A heterogeneous image reconstruction system for clinical Magnetic Resonance

Grzegorz Tomasz Kowalik¹, Jennifer Anne Steeden¹, Bejal Pandya¹, David Atkinson², Andrew Taylor¹, and Vivek Muthurangu¹

¹Institute of Cardiovascular Science, UCL Centre for Cardiovascular Imaging, London, United Kingdom, ²Centre for Medical Imaging, UCL Division of Medicine, London, United Kingdom



MRI – general overview

- Imaging by exploiting tissue magnetic properties
- Non-ionising procedure
- Good contrast between soft tissues
- Applications
 - Brain imaging
 - Cancer diagnosis
 - Fat quantification
 - Cardiac imaging
 - and many more



Imaging process



Undersampling





 \mathbf{S}



Cartesian SENSE



 $p = CSM^{-1}S$

Arbitrary trajectory



SENSE for arbitrary trajectories



Cardiac MR – flow quantification

- Cardiac imaging requires fast acquisition
- Requires 2 sets of *k*-space data
- Real-time spiral PCMR sequence
 - High spatiotemporal resolution (~44ms/Flow-frame)
 - Slow image reconstruction



Project goals

- Challenges
 - Use of advanced MRI sequences is limited by their reconstruction time
 - GPU implementations exist but run in offline mode
- Proposed solution
 - GPU based image reconstructor integrated into scanner's system
- Benefits
 - Seamless reconstruction process
 - Translation of advanced MRI algorithms into clinical environment



Continuous cardiac output assessment

- Complete overview of cardiovascular system
- Theoretically possible but practically not feasible
 ~10min of acquisition → ~1.5h of reconstruction
- Reconstruction has to be faster than acquisition
- We need a super-computer under a desk



Implementation

- Sensitivity Encoding for arbitrary trajectories
 - Algorithm's description
 - Reconstruction bottleneck
 - Our GPU implementation
- Networking scheme
 - Remote execution
 - Data transfer management



SENSE - mathematical formulation

• Imaging process is based on a set of linear equations

$$E\rho = s$$
$$\rho = (E^H E)^{-1} E^H s$$

- *E*, *E*^{*H*} evaluate into
 - Gridding
 - FFT
 - Matrix combinations with *coil sensitivity maps*



Reconstruction bottleneck - Gridding



- Convolution onto Cartesian grid $\hat{f}(\omega) \ast \hat{g}(\omega) \Leftrightarrow f(x) \cdot g(x)$
- No data dependency
- CPU implementation
 - Task is split across multiple threads
 - Gridding kernel values are stored in shared array
 - Up to 89% of reconstruction time



Gridding – GPU implementation



- Input-driven assignment
 - Optimal number of memory reads
 - Non-coalesced memory writes
 - Accumulative global memory writes

Coarse-grained

 Shared memory as software managed cache

Output-driven assignment

- Requires pre-sorting of input data
- Optimal number of memory writes requires sub-optimal number of memory reads
- Optimal number of memory reads requires padding
- Shared memory as software managed cache

A. Gregerson, *Memory* (2007) (available at http://www.nvidia.com/docs/IO/47905/ECE757_Project_Report_Gregerson.pdf).

Gridding – GPU implementation



- Convolution as matrix multiplication $S_{N_s,N_c} = G_{N_s,N_i}\rho_{N_i,N_c}$ $\rho_{N_i,N_c} = G^H_{N_s,N_i}S_{N_s,N_c}$
- Heavily sparse matrix
 - $N_i = 128 \times 128 N_s = 2205 \times 3$ Kernel size = 8x8
 - − Full-size \rightarrow 108380160
 - − Non-zero values → 423360

Less than 0.4%

Compressed Sparse Row (CSR) Format

GPU implementation

- CUDA 4.0 toolkit
 - cublas library linear algebra
 - cusparse library sparse matrix operations
 - cufft library fast Fourier Transformations
- The algorithm was fully implemented on GPU
 - Synchronisation is needed only to check iteration process convergence



Networking (1)



Networking (2)



Methods (1)

- Native reconstruction system
 - 8 Intel Xeon E5440 2.83 GHz (4 cores)
 - 16 GB RAM
 - C++ based, multi-threaded programing environment
- Network connection
 - Half-duplex, 1Gbps, ethernet connection
- External computer
 - Intel i7 920, 2.66 GHz (4 cores)
 - 9GB RAM
 - GTX 480 1.5GB, 480 CUDA cores



Methods (2)

- Validation study
 - 60 frames (retrospective reconstruction)
- Continuous flow measurement
 - 20 healthy volunteers
 - Aortic flow quantification during an exercise
 - 13980 frames (online)
 - ~10 minutes acquisition
 - ~6GB of raw data



Results - CPU vs GPU implementation

- Validation: -0.4 ± 0.8ml
- Timing

		CPU [ms]	GPU [ms]	CPU / GPU
Per iteration	FFT	287.67	73.95	4
	Gridding	2674.75	58.48	46
	Matrix combination	245.69	4.24	58
	Preconditioning	52.95	1.00	53
	Total	3288.32	144.83	23
Per 60 frames (test data set)	Total	24115.24	1581.67	15

Tab. 1. Comparison of execution times of the PCMR reconstruction implementations



Results - system workload

System workload



Fig. 1. Alternating colours represent two different processing buffers.

		CPU [ms]	GPU [ms]	CPU / GPU
Per 13980 frames	Total	5618.85*	629.24	9
(buffered recon.)	From acquisition end	4998.61*	9.00	556

Tab. 2. Timing for the exercise study.

* CPU times for the entire dataset of 13980 frames were estimated from the CPU reconstruction time required for a subset of 60 frames.

Results - continuous cardiac output



Fig. 2. An example of flow data acquired during continuous real-time PCMR during exercise. Botton graphs show 20s section of the total data taken at rest, mid exercise and recovery.

Results - continuous cardiac output



Fig. 3. Averaged exercise data based on continuous flow measurements from the population of 20 volunteers.



Conclusion

- Online reconstruction of real-time MR data is feasible using integrated GPU reconstructor
- Advanced MRI techniques become feasible within clinical environment
- Data available within seconds to clinicians
- Full integration provides seamless reconstruction

We believe, integrated GPU reconstruction has the potential to revolutionize the type of MRI sequences are performed on patients and could improve patient diagnosis and management

Thank you

Any questions ?

Great Ormond Street NHS Hospital for Children





â I