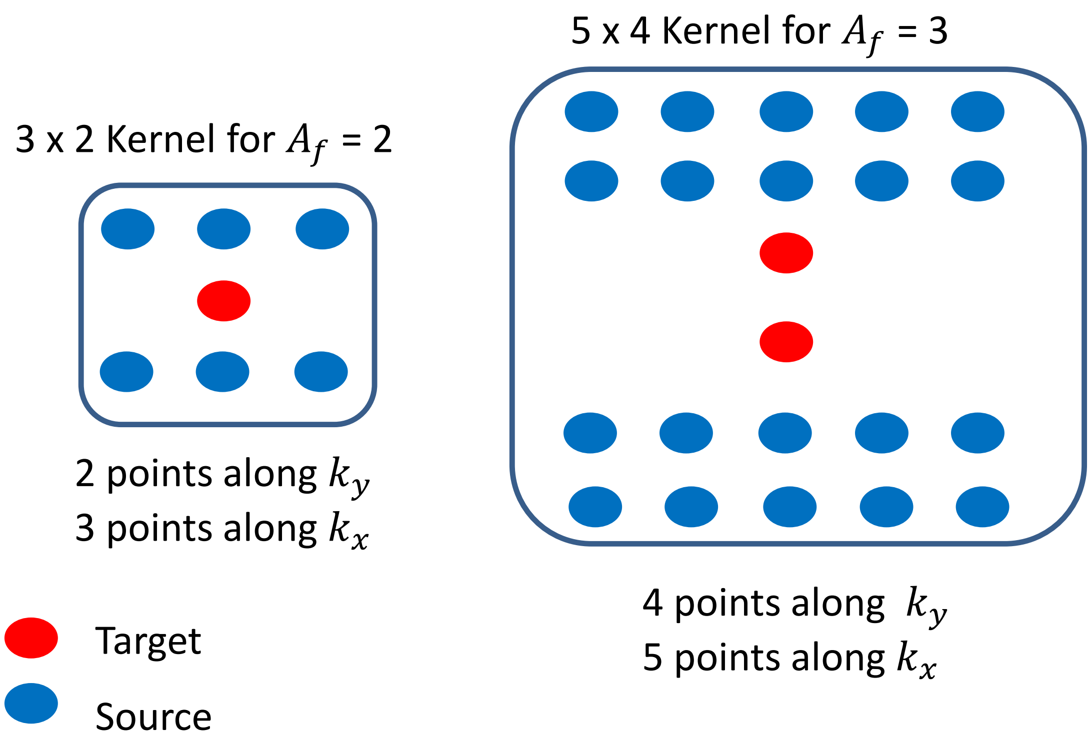
GRAPPA Reconstruction

- **Calibrations Phase (GRAPPA)**



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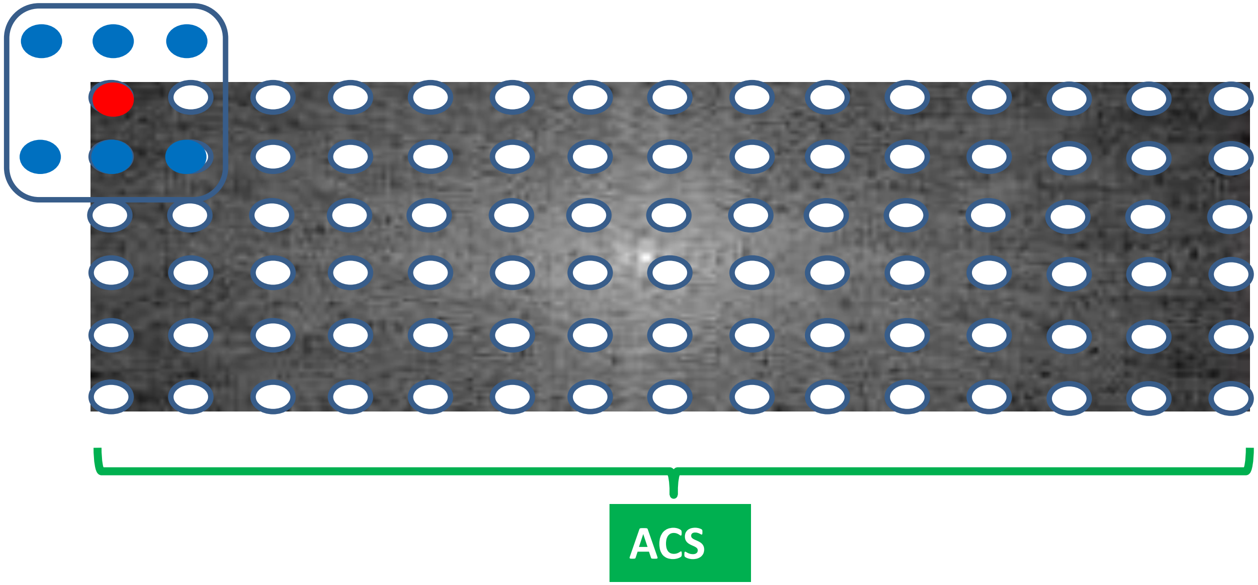
GRAPPA Reconstruction

- Calibrations Phase $(N_C = 1)$



$$t_{m\,xl} = S_{m\times n} \times w_{n\times l}$$

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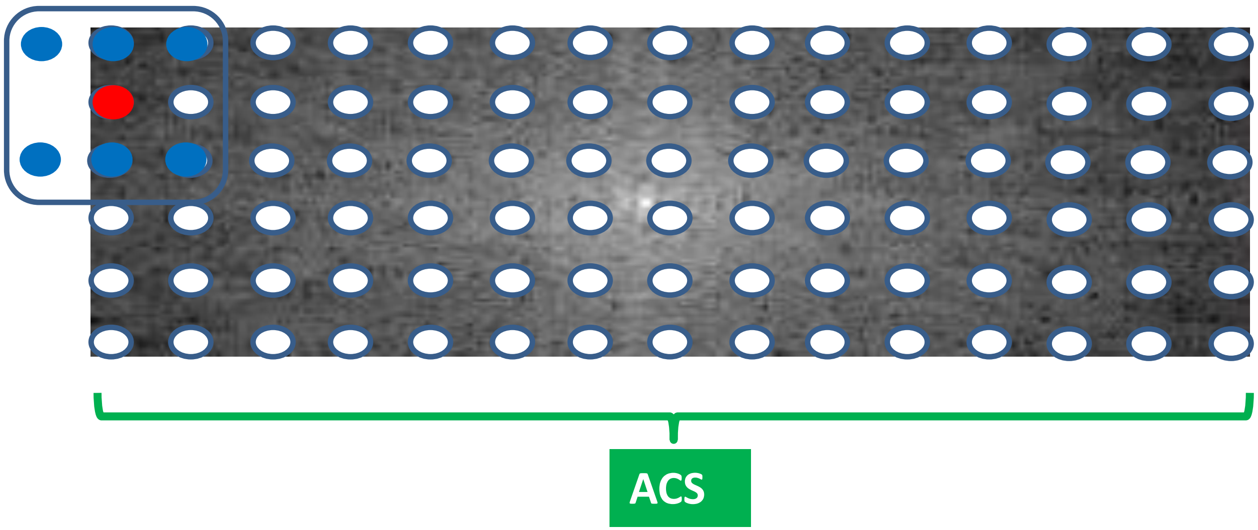
GRAPPA Reconstruction

- Calibrations Phase (N_C =1)



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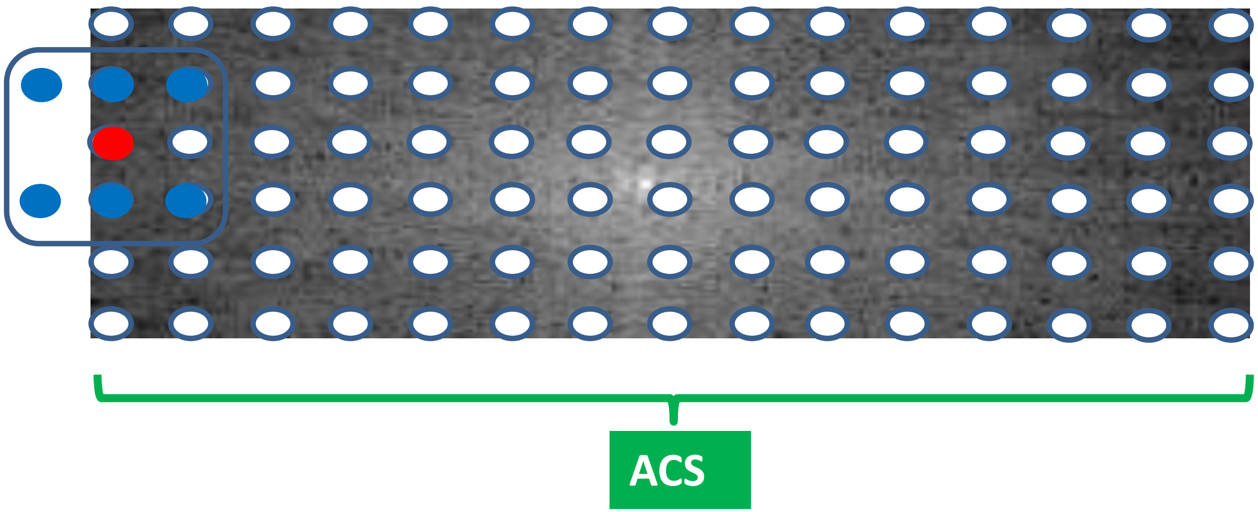

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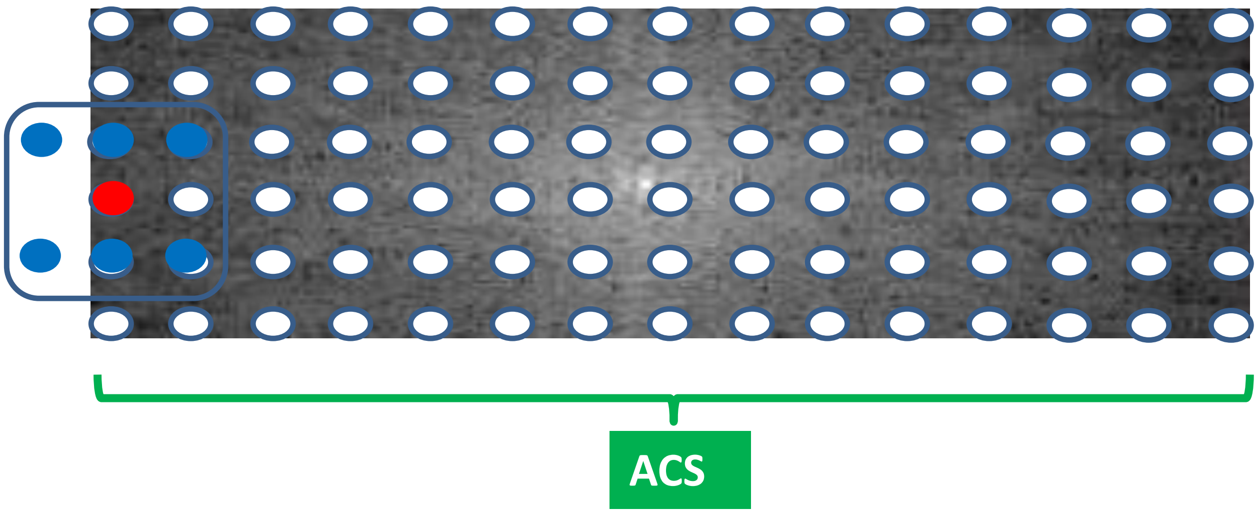
GRAPPA Reconstruction

- Calibrations Phase (N_C =1)



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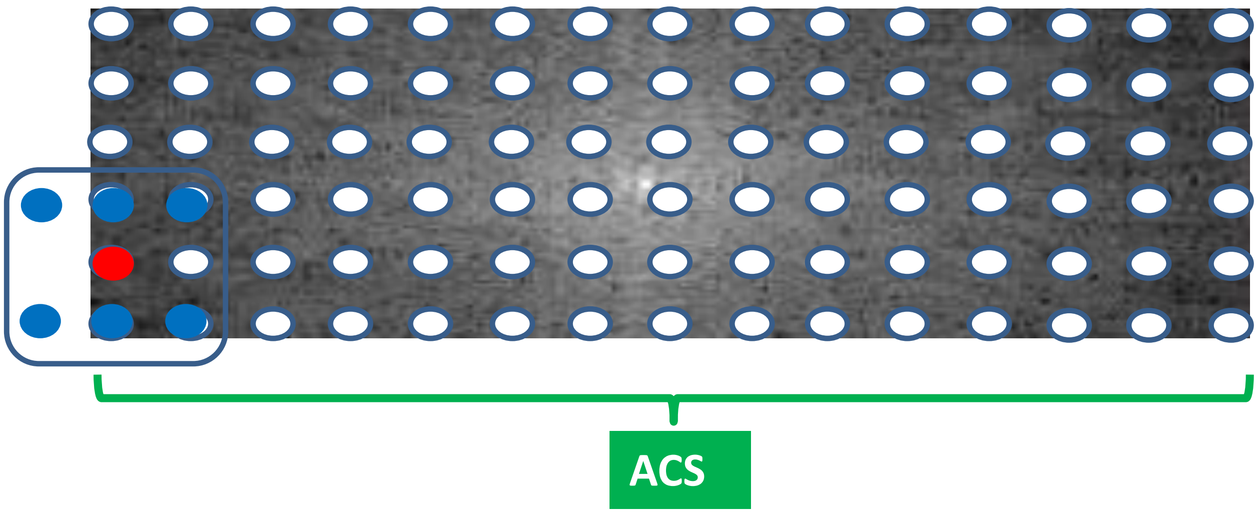
GRAPPA Reconstruction

- **Calibrations Phase (N_C =1)**



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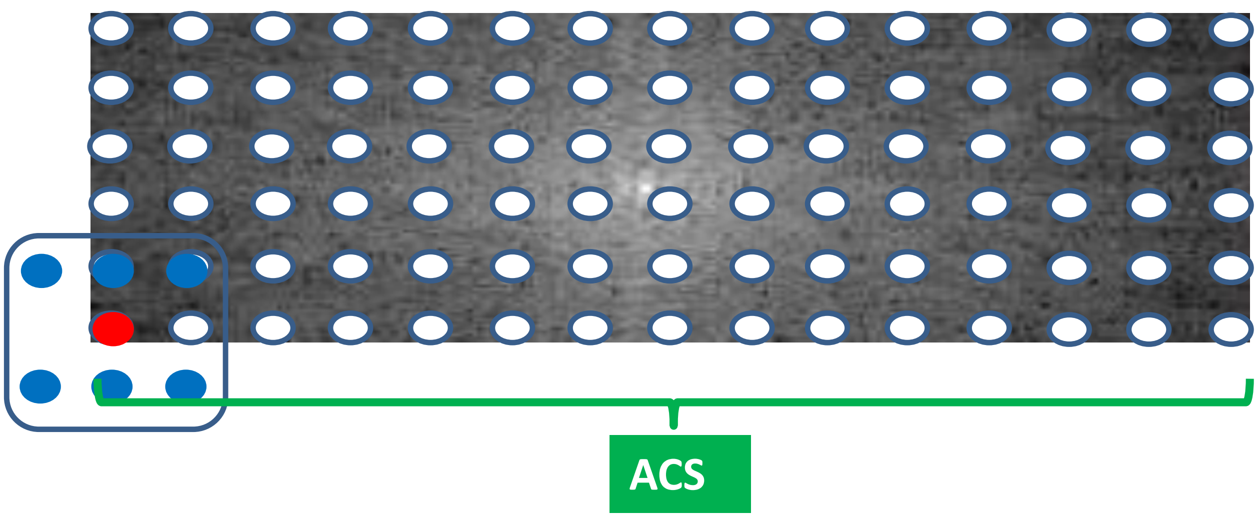
GRAPPA Reconstruction

- **Calibrations Phase (N_C =1)**



GRAPPA calibration equation $\Rightarrow$ $t_{m\,xl} = S_{m\times n} \times w_{n\times l} \quad (m > n)$

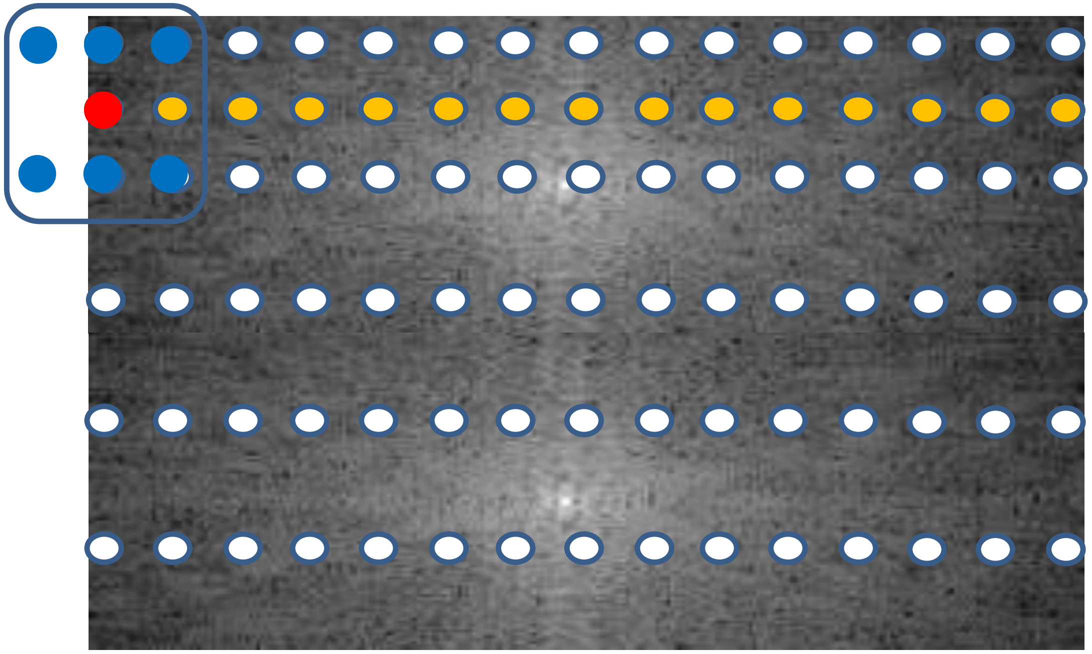
GRAPPA weight Sets $\Rightarrow$ $w_{n\times l} = (S_{m\times n}{}^{H} S_{m\times n})^{-1}(S_{m\times n}{}^{H} t_{m\,xl})$

$where,\ m = N_p N_F, n = d_x d_y N_c$ and $l = N_C(a_f - 1)$

Outline

GRAPPA Reconstruction

- **Synthesis Phase (N_C =1)**



$$t_{\mathrm{m}\,xl} = S_{\mathrm{m}\times n} \times w_{\mathrm{n}\times l}$$

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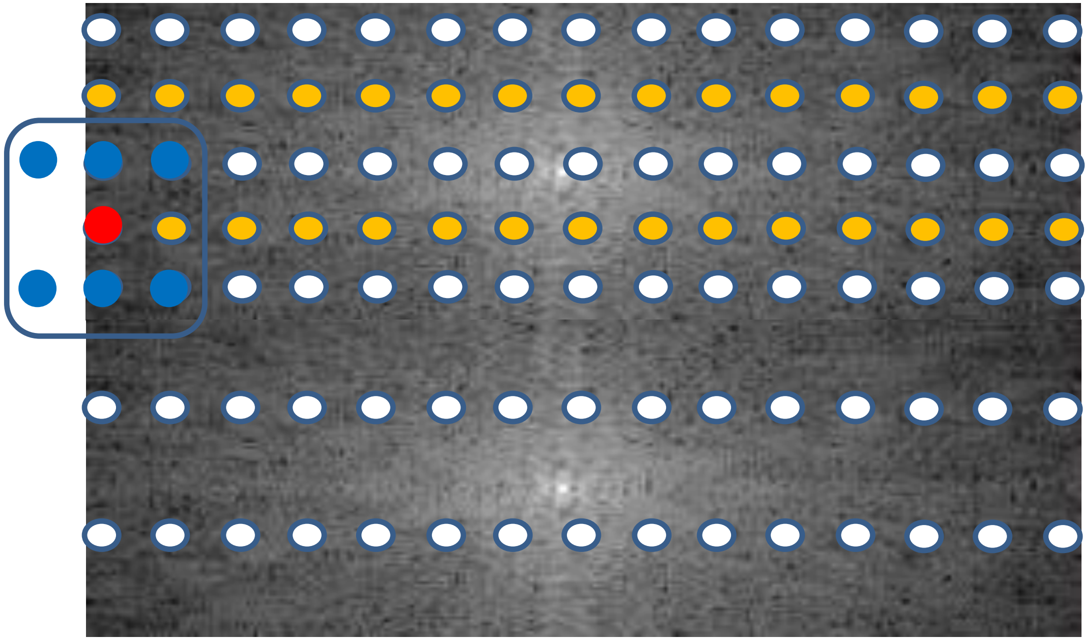
- Synthesis Phase (N_C =1)



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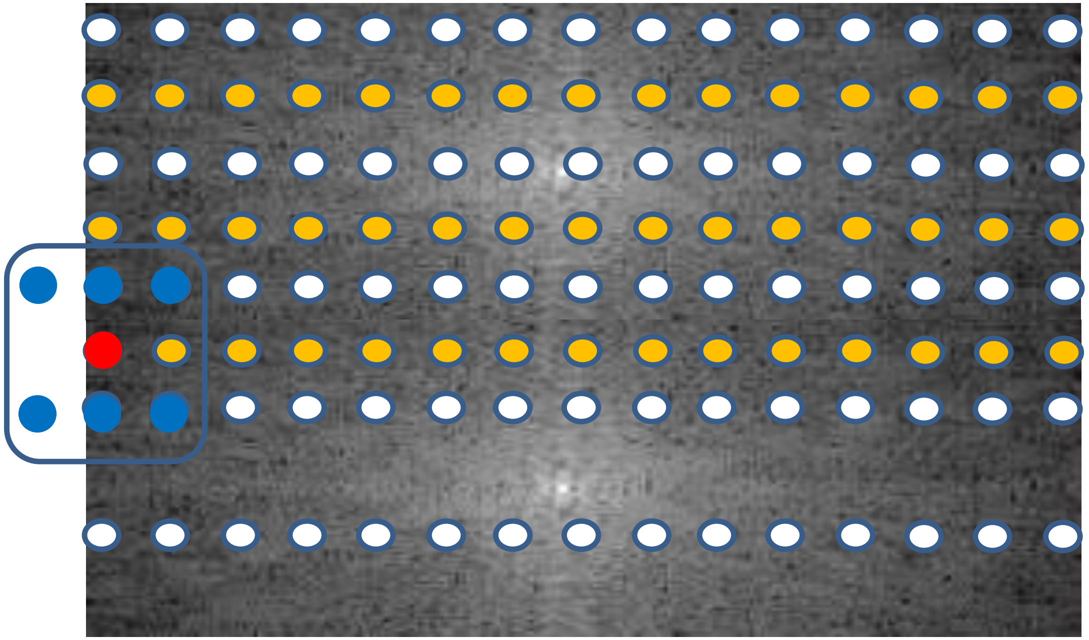

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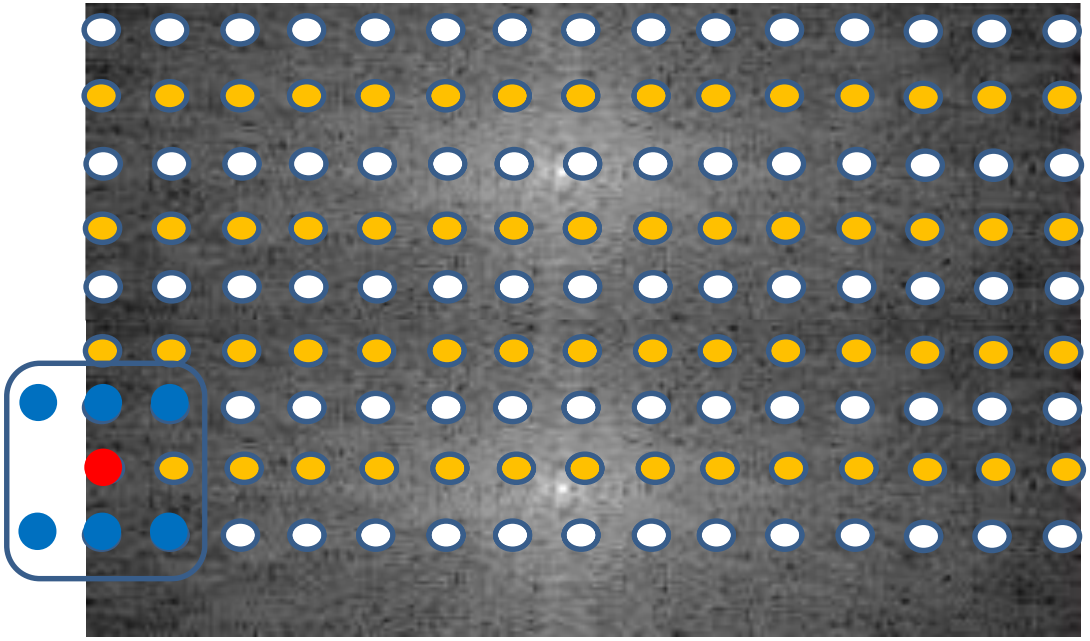

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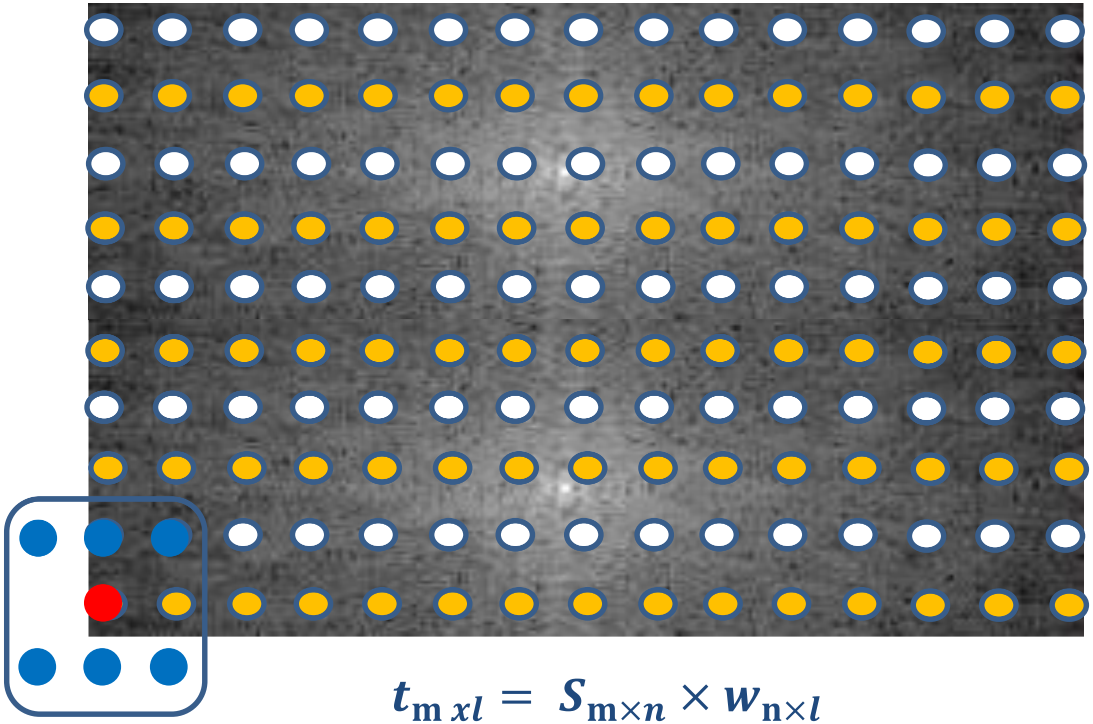

$$t_{m\,xl} = S_{m\times n} \times w_{n\times l}$$

Outline

GRAPPA Reconstruction

- **Major Challenge**

Practical gains in the performance of parallel imaging using GRAPPA are offset by the long image reconstruction time

- **Keys Issues**

i. Multiple sequential GRAPPA kernel fittings on the auto-calibration signals (ACS lines)

ii. Estimation of GRAPPA weight sets (W_{nxl}) by finding least squares solution to a large over-determined system of linear equations

$$\hat{w} = \min_{w} ||Sw - t||^2$$

iii. Iterative sequential convolutional kernel fittings

Outline

GRAPPA Reconstruction

- **Objective**

To meet the rising demands of fast image processing in real-time clinical applications

- **Keys features**

i. Parmeterizable (ACS lines, A_f , Kernel sizes)

ii. Parallel fittings of GRAPPA kernel on ACS lines

iii. Parallel estimations of the reconstruction coefficients;

iv. Parallel interpolations in the under-sampled *k*-space of receiver coils.

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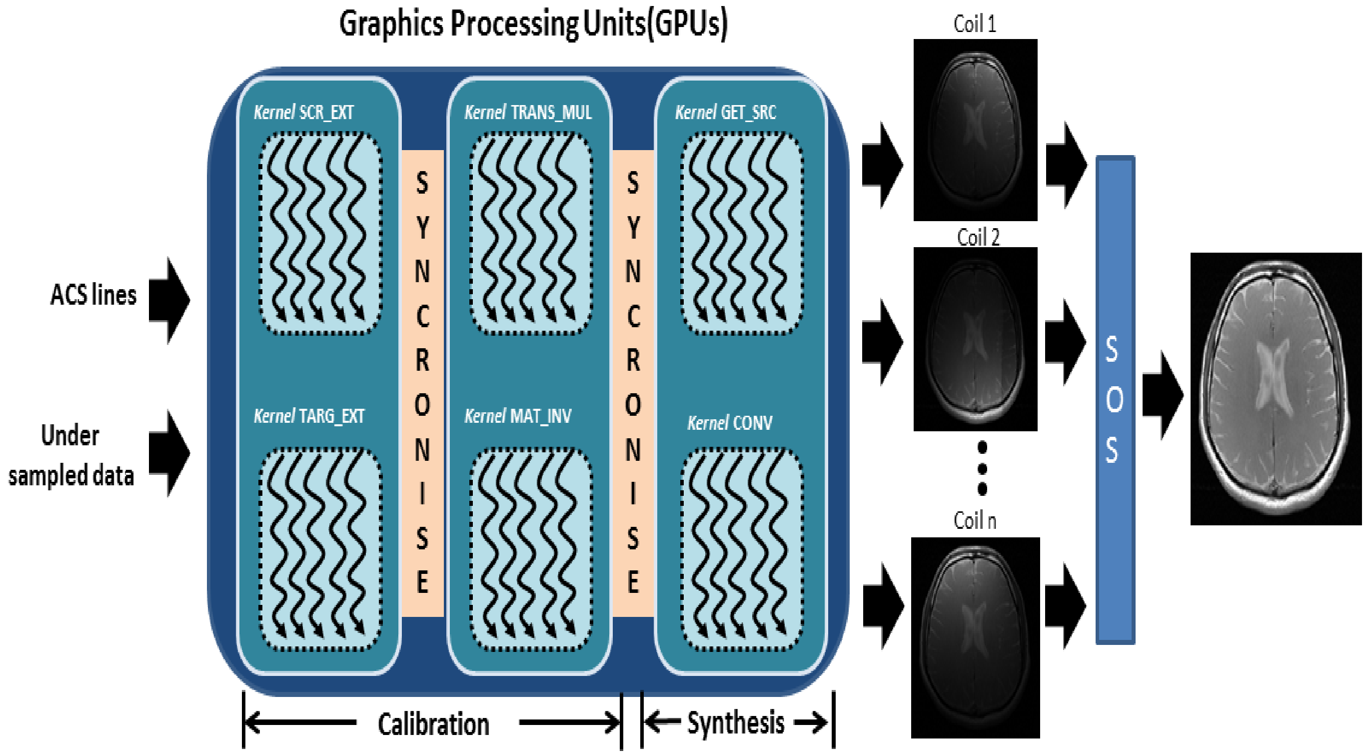
GPU based GRAPPA Reconstruction using CUDA

Proposed Architecture



**'Iterative Schemes to Solve Low-Dimensional Calibration Equations in Parallel MR Image Reconstruction with GRAPPA' (Inam, Omair, Omer, H et al), BioMed research international, vol 2017

Outline

GPU based GRAPPA Reconstruction using CUDA

Optimized CUDA kernels

- *kernel_SRC_EXT*
- *kernel*_TARG_EXT
  - Performs concurrent GRAPPA kernel fittings on the ACS lines to collect the calibration data points in the source $(S_{\mathrm{m}\times n})$ and target $(T_{\mathrm{m}\times l})$ matrices
- *kernel*_TRANS_MUL
  - Estimation of GRAPPA weight sets (W)

$$W_{\mathrm{n}\times l} = (S_{\mathrm{m}\times n}{}' S_{\mathrm{m}\times n})^{-1} S_{\mathrm{m}\times n}{}' \times T_{\mathrm{m}\times l}$$

- *kernel*_MAT_INV
  - Complex matrix Inversion
    - Parallelized Gauss Jordan algorithm
  - Complex matrix-matrix multiplications
    - Tile partitioning
- *kernel*_GET_SRC
  - Performs parallel kernel fittings to extract a new set of source matrices (S_{new})
- *kernel*_CONV
  - Performs parallel convolutions for interpolation of the under-sampled *k*-space data in each receiver coil.

Outline

GPU based GRAPPA Reconstruction using CUDA

METHODOLOGIES

Hardware specifications

Features	CPU	GPU
Model	Core i7-4790	NVIDIATesla-K40c
Cores	4	2880
Clock Speed	3.60 GHz	745 MHz
Memory	16 GB	12GB

Data acquisition details (Human Head)

Scanner	1.5T GE
No. of receiver coils	8
Matrix Size	256 x 256
TR (ms)	500
TE (ms)	10
FOV $(mm)^2$	200
Slice thickness(mm)	3mm
Flip angle	50^0

In-vivo

8-channel human head dataset acquired on 1.5T scanner, **St Mary's Hospital London**.

Outline

GPU based GRAPPA Reconstruction using CUDA

RESULTS

	GPU-enabled-GRAPPA (Proposed Method)			CPU-based GRAPPA	Speed up
	Processing time (p) (ms)	Memory Latency(m) (ms)	$\tau_{gpu} = p + m$ (ms)	τ_{cpu} (ms)	$\frac{\tau_{cpu}}{\tau_{gpu}}$
Calibration	900	5	905	7955	9x
Synthesis	100	20	120	1154	10x
Total	1000	25	1025	9109	9x

GRAPPA reconstruction time for 8-channel 1.5T *in-vivo* human head data using kernel size [2x3] and no of ACS lines=32

Outline

GPU based GRAPPA Reconstruction using CUDA

RESULTS

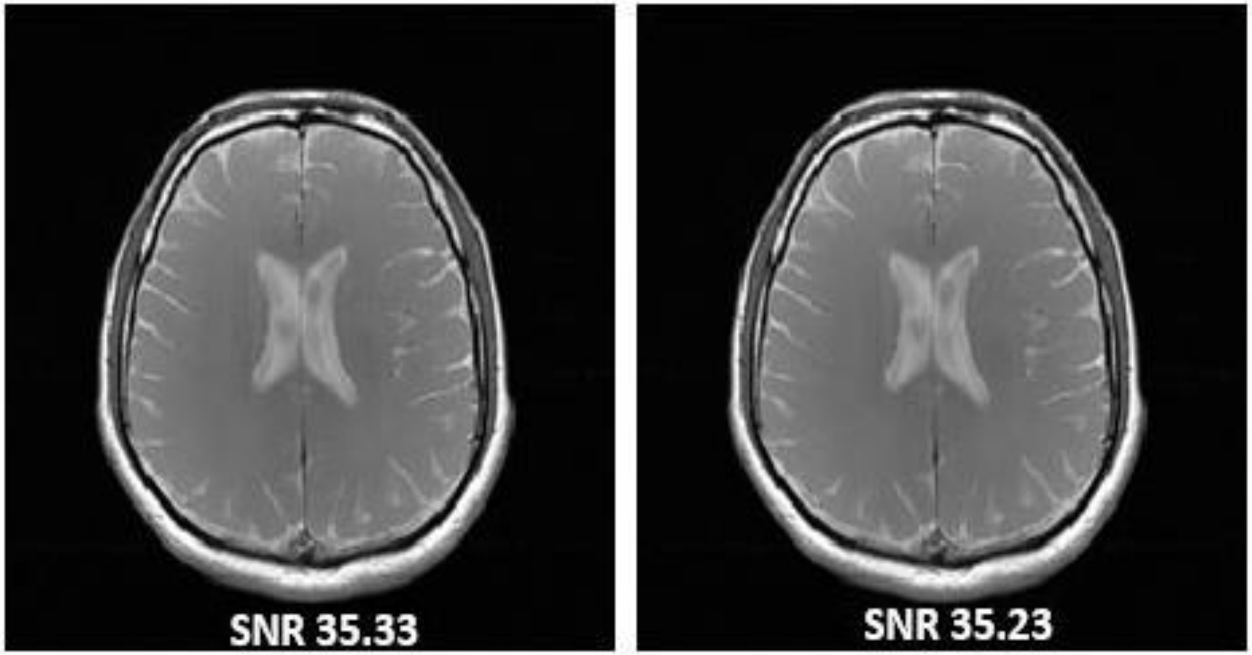
	GPU-enabled-GRAPPA (Proposed Method)			CPU-based GRAPPA	Speed up
	Processing time (p) (ms)	Memory Latency(m) (ms)	$\tau_{gpu} = p + m$ (ms)	τ_{cpu} (ms)	$\frac{\tau_{cpu}}{\tau_{gpu}}$
Calibration	4756	34	4790	74922	16x
Synthesis	160	50	210	2581	12x
Total	4916	84	5000	77503	15x

GRAPPA reconstruction time for 8-channel 1.5T *in-vivo* human head data using kernel size [4x7] and no of ACS lines=48

Outline

GPU based GRAPPA Reconstruction using CUDA

RESULTS



GRAPPA reconstruction results (CPU *vs* GPU) of 8-channel 1.5T *in-vivo* human head using kernel size [2x3] and no of ACS lines=32. **(Left)** Image reconstructed using CPU-based-GRAPPA; **(Right)** Image reconstructed using GPU-enabled-GRAPPA

Outline

GPU based GRAPPA Reconstruction using CUDA

CONCLUSION

- Proposed frame work is scalable to different GRAPPA parameter settings
- Significantly reduces the latency of the calibration and synthesis phases, thereby resulting up to 15x speedup (8-channel 1.5T human head dataset)
- Proposed method is a suitable choice to accelerate the GRAPPA reconstruction process as the thread creation and memory transfer overheads are negligible (i.e. a memory latency is 0.017% of the total reconstruction time)
- Future: Cardiac MRI (32 channel receiver coil)

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  - GPU based Gridding
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- Acknowledgements

SENSE Reconstruction Method

Outline

SENSE Reconstruction

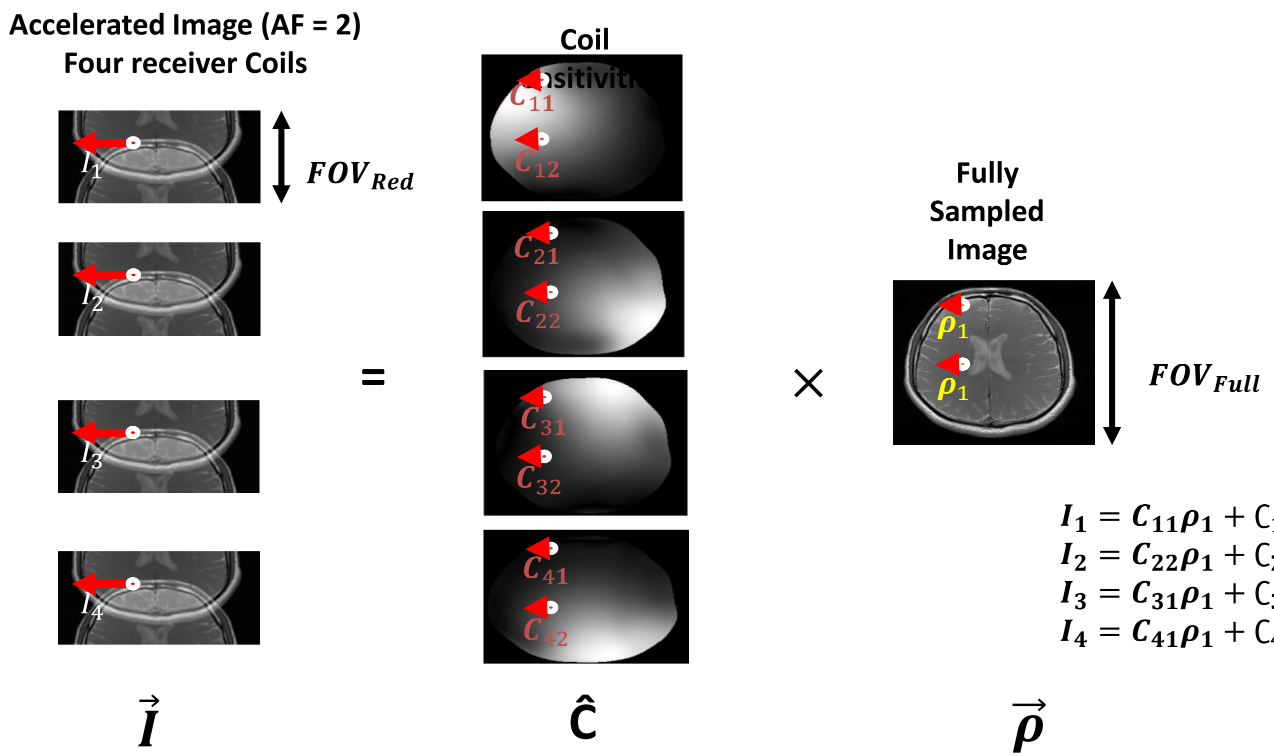
- Performs reconstruction in Image Space
- Siemens (***mSENSE***)
- GE (***ASSET***)
- Philips (***SENSE***)
- Hitachi (***RAPID*** - "Rapid Acquisition through Parallel Imaging Design")
- Canon (***SPEEDER***)
- Involves 4 steps
  1. Sensitivity Maps Estimation
  2. Acquired Partia *k*-Space
  3. Reconstruct partial FOV images from each coil
  4. Combined partial FOV images by matrix inversion

****Preussmann KP, Weiger M, Scheidegger MB, Boesiger P. 1999. SENSE: sensitivity encoding for fast `MRI. Magn Reson Med 42:952–962**

Outline

SENSE Reconstruction

- **Combining aliased images**



$$I_1 = C_{11}\rho_1 + C_{12}\rho_2$$
$$I_2 = C_{22}\rho_1 + C_{22}\rho_2$$
$$I_3 = C_{31}\rho_1 + C_{32}\rho_2$$
$$I_4 = C_{41}\rho_1 + C_{42}\rho_2$$

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SENSE Reconstruction

- **Inversion**

Inverse of Rectangular Matrix

$$\begin{aligned} I_1 &= C_{11}\rho_1 + C_{12}\rho_2 \\ I_2 &= C_{22}\rho_1 + C_{22}\rho_2 \\ I_3 &= C_{31}\rho_1 + C_{32}\rho_2 \\ I_4 &= C_{41}\rho_1 + C_{42}\rho_2 \end{aligned} \Rightarrow \boxed{\begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \end{bmatrix} = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \\ C_{31} & C_{32} \\ C_{41} & C_{42} \end{bmatrix}} \times \begin{bmatrix} \rho_1 \\ \rho_2 \end{bmatrix}$$

Unknown Image Matrix to be reconstructed

Aliased Image Matrix

Encoding Matrix

$$\vec{I} = \hat{C} \times \vec{\rho}$$

$$\vec{\rho} = \hat{C}^{-1} \times \vec{I}$$

- Due to size of encoding matrix, direct inversion is computational expensive
  - $\hat{C}$ = **131072** $\times$ **65536** for Image size = 256 $\times$ 256 having AF =2 with 4 receiver coils
- Encoding matrix is divided into smaller sub matrices
  - Inverse of each sub-matrix is sequentially computed
- Generally those submatrices are **rectangular matrices**
  - Matrix decomposition methods are required to take inverse of rectangular matrix instead of simple inverse techniques

Outline

SENSE Reconstruction

- **Major Challenge**

Inversion of the rectangular encoding matrix is the most computationally expensive task in SENSE algorithm

- **Keys Issues**

A fast (with optimal computational complexity) and stable algorithm is required to perform the inversion of the encoding matrix in SENSE reconstruction

SENSE Reconstruction

- **Objective**

To meet the rising demands of fast image processing in real-time clinical applications

- **Keys features**

i. Parametrizable (image sizes, Af)

ii. Parallel matrix inversions using QR-decomposition

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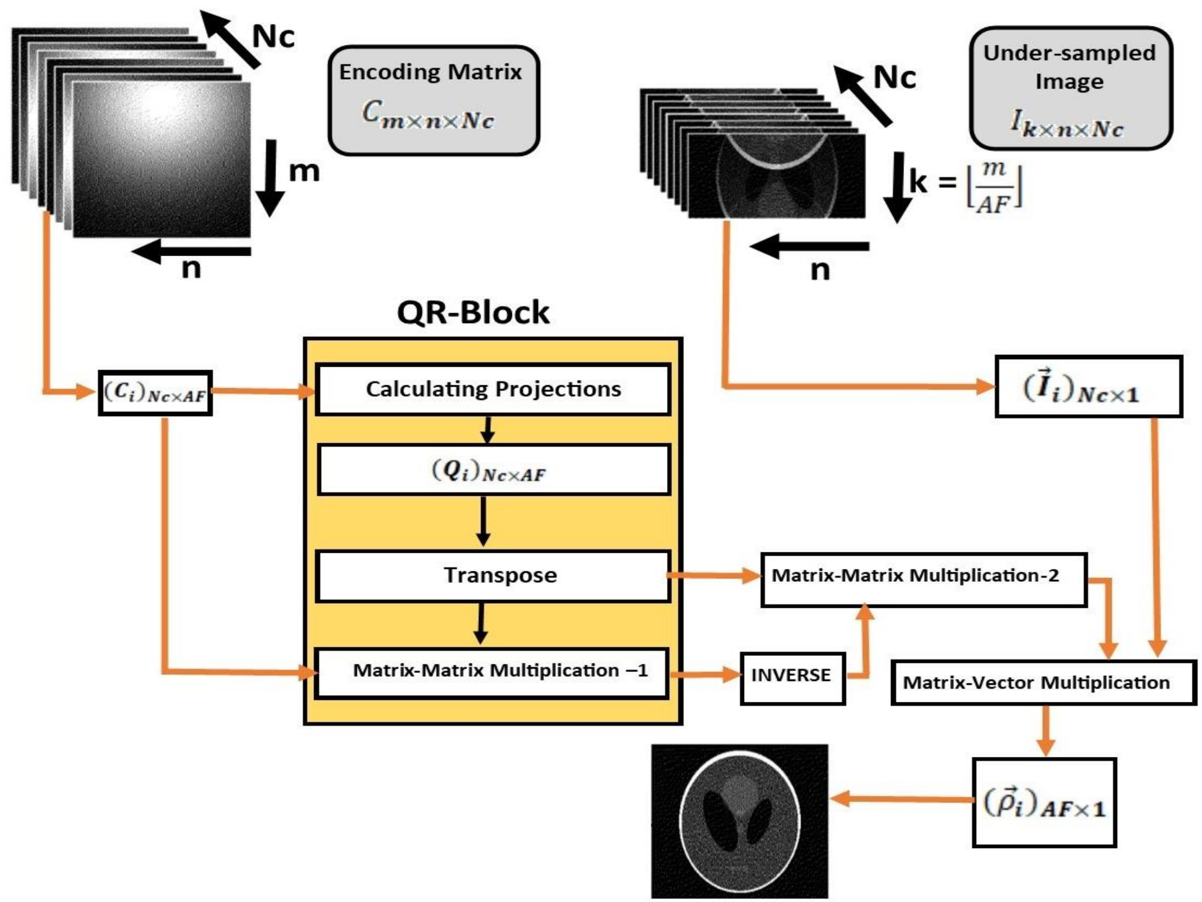
GPU based SENSE using CUDA

Proposed Architecture



** 'QR-decomposition based SENSE reconstruction using parallel architecture' (Ullah, Irfan, Omer, H et al), In Computers in biology and medicine, Elsevier, volume 95, 2018.

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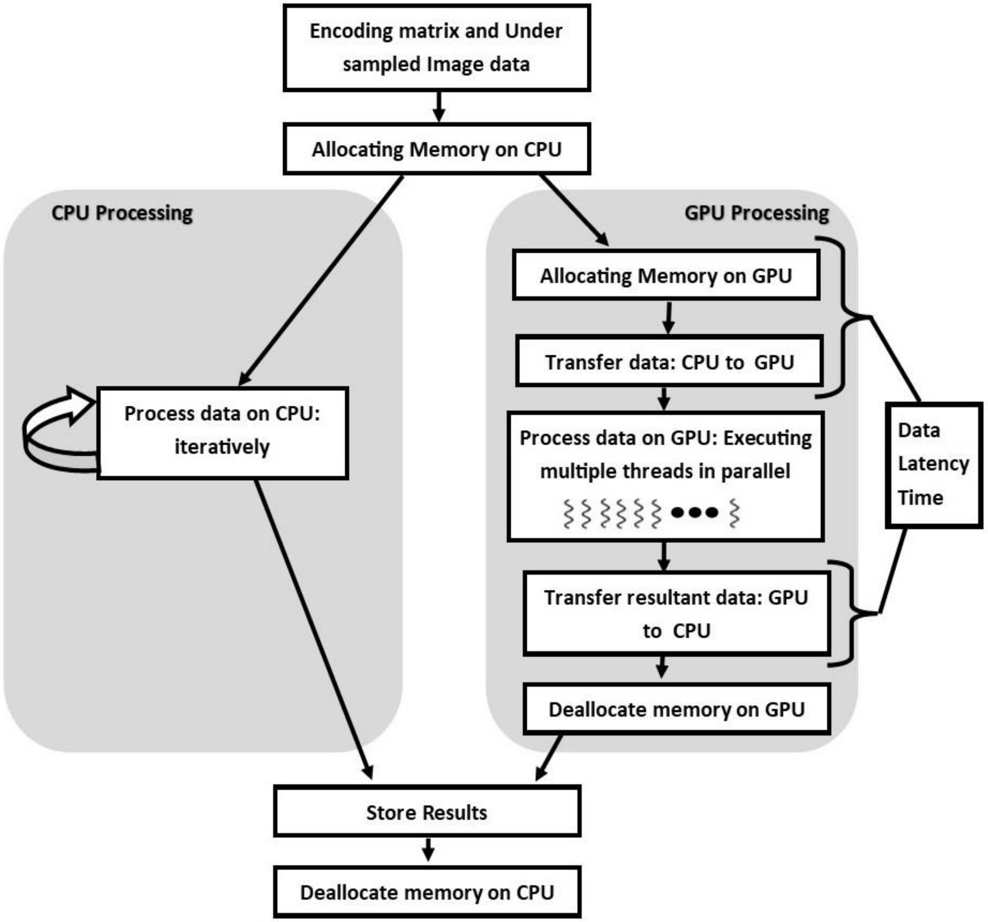
GPU based SENSE Reconstruction using CUDA

Proposed Architecture



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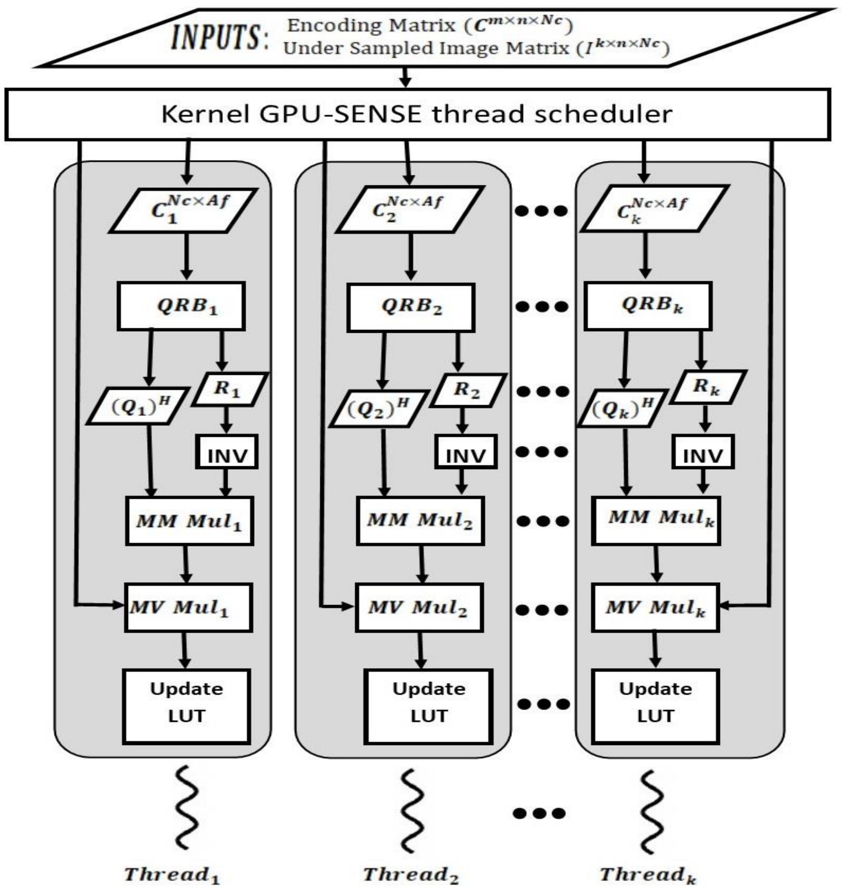
GPU based SENSE Reconstruction using CUDA

Proposed Architecture



Outline

GPU based SENSE Reconstruction using CUDA

Proposed Architecture

- ***In-vivo***
  - St. Mary's Hospital London, UK
  - University Hospitals of Cleveland, Case Western Reserve University (CWRU), USA

Data	Receiver coils	Scanner	AFs	Image size	Slice thickness
Phantom dataset	8	1.5 T GE scanner	2,3,4	256 x 256	3mm
Human head dataset	8	1.5 T GE scanner	2,3,4	256 x 256	3mm
Human head dataset	12	3T. Siemens Skyra scanner	2,4,6	448 x 224	5mm
Cardiac dataset (11 frames)	30	3T. Siemens Skyra scanner	5,8,12	512 x 252	8mm

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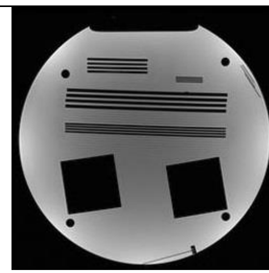
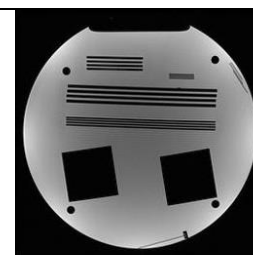
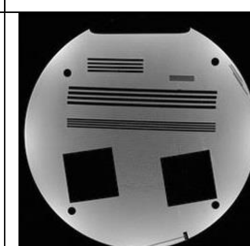
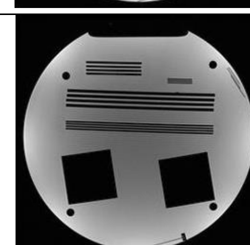
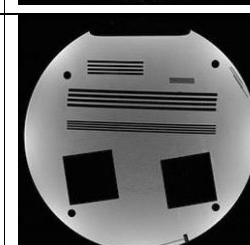
GPU based SENSE Reconstruction using CUDA

Proposed Architecture

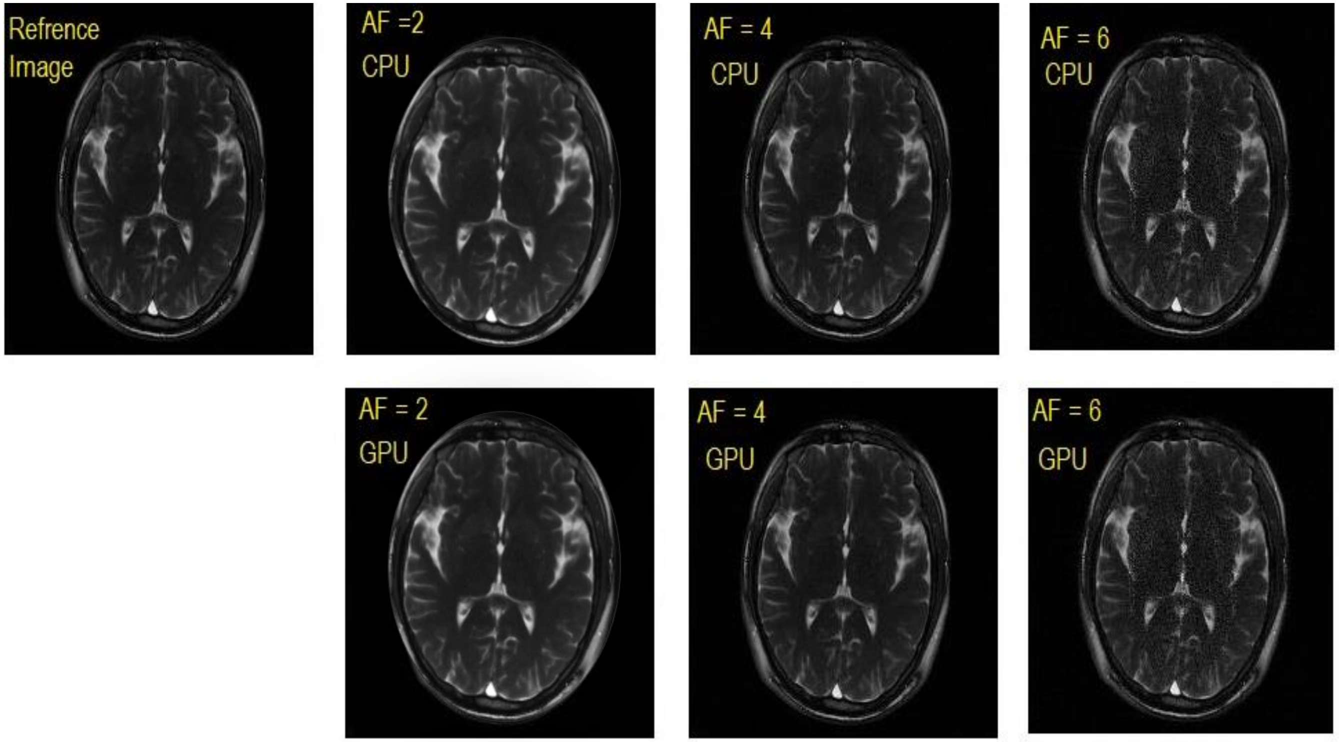
 Reference Image		(a)	(b)	(c)
		AF = 2	AF= 4	Difference image between the reconstructed image and the reference image at AF = 4
(d)	CPU Reconstructed Images			
(e)	GPU Reconstructed images			

Reconstructed Images of Phantom, receiver coil = 8, Af = 2 and 4

Outline

GPU based SENSE Reconstruction using CUDA

Proposed Architecture

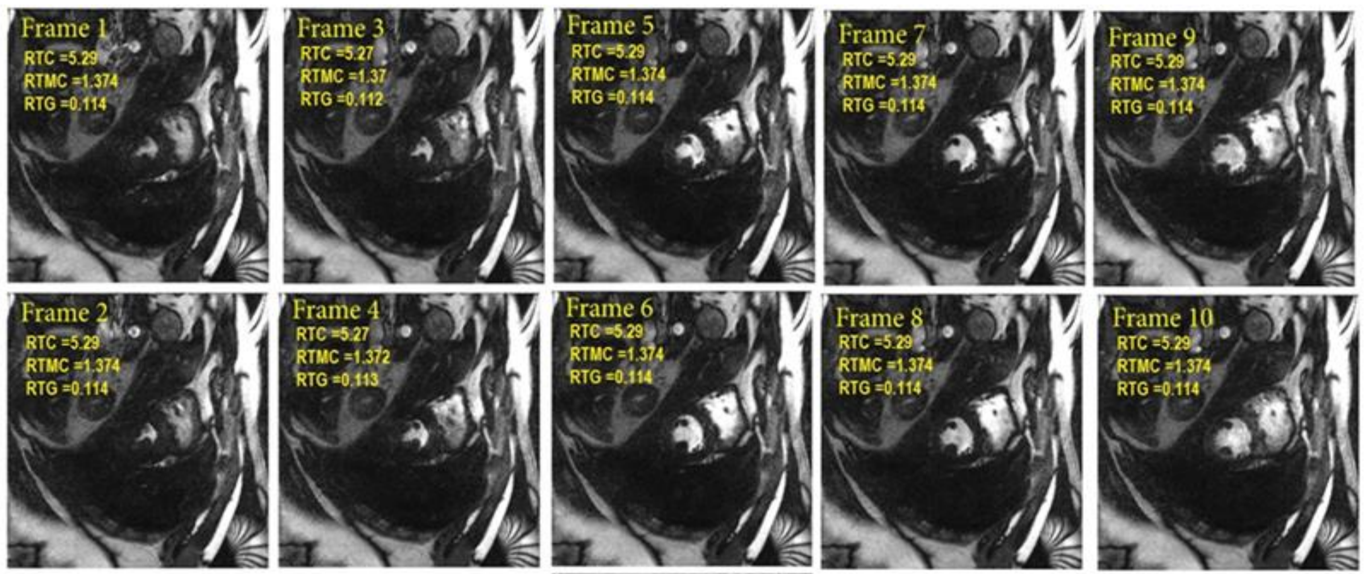


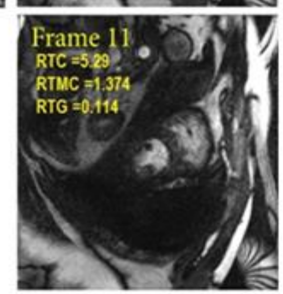
Visual Result for in Vivo human head dataset, Receiver coils = 12, AF = 2,4 and 6

Outline

GPU based SENSE Reconstruction using CUDA

Proposed Architecture





Visual Result for 30 channel Cardiac Dataset, AF = 5, 11 Frames

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GPU based GRAPPA Reconstruction using CUDA

RESULTS

Dataset Type and Dimension	AF	Reconstruction Time GPU (ms)				Total Time GPU (ms)	Artifact Power
		Data Latency Time			GPU processing time		
		Memory Allocation	$DT_{C\to G}$	$DT_{G\to C}$			
Phantom Dataset 256X256	2	0.12	1.517	0.8	4.76	7.2	1.4076×10^{-5}
	3	0.13	1.55	0.8	9.523	12	7.6958×10^{-5}
	4	0.126	1.49	0.8	15.685	18.1	2.8146×10^{-4}
In-Vivo Human Head Dataset 256X256 (8 coils)	2	0.12	1.517	0.8	5.023	7.46	2.1132×10^{-5}
	3	0.13	1.55	0.8	9.7	12.18	5.381×10^{-5}
	4	0.14	1.49	0.8	15.96	18.39	1.516×10^{-4}
In-Vivo Human Head Dataset 448X224 (12 coils)	2	0.16	7.5	1.2	8.73	17.59	9.0731×10^{-4}
	4	0.18	7.4	1.2	21.38	30.16	2.1×10^{-3}
	6	0.20	7.49	1.2	52.2	61.09	3.41×10^{-2}
Cardiac Dataset 512X252 (30 coils) 11 frames	5	0.24	20.2	1.7	92.41	114.55	3.8×10^{-3}
	8	0.24	20.4	1.7	205.39	227.73	3.25×10^{-2}
	12	0.27	20.6	1.7	441.26	463.83	1.623×10^{-1}

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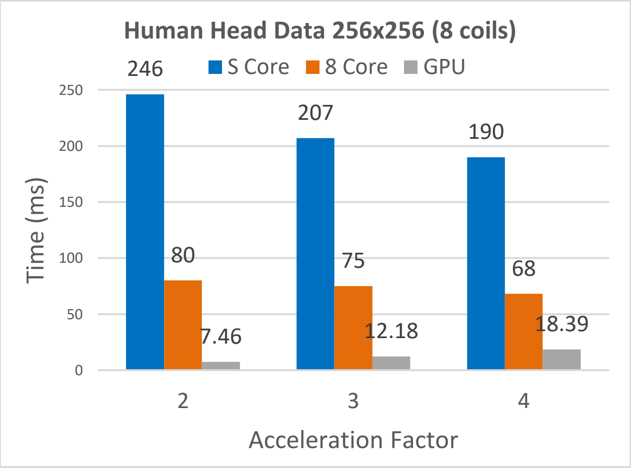
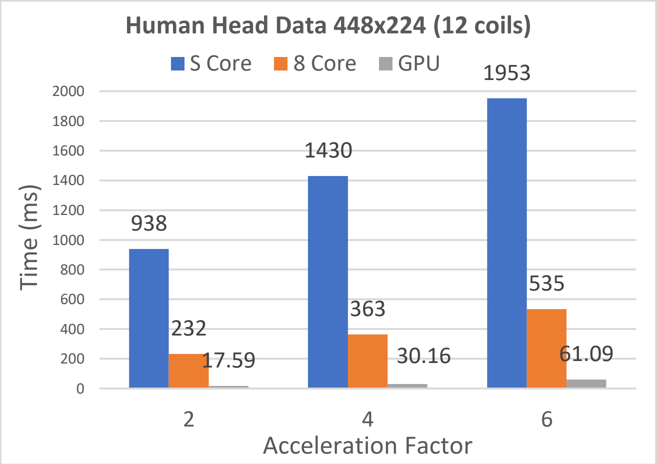
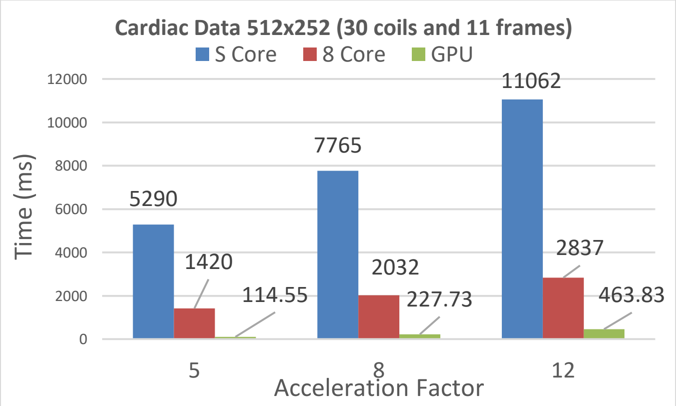
GPU based SENSE Reconstruction using CUDA

RESULTS







GPU based SENSE Reconstruction using CUDA

CONCLUSION

- QR-decomposition is proposed for the rectangular encoding matrix inversion in SENSE reconstruction.
- The inherent parallelism of the proposed method is exploited by implementing it on a parallel platform(GPU) to further reduce the reconstruction time
- The proposed method is fully parametrizable

Outline

Non-Cartesian Parallel Imaging

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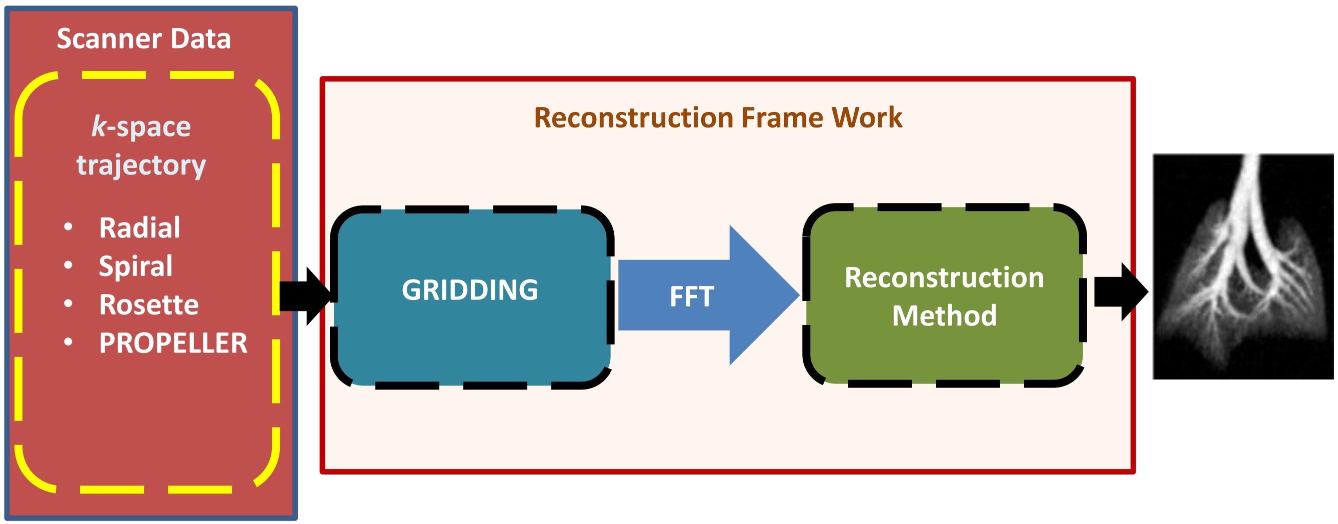
Non-Cartesian Parallel MRI

- **Reconstruction Methods**
  - Radial GRAPPA
  - Spiral GRAPPA
  - Pseudo Cartesian GRAPPA
  - CG-SENSE
- **Gridding**
  - NUFFT
  - GROG
  - SC-GROG



Outline

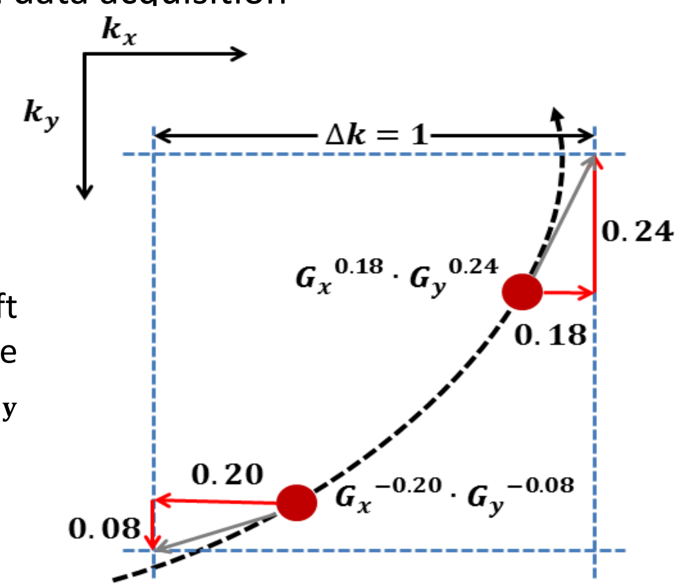
Non-Cartesian Parallel MRI

- **Self Calibration GRAPPA Operator Gridding**
  - Extended version of GROG
  - Uses the properties of GRAPPA operator
  - Shifts each non-Cartesian sample in a k-space by smaller intervals (δx and δy) in k_x and k_y directions

$$s(k_x + \delta_x, k_y + \delta_y) = G_x^{\delta x} \cdot G_y^{\delta y} \cdot s(k_x, k_y)$$

  - Does not require additional data acquisition
  - Works in two stages:
    1) Self-Calibration
    2) Gridding

GROG weights are applied to shift non-Cartesian data points in a *k*-space by smaller intervals in $\mathbf{k_x}$ and $\mathbf{k_y}$ directions.



**‘Self-calibrating GRAPPA operator gridding for radial and spiral trajectories’ N Seiberlich, F Breuer, M Blaimer, P Jakob, M Griswold, Magnetic Resonance in Medicine, Vol 59, 2008

Outline

Non-Cartesian Parallel MRI

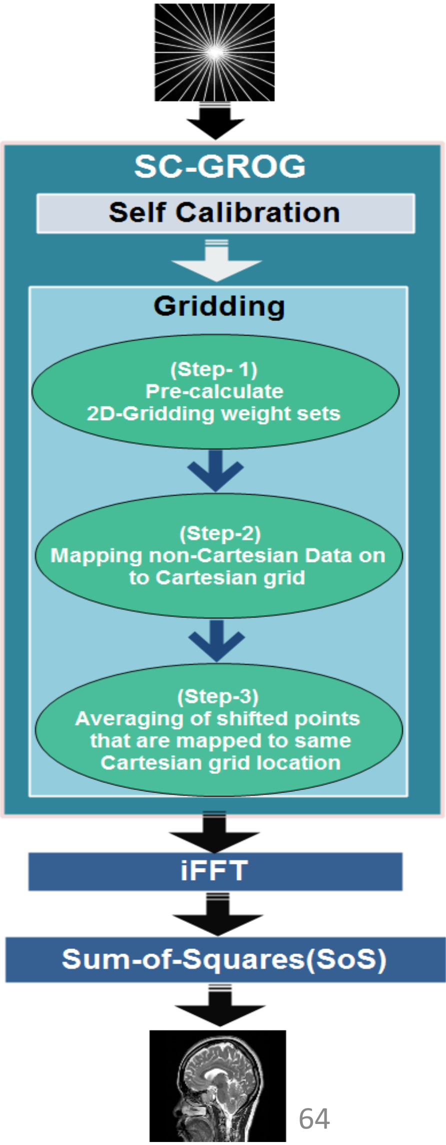
- **Self Calibration GRAPPA Operator Gridding**
  - Conventional SC-GROG

Step 1 : Calculate all the possible combinations of 2D gridding weight sets for smaller shifts ($G_x^{\delta x}$, $G_y^{\delta y}$)

Step 2: Sequential Mapping

$$s\left(k_x+\delta_x, k_y+\delta_y\right) = G_{xy}(\delta x, \delta y) \cdot s\left(k_x, k_y, k_z\right)$$

Step 3: Sequential Averaging



Outline

GPU based SC-GROG using CUDA

- **Objective**

Accelerating non-Cartesian parallel Imaging using GPU based SC-GROG

- **Keys Features**

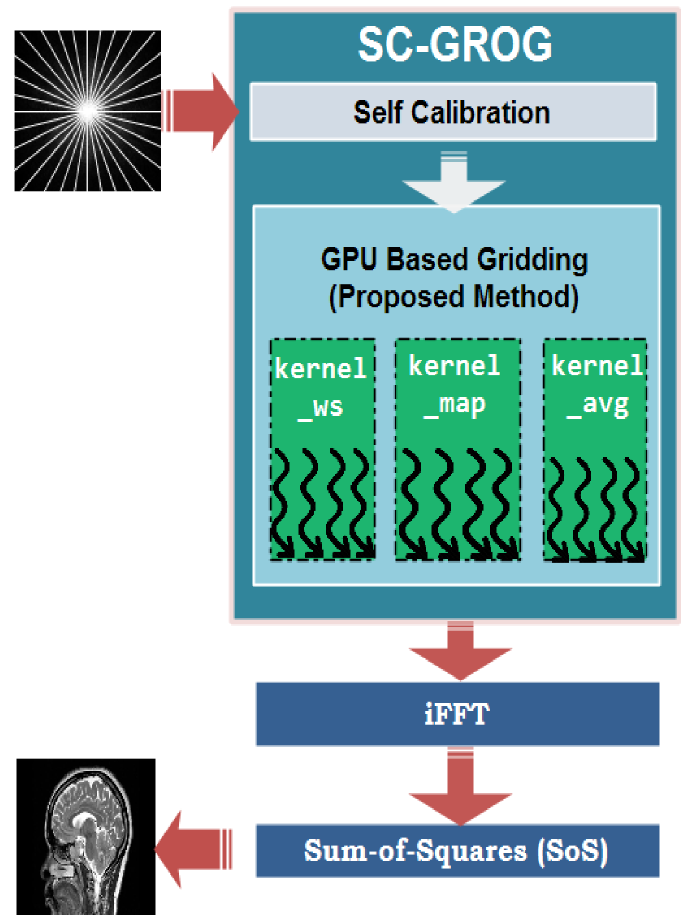
i. Parametrizable (Radial projections, coils and image size)
ii. Implementation of LUTs to update and store 2D gridding weight sets in parallel
iii. Parallel access to LUTs for concurrent shifting of the non-Cartesian samples to their nearest Cartesian grid locations (to avoid race condition)
iv. The total number of points shifted at the same Cartesian location are averaged in parallel

GPU based SC-GROG using CUDA

Outline

PROPOSED ARCHITECTURE

- Self-Calibration (CPU)
- Gridding (GPU)
  - **1) kernel_ws**
  - **2) kernel_map**
  - **3) kernel_avg**
- Employs look-up-tables (LUTs) to avoid race conditions



**'GPU-accelerated self-calibrating GRAPPA operator gridding for rapid reconstruction of non-cartesian MRI data' (Inam, Omair, Omer, H et al), Applied Magnetic Resonance, Springer, volume 48, 2017

GPU based SC-GROG using CUDA

MEHODOLOGIES

- **Radial Data sets (*In-vivo*)**
  - St. Mary’s Hospital London, UK
  - University Hospitals of Cleveland, Case Western Reserve University (CWRU), USA

Data	Channels	Scanner	Projections	Read out points
Cardiac data sets	30	3T (GE)	144	256
Human head data	12	3T (Siemens Skyra)	256	256

- **Phantom**
  - Standard Shepp-Logan phantom (simulated 24-channel, with 64 to 400 projections, 256 readout points
- **Simulation Platforms**
  - CPU: Intel(R) Core(TM) i5-3210M @ 2.50GHz, 2501MHz, Memory 4GB
  - NVIDIA GeForce GTX 780 (876 MHz, 2880 shared cores, 3GB Memory)

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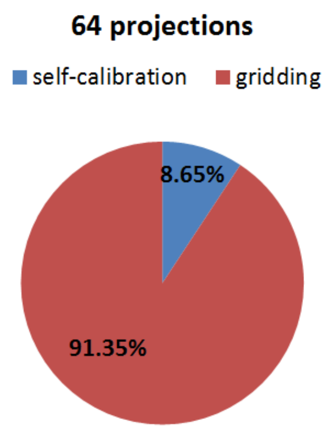
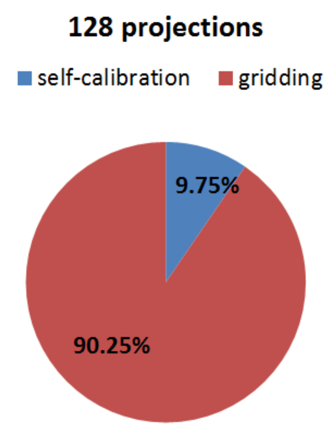
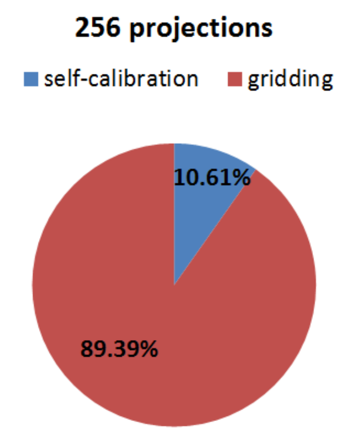
GPU based SC-GROG using CUDA

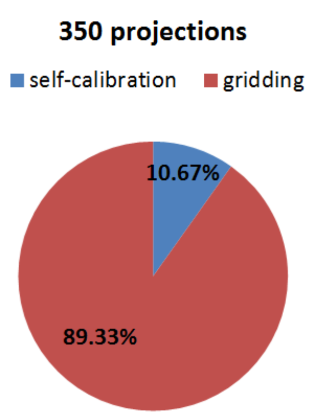
METHODOLOGIES

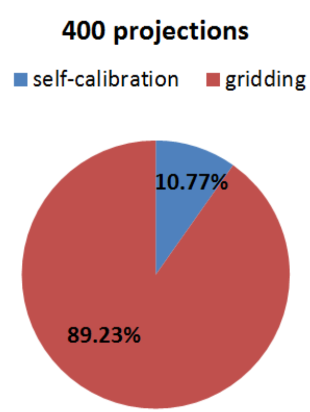
Self-Calibration and Gridding process as % of total computation time











Simulated Shepp-Logan phantom with different no of radial projections ranging from 64 to 400

Outline

GPU based SC-GROG using CUDA

RESULTS

Performance comparison between GPU-based gridding and CPU-based gridding

Simulated Shepp-Logan phantom using 24-channel coil array			
No. of Projections	CPU-based Gridding $T_{Grid_{cpu}}$ (sec)	GPU-based Gridding $T_{Grid_{gpu}}$ (sec)	Speed-up $= \frac{T_{Grid_{cpu}}}{T_{Grid_{gpu}}}$
64	3.0	0.234	12.82x
128	5.77	0.294	19.55x
256	11.29	0.441	25.60x
350	15.27	0.525	29.085x
400	17.50	0.571	30.64x

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GPU based SC-GROG using CUDA

RESULTS

Overall speedup gain in the total computation time of SC-GROG

Simulated Shepp-Logan phantom using 24-channel coil array

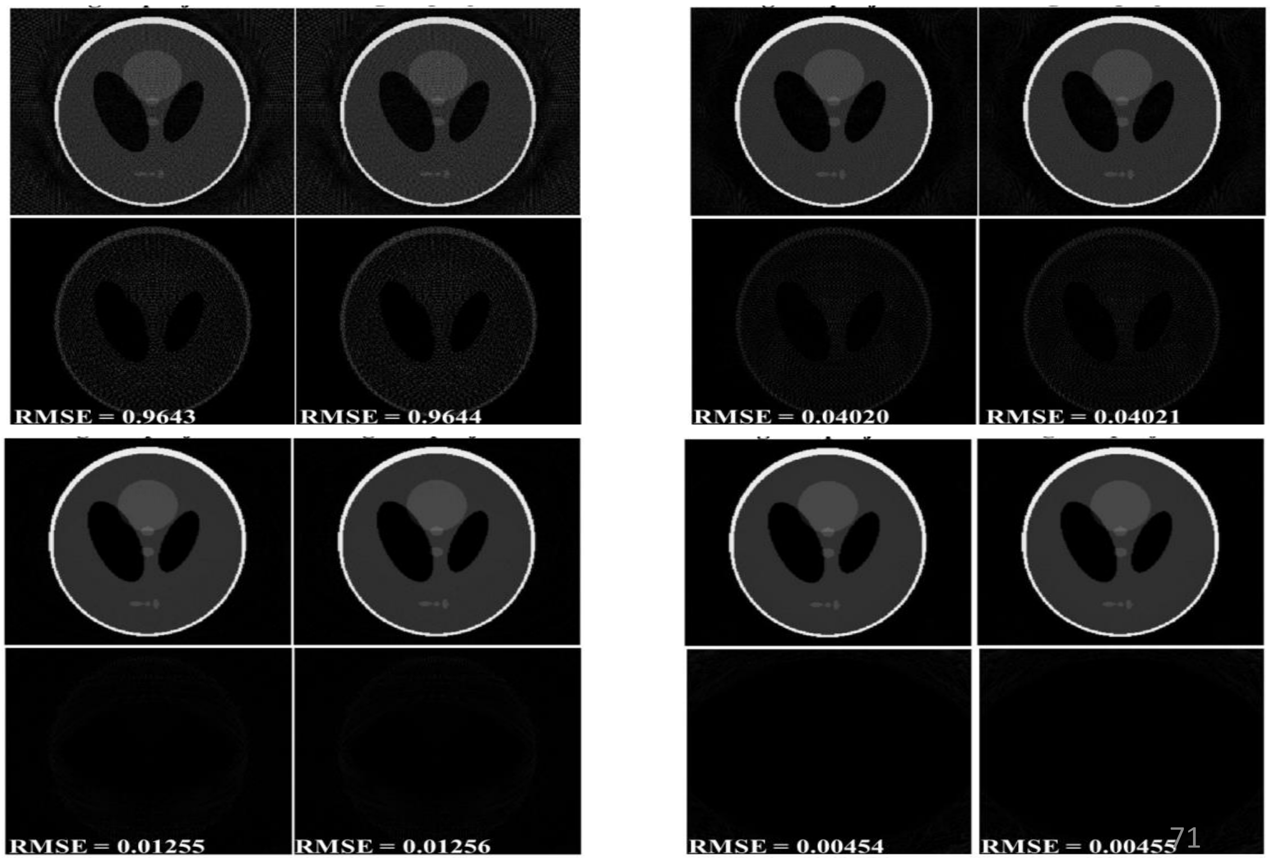
No. of Projections	$T_{SelfCal\_cpu}$ (sec)	T_{Grid_cpu} (sec)	T_{Grid_gpu} (sec)	$T_{cpu} = T_{SelfCal_{cpu}} + T_{Grid\_cpu}$ (sec)	$T_{gpu} = T_{SelfCal_{cpu}} + T_{Grid\_gpu}$ (sec)	Overall Speedup $= \frac{T_{cpu}}{T_{gpu}}$ (sec)
64	0.284	3	0.234	3.284	0.518	6.33x
128	0.621	5.75	0.294	6.371	0.915	6.96x
256	1.34	11.29	0.441	12.63	1.781	7.09x
350	1.823	15.27	0.525	17.093	2.348	7.27x
400	2.112	17.501	0.571	19.613	2.683	7.31x

Outline

GPU based SC-GROG using CUDA

RESULTS

Comparison between the GPU-based SC-GROG and CPU-based SC-GROG reconstruction results



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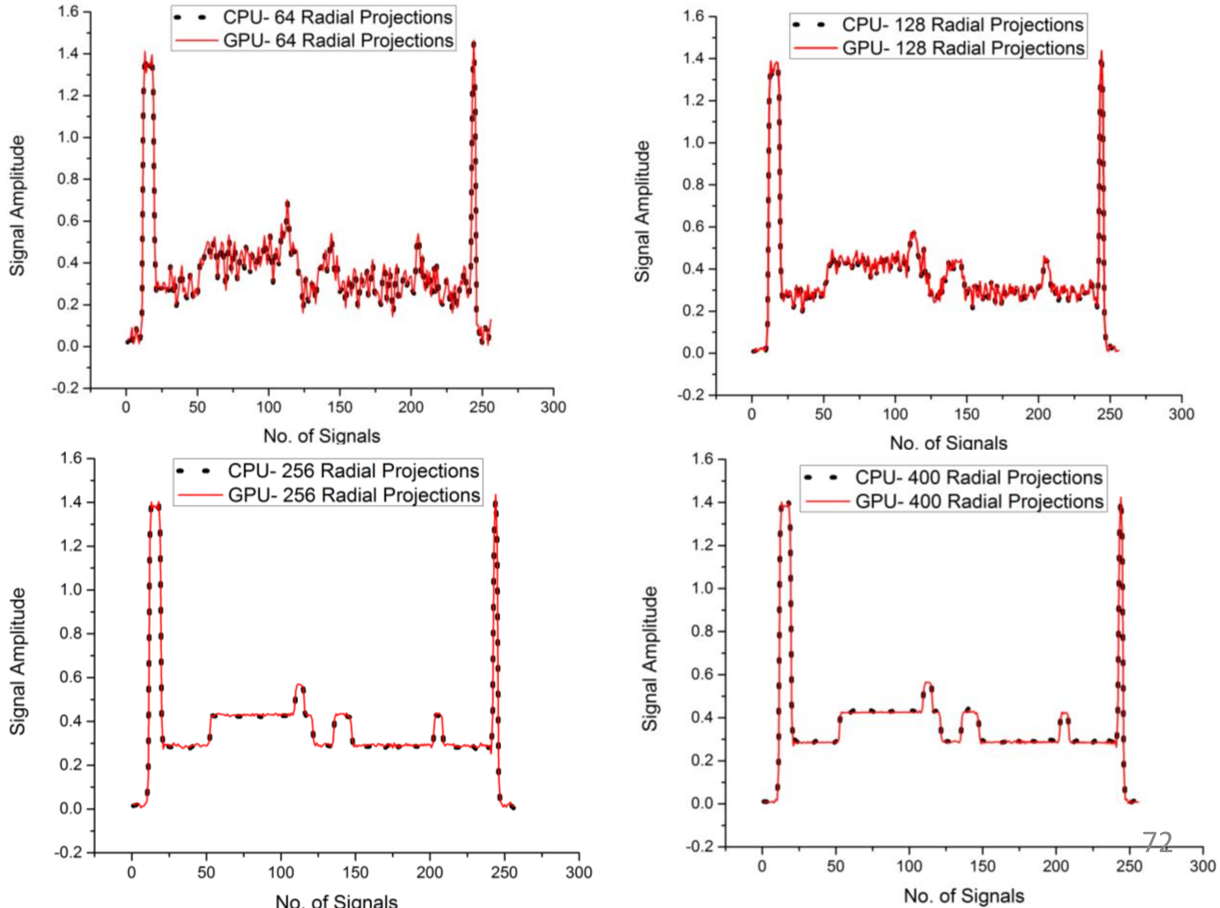
- Magnetic Resonance Finger printing
- Acknowledgements

GPU based SC-GROG using CUDA

RESULTS

Comparison of the center line profiles of the reconstructed images between the GPU-based SC-GROG and CPU-based SC-GROG



Outline

- MPIRG at Glance
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- **Parallel MRI**
  - GRAPPA
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  - SENSE
  - GPU based SENSE
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GPU based SC-GROG using CUDA

RESULTS

Speedup gains in the gridding operation

12-channel human head radial data			
No. of Projections	CPU-based Gridding T_{Grid_cpu} (sec)	GPU-based Gridding T_{Grid_gpu} (sec)	Speed-up $= \frac{T_{Grid\_cpu}}{T_{Grid\_gpu}}$
256	2.93	0.14	20.92x

Overall speedup in SC-GROG

12-channel human head radial data						
No. of Projections	$T_{SelfCal\_cpu}$ (sec)	T_{Grid_cpu} (sec)	T_{Grid_gpu} (sec)	$T_{cpu} = T_{SelfCal_{cpu}} + T_{Grid\_cpu}$ (sec)	$T_{gpu} = T_{SelfCal_{cpu}} + T_{Grid\_gpu}$ (sec)	Overall Speedup $= \frac{T_{cpu}}{T_{gpu}}$ (sec)
256	0.324	2.93	0.14	3.254	0.464	7.01x

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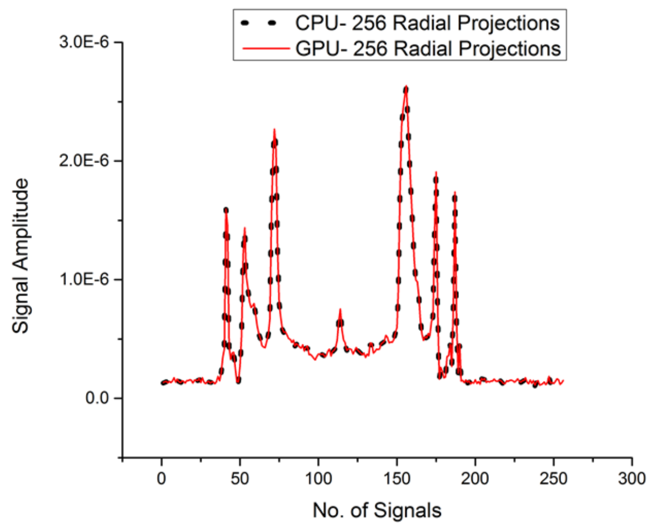
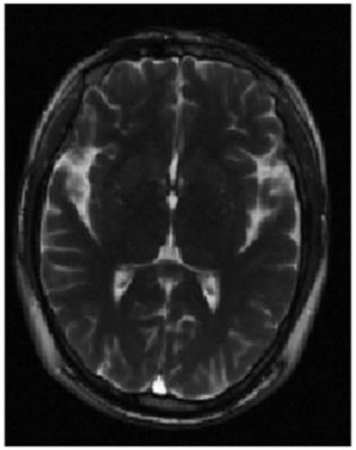
GPU based SC-GROG using CUDA

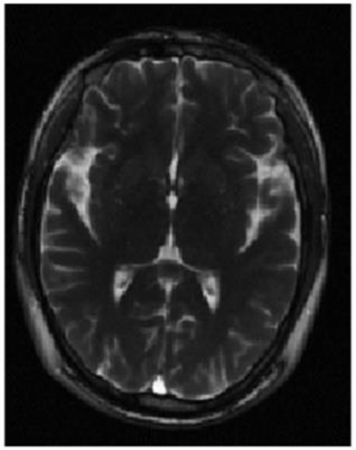
RESULTS



Reconstructed Image using CPU-based-SC-GROG



Reconstructed Image using GPU-based-SC-GROG



12-channel human head data set with 256 projections and base matrix 256x256

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GPU based SC-GROG using CUDA

RESULTS

Speedup gains in the gridding operation

30-channel cardiac radial data			
No. of Projections	CPU-based Gridding T_{Grid_cpu} (sec)	GPU-based Gridding T_{Grid_gpu} (sec)	Speed-up $= \frac{T_{Grid\_cpu}}{T_{Grid\_gpu}}$
144	8.9	0.324	27.46x

Overall speedup in SC-GROG

30-channel cardiac radial data						
No. of Projections	$T_{SelfCal\_cpu}$ (sec)	T_{Grid_cpu} (sec)	T_{Grid_gpu} (sec)	$T_{cpu} = T_{SelfCal_{cpu}} + T_{Grid\_cpu}$ (sec)	$T_{gpu} = T_{SelfCal_{cpu}} + T_{Grid\_gpu}$ (sec)	Overall Speedup $= \frac{T_{cpu}}{T_{gpu}}$ (sec)
144	1.073	8.9	0.324	9.973	1.397	7.13x

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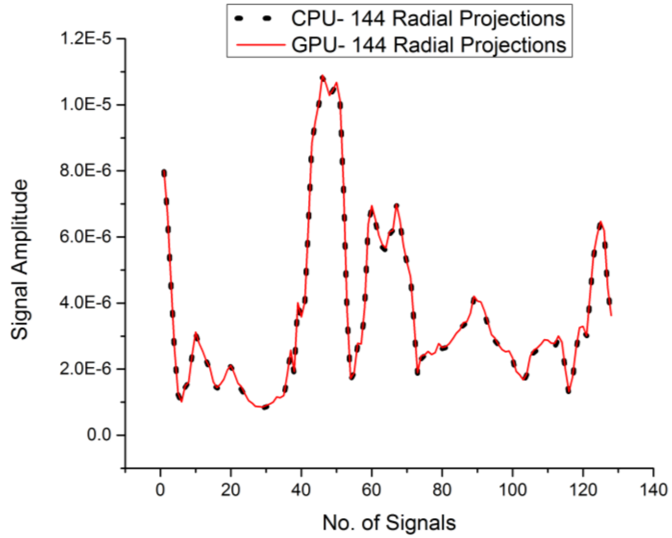
GPU based SC-GROG using CUDA

RESULTS



30-channel cardiac data with 144 projections, 25 frames and base matrix 128x128

GPU based SC-GROG using CUDA

CONCLUSION

- Proposed frame work is scalable to different gridding parameters and can be used with many non-Cartesian parallel MRI methods e.g. CG-SENSE, radial GRAPPA, Pseudo Cartesian GRAPPA etc.
- Parameterizable
- Employs loo*k*-up-table (LUT) based kernels of CUDA to accelerate SC-GROG gridding operations
- Avoids race condition
- GPU-based SC-GROG can accelerate the data gridding process by factors ranging from 12 to 30
- Reduces the overall computation time of SC-GROG by factors ranging from 6 to 7 without compromising the quality of the reconstructed images

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Magnetic Resonance Fingerprinting

**‘Magnetic resonance fingerprinting’ D Ma, V Gulani, N Seiberlich, K Liu, JL Sunshine, JL Duerk, MA Griswold Nature 495 (7440), 187

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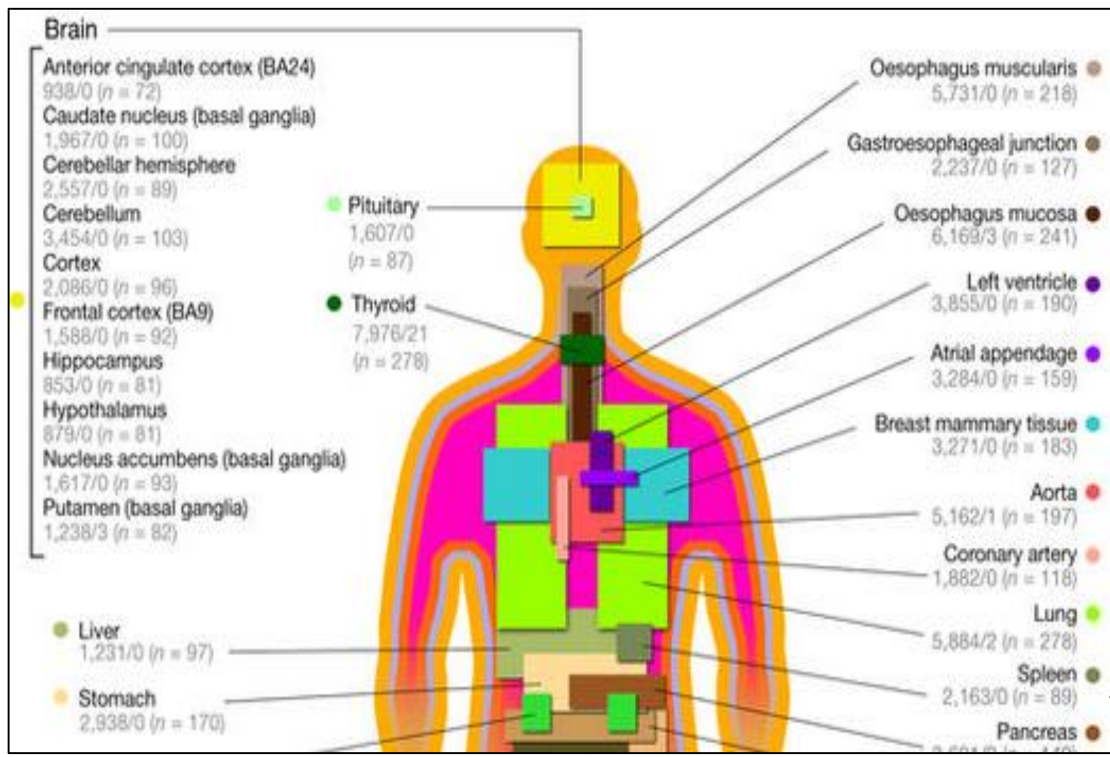
Magnetic Resonance Fingerprinting (MRF)

Randomized Acquisition ⇒ Pattern Recognition ⇒ Information



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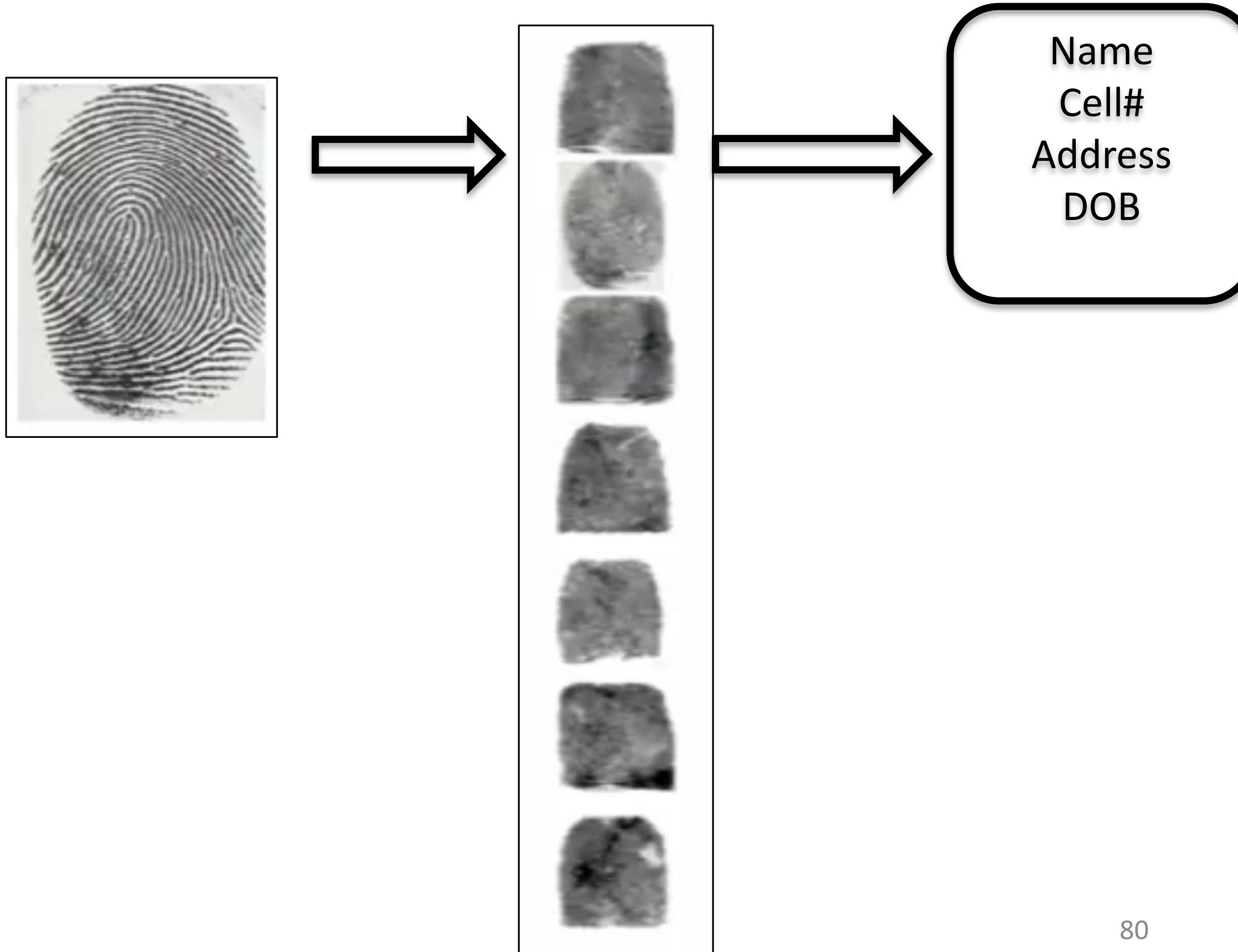
Magnetic Resonance Fingerprinting (MRF)



Outline

Magnetic Resonance Fingerprinting (MRF)

- MRF is a novel approach that consists of:
  - Data Acquisition, Post Processing and Visualization
- Revolutionizing MR Imaging
- Provides quantitative maps
- Local changes in T1 and T2 have been measured in diseases (Table)

Neurological	Psychological	Genetic
Alzheimer's Parkinson's Multiple sclerosis	Epilepsy Autism Schizophrenia	Cancer

Table Diseases known to have caused local changes in T1 and T2 relaxation times

Outline

Magnetic Resonance Fingerprinting (MRF)

- **Major Challenge**

The execution of MRF algorithms requires a considerable amount of computation time. Therefore, main limitation of MRF in clinical realization is the computation complexity.

- **Keys Issues**

MRF quantitatively examines many magnetic resonance tissue parameters simultaneously by sequentially processing the data majorly due to the limitation of the data processing hardware(limited number of computational cores in CPU)

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Magnetic Resonance Fingerprinting (MRF)

- **Objective**

To reduce the computation complexity of MRF algorithms that is an important step toward the clinically realization of the MRF technology

- **Keys features**

i. Parametrizable (MRF dictionary size)

ii. MRF algorithm is accelerated without any functional modifications in the native MRF algorithm

iii. MRF algorithm is accelerated without reducing data to be processed in the native MRF algorithm

**Magnetic Resonance Fingerprinting (MRF) implementation on Graphical Processing Unit (GPU) for exploiting inherent parallelism (I. Ullah, Seiberlich, M. Griswold, H. Omer et al), 33rd Annual Scientific Meeting of ESMRMB 2016, 2016, Vienna, Austria, 2016

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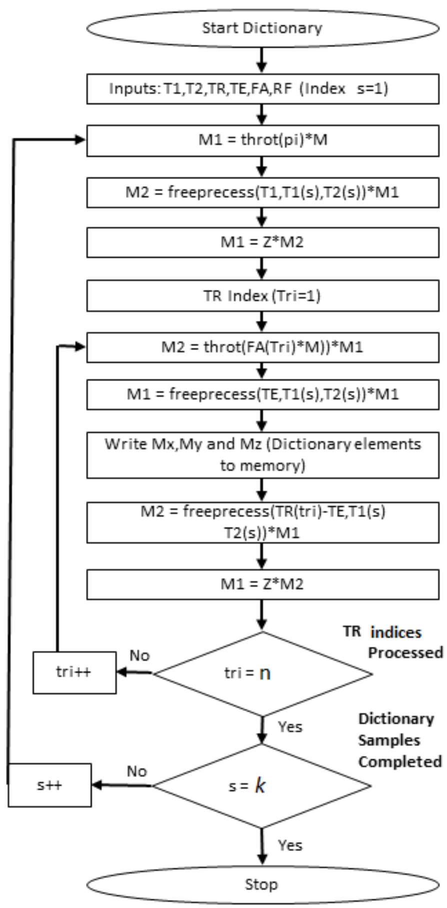
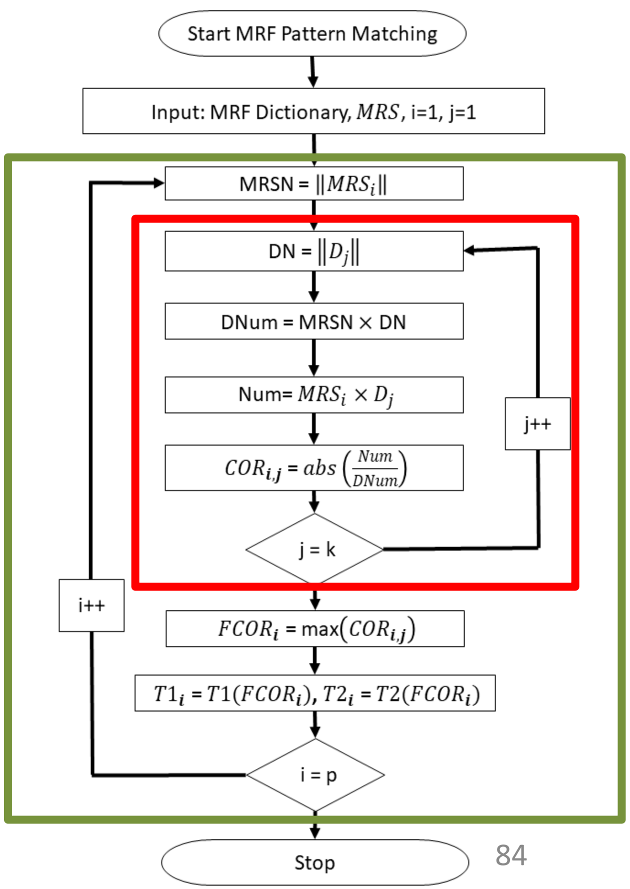
MRF Magnetic Resonance Fingerprinting (MRF) ON CPU

MRF Dictionary Algorithm



MRF Pattern Matching Algorithm



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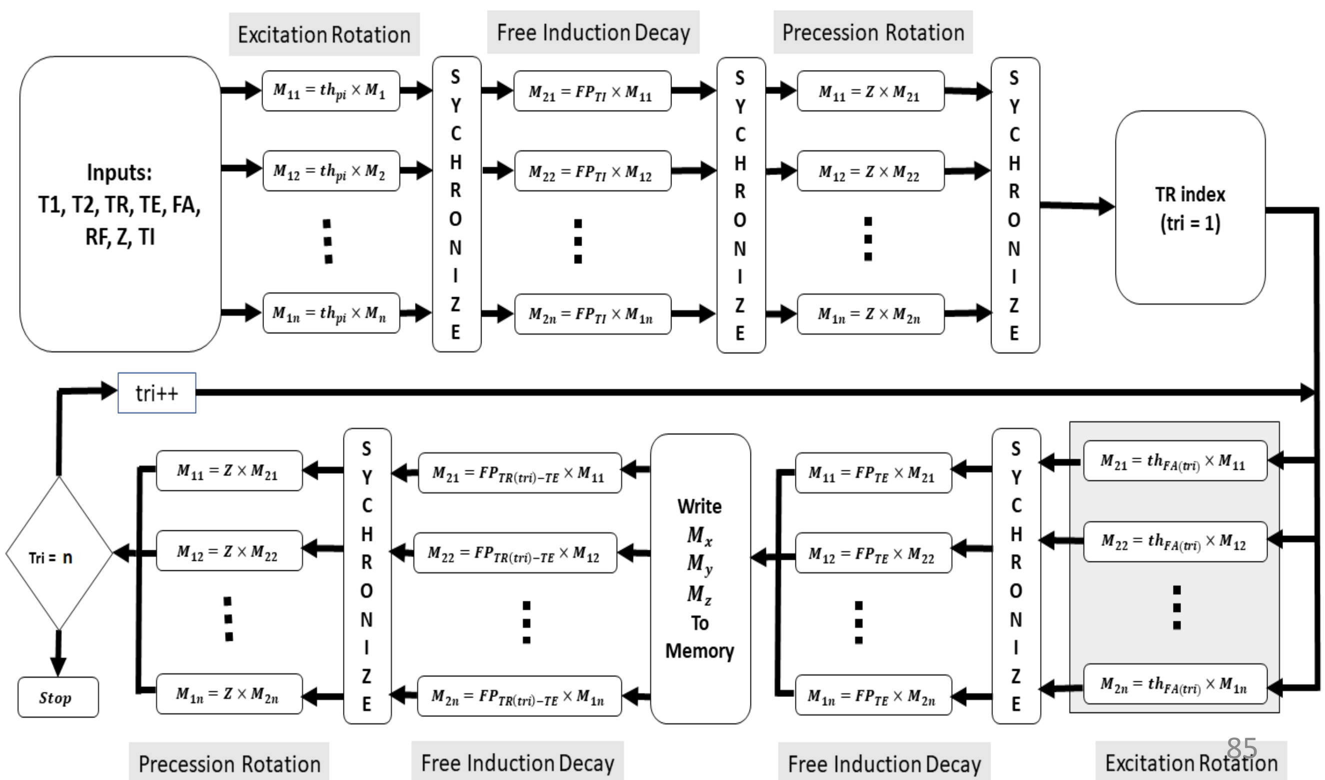
GPU based MRF Magnetic Resonance Fingerprinting (MRF) using CUDA

PROPOSED PARALLEL FRAME WORK FOR DICTIONARY ALGORITHM



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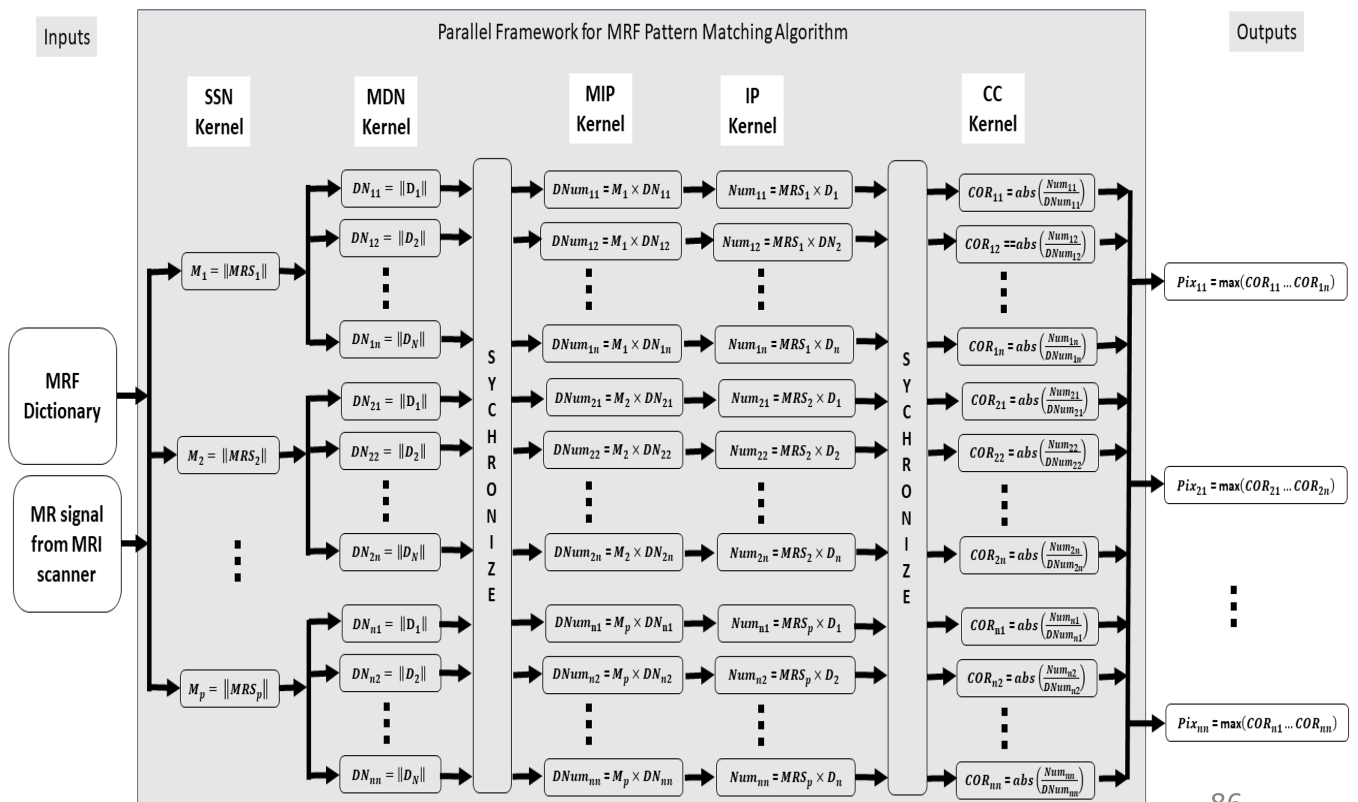
PROPOSED PARALLEL FRAME WORK FOR PATTERN MATCHING



Outline

GPU based MRF Magnetic Resonance Fingerprinting (MRF) using CUDA

RESULTS

- ***In-vivo***
  - Variable density spiral sampling Brain dataset from Case Western Reserve University, USA

Data	Coils	Scanner	Image size
Human head dataset	32	1.5T Espree, Siemen Healthcare Scanner	192x192

- **CPU**
  - Intel Core i7 – 4510U @ 2.16 GHz with 8Gb RAM
- **NIVIDIA GPUs**
  - Tesla k40C, GTX 780, GTX 560, GT 630m

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GPU based MRF Magnetic Resonance Fingerprinting (MRF) using CUDA

RESULTS

MRF Dictionary	NVIDIA GT 630m	NVIDIA GTX 560	NVIDIA GTX 780	NVIDIA Tesla k40c
Computational Time(seconds)	602.25	491.53	226	210

MRF Pattern Matching Algorithm	NVIDIA GT 630m	NVIDIA GTX 560	NVIDIA GTX 780	NVIDIA Tesla k40c
Computational Time(seconds)	715.115	164.656	54.186	50

MRF Algorithm	4th Gen Core-i7		NVIDIA Tesla k40C	Speed-up using parallel framework for MRF	
	MATLAB	C++	Data Processing time	w.r.t MATLAB	w.r.t C++
Computation Time	348 mins	90 mins	4.5 mins	69.6 x	18x

GPU based MRF Magnetic Resonance Fingerprinting (MRF) using CUDA

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Reference Images (Matlab)

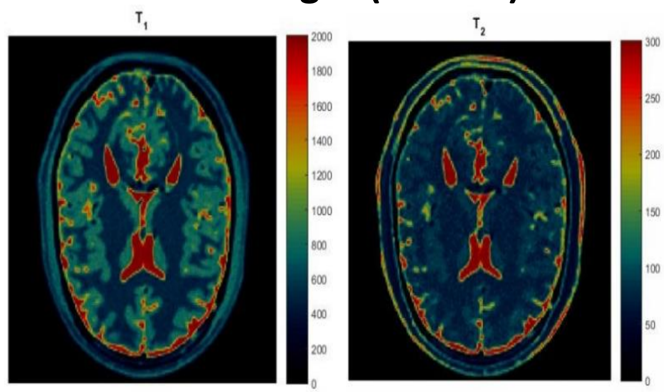


Figure 4. Intensity Maps constructed using the conventional MRF algorithms (MATLAB)

Reconstructed Images (CUDA)

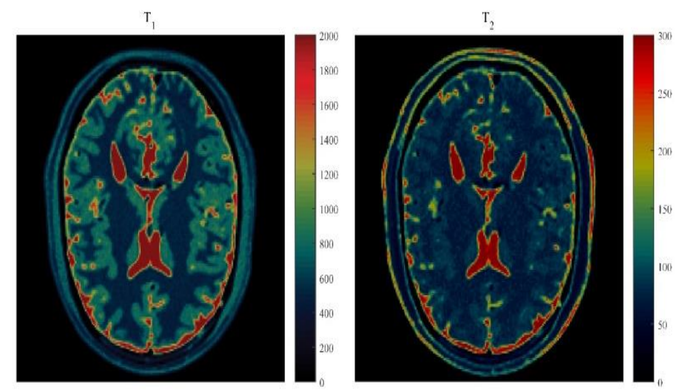


Figure 6. Intensity Maps constructed using our MRF Integrated CUDA Application

Reconstructed Images (C++)

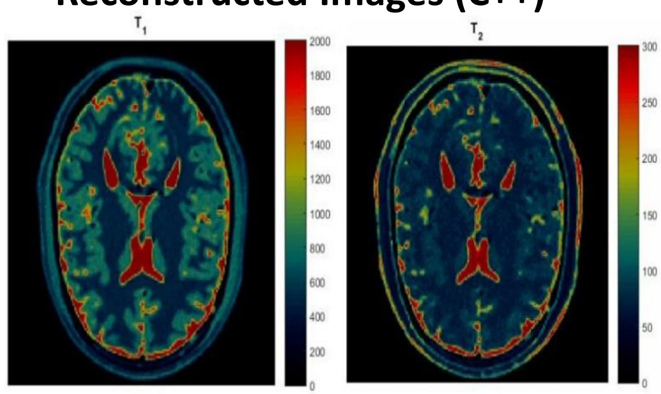


Figure 5. Intensity Maps constructed using our C++ implementation

Difference Images

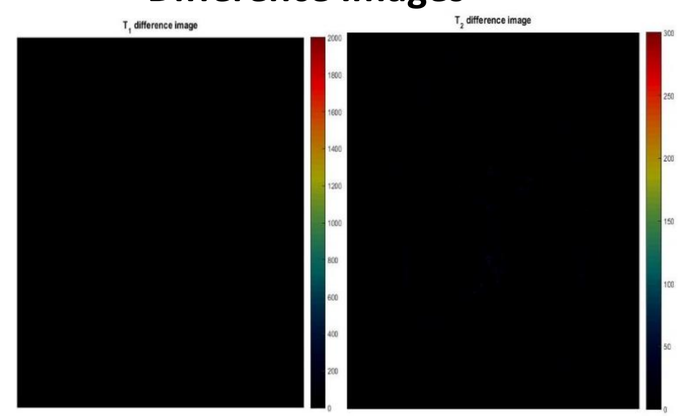


Figure 7. Difference between reference maps and maps reconstructed using CUDA application

Outline

GPU based MRF Magnetic Resonance Fingerprinting (MRF) using CUDA

CONCLUSION

- Accelerated image reconstruction without any compromise on the quality of image
- MRF algorithm is accelerated without any functional modifications or reducing data to be processed in the native MRF algorithm
- Proposed parallel framework has the potential to process MRF algorithm in clinical feasible Computation time

Acknowledgements

- Donated 6 state-of-art GPUs for MIPRG lab
- **Tesla K40c (1)**
  - 2880 cores
  - GDDR5 memory
  - 12 GB
  - Bus width 384 bit
- **GTX 780 ti (5)**
  - 2880 cores
  - GDDR5 memory
  - 4 GB
  - Bus width 384 bit

Publications

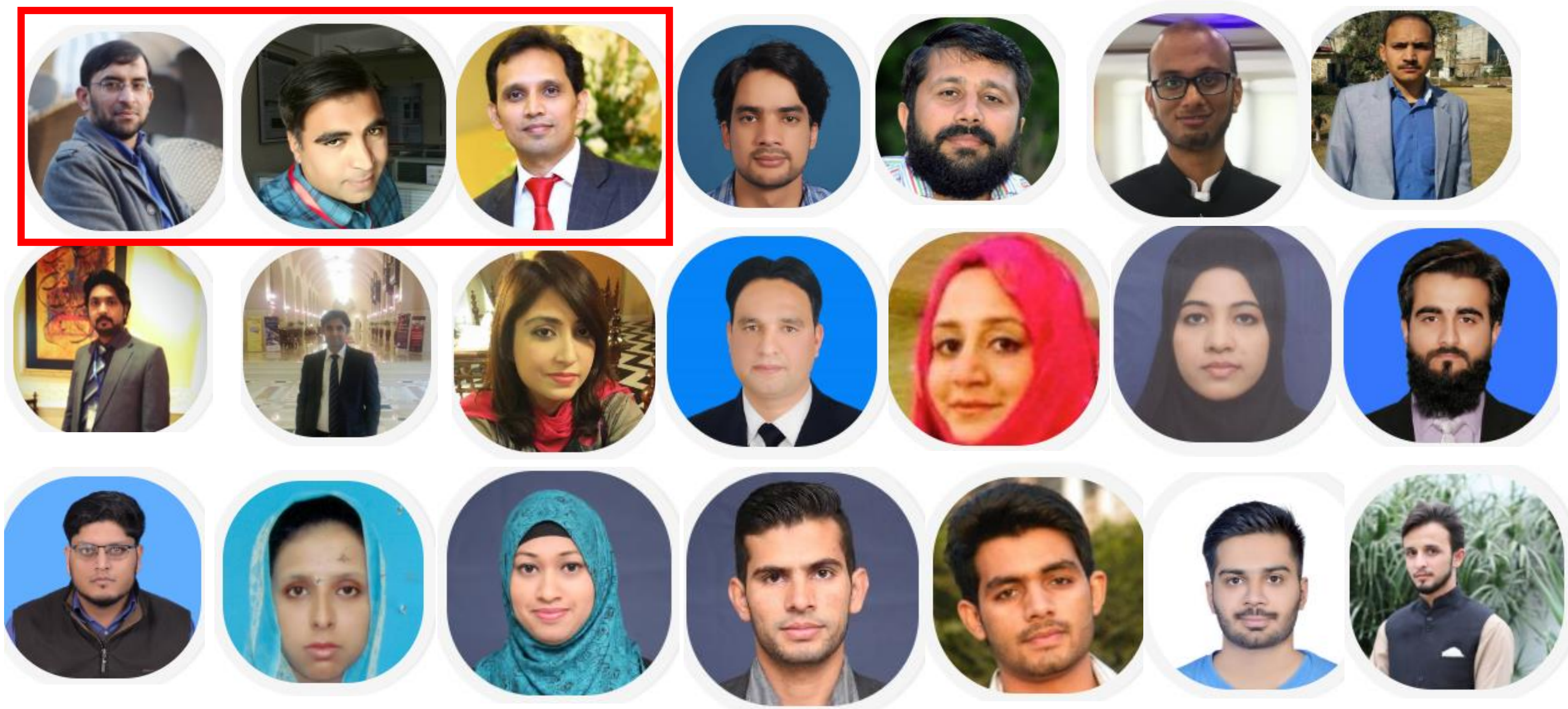
Journal Publications

1. Wavelet-based de-noising algorithm for images acquired with parallel magnetic resonance imaging (MRI) (Delakis, Ioannis, Hammad, Omer and Kitney, Richard I), In Physics in Medicine & Biology, IOP Publishing, volume 52, 2007.
2. A graphical generalized implementation of SENSE reconstruction using Matlab (Omer, Hammad and Dickinson, Robert), In Concepts in Magnetic Resonance Part A, Wiley Online Library, volume 36, 2010
3. Regularization in parallel MR image reconstruction (Omer, Hammad and Dickinson, Robert), In Concepts in Magnetic Resonance Part A, Wiley Online Library, volume 38, 2011
4. Phased array coil for implementing parallel MRI in intravascular imaging: A feasibility study (Omer, Hammad, Dickinson, Robert J and Awan, Shakil A), In Concepts in Magnetic Resonance Part A, Wiley Online Library, volume 43, 2014
5. modified POCS-based reconstruction method for compressively sampled MR imaging (Shah, Jawad, Qureshi, Ijaz, Omer, Hammad and Khaliq, Amir), In International Journal of Imaging Systems and Technology, Wiley Online Library, volume 24, 2014
6. Regularization-based SENSE reconstruction and choice of regularization parameter (Omer, Hammad, Qureshi, Mahmood and Dickinson, Robert J), In Concepts in Magnetic Resonance Part A, Wiley Online Library, volume 44, 2015
7. Compressively Sampled MRI Recovery Using Modified Iterative-Reweighted Least Square Method (Haider, Hassaan, Shah, Jawad Ali, Qureshi, Ijaz Mansoor, Omer, Hammad and Kadir, Kushsairy), In Applied Magnetic Resonance, Springer, volume 47, 2016
8. Sensitivity Maps Estimation Using Eigenvalues in Sense Reconstruction (Irfan, Amna Shafa, Nisar, Ayisha, Shahzad, Hassan and Omer, Hammad), In Applied Magnetic Resonance, Springer, volume 47, 2016
9. An Adaptive Algorithm for Compressively Sampled MR Image Reconstruction Using Projections onto lp-Ball (Kaleem, Muhammad, Qureshi, Mahmood and Omer, Hammad), In Applied Magnetic Resonance, Springer, volume 47, 2016
10. Compressively Sampled MR Image Reconstruction Using POCS with g-Factor as Regularization Parameter (Kaleem, Muhammad, Qureshi, Mahmood and Omer, Hammad), In Applied Magnetic Resonance, Springer, volume 47, 2016
11. Image reconstruction using compressed sensing for individual and collective coil methods (Qureshi, Mahmood, Junaid, Muhammad, Najam, Asadullah, Bashir, Daniyal, Ullah, Irfan, Kaleem, Muhammad and Omer, Hammad), In Biomedical Research, Allied Academies, 2016
12. A Matlab-Based Advance MR Image Reconstruction Package with Interactive Graphical User Interface (Shahid, Ali Raza, Ahmed, Zaki, Raza, Abbas, Tariq, Yasir, Abbasi, Muddassar and Omer, Hammad), In Applied Magnetic Resonance, Springer, volume 47, 2016.
13. Parallel MRI reconstruction algorithm implementation on GPU (Shahzad, H, Sadaqat, MF, Hassan, B, Abbasi, W and Omer, H), In Applied Magnetic Resonance, Springer, volume 47, 2016.
14. GPU-accelerated self-calibrating GRAPPA operator gridding for rapid reconstruction of non-cartesian MRI data (Inam, Omair, Qureshi, Mahmood, Malik, Shahzad A and Omer, Hammad), In Applied Magnetic Resonance, Springer, volume 48, 2017
15. Iterative Schemes to Solve Low-Dimensional Calibration Equations in Parallel MR Image Reconstruction with GRAPPA (Inam, Omair, Qureshi, Mahmood, Malik, Shahzad A and Omer, Hammad), In BioMed research international, Hindawi, volume 2017, 2017
16. Line Profile Measure as a Stopping Criterion in CG-SENSE Algorithm (Khan, Mahwish, Aslam, Taquwa, Shahzad, Hassan and Omer, Hammad), In Applied Magnetic Resonance, Springer, volume 48, 2017
17. Singular Value Decomposition Using Jacobi Algorithm in pMRI and CS (Qazi, Sohaib A, Saeed, Abeera, Nasir, Saima and Omer, Hammad), In Applied Magnetic Resonance, Springer, volume 48, 2017
18. Journey through k-space: an interactive educational tool (Qureshi, Mahmood, Kaleem, Muhammad and Omer, Hammad), In Biomedical Research, Biomedical Research, 2017
19. FPGA implementation of real-time SENSE reconstruction using pre-scan and Emaps sensitivities (Siddiqui, Muhammad Faisal, Reza, Ahmed Wasif, Shafique, Abubakr, Omer, Hammad and Kanesan, Jeevan), In Magnetic resonance imaging, Elsevier, volume 44, 2017
20. Accelerating MRI Using GROG Gridding Followed by ESPIRiT for Non-Cartesian Trajectories (Aslam, Ibtisam, Najeeb, Faisal and Omer, Hammad), In Applied Magnetic Resonance, Springer, volume 49, 2018
21. Compressively sampled MR image reconstruction using generalized thresholding iterative algorithm (Elahi, Sana, Omer, Hammad and others), In Journal of Magnetic Resonance, Elsevier, volume 286, 2018
22. Optimizing Image Reconstruction in SENSE Using GPU (Qazi, Sohaib A, Nasir, Saima, Saeed, Abeera and Omer, Hammad), In Applied Magnetic Resonance, Springer, volume 49, 2018
23. Accelerating Parallel Magnetic Resonance Imaging using p-thresholding based Compressed-Sensing (Ullah, Irfan, Inam, Omair, Aslam, Ibtisam and Omer, Hammad), In Applied Magnetic Resonance, Springer, 2018
24. QR-decomposition based SENSE reconstruction using parallel architecture (Ullah, Irfan, Nisar, Habab, Raza, Haseeb, Qasim, Malik, Inam, Omair and Omer, Hammad), In Computers in biology and medicine, Elsevier, volume 95, 2018

Conference Publications

74 international conference papers (Full Details on : www.miprg.com)

MIPRG Team



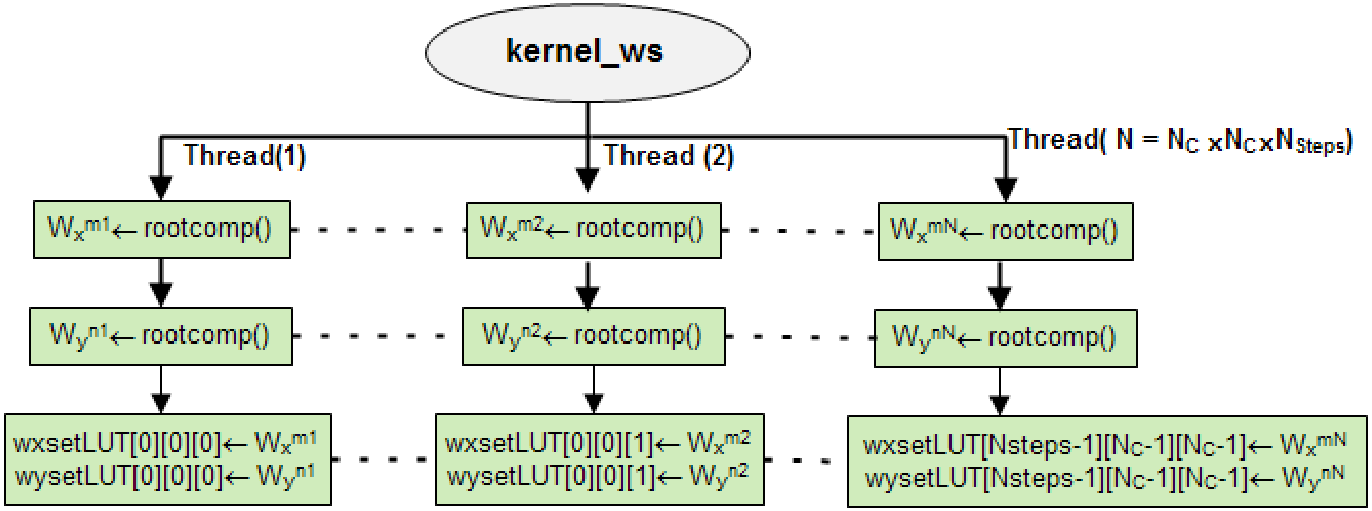
Questions?

Outline

GPU based SC-GROG using CUDA

OPTIMIZED CUDA KERNELS

- 2D weight sets for each shift are calculated in parallel
- LUTs (wxsetLUT and ywsetLUT) are updated in parallel to store all the 2D gridding weight sets



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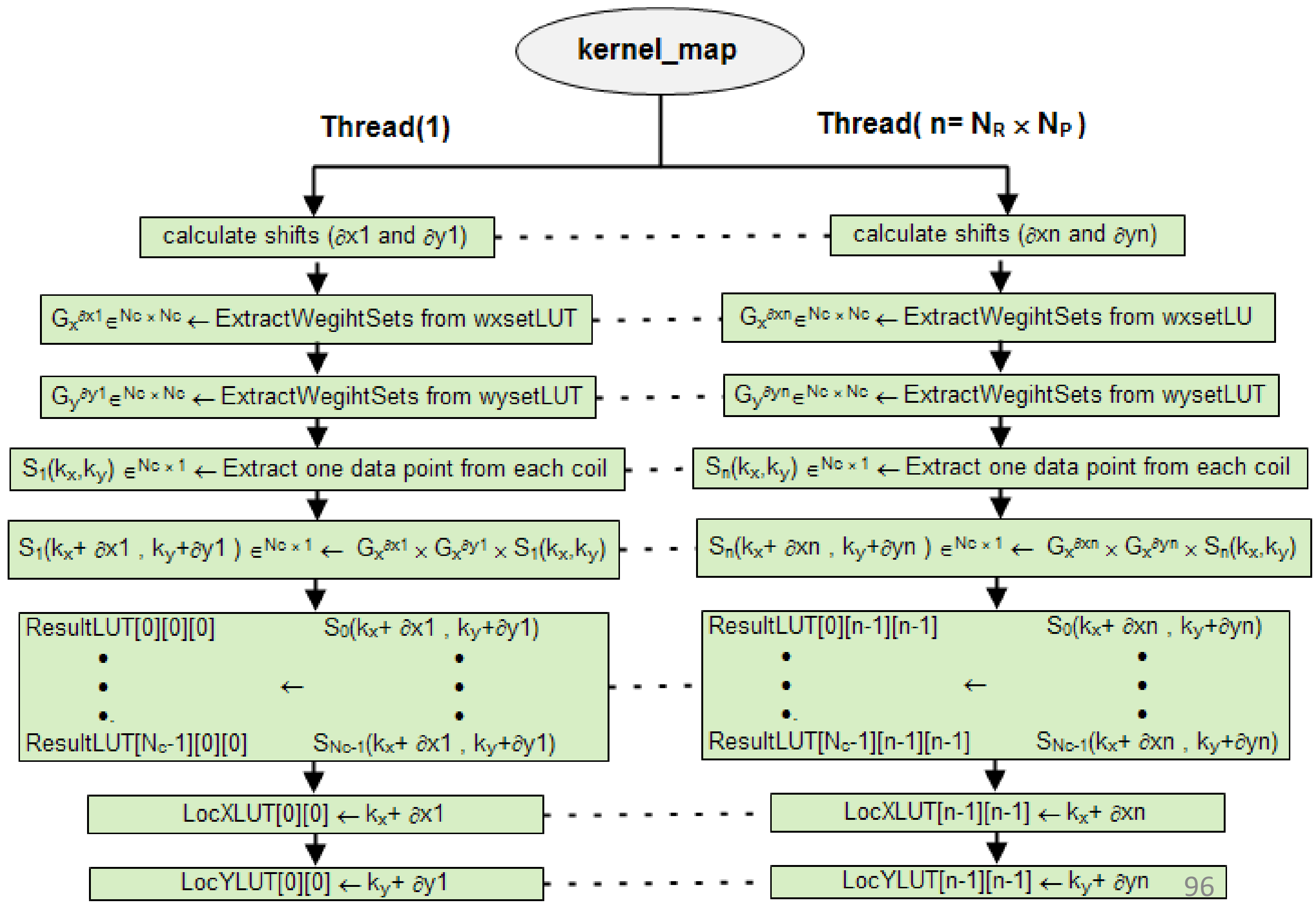
GPU based SC-GROG using CUDA

OPTIMIZED CUDA KERNELS



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