



Anno 2012
Protocollo: RBFR12JF2Z_002



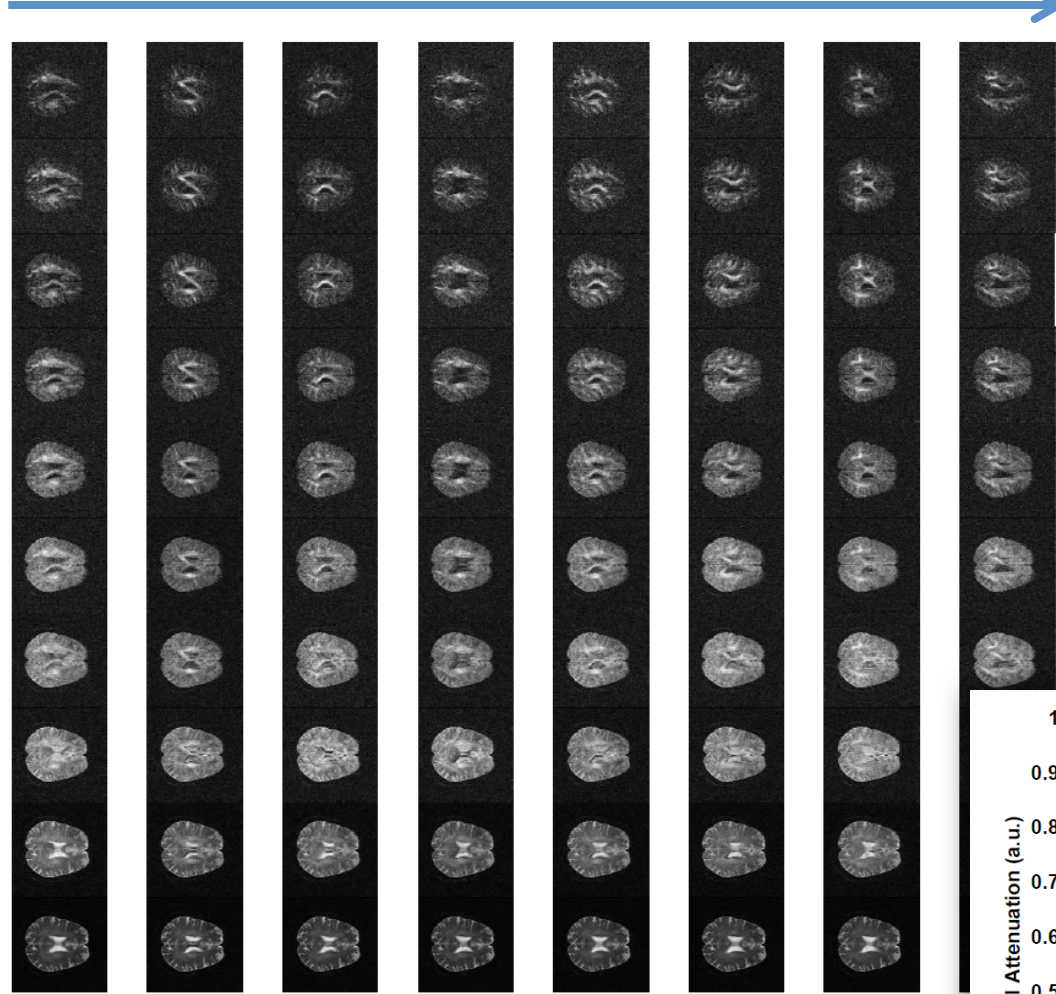
Unità A2: Imaging NMR, Roma

Accelerazione della ricostruzione di immagini
NMR ottenute con il metodo del contrasto in
diffusione

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direction



Typical NMR
imaging
post-processing

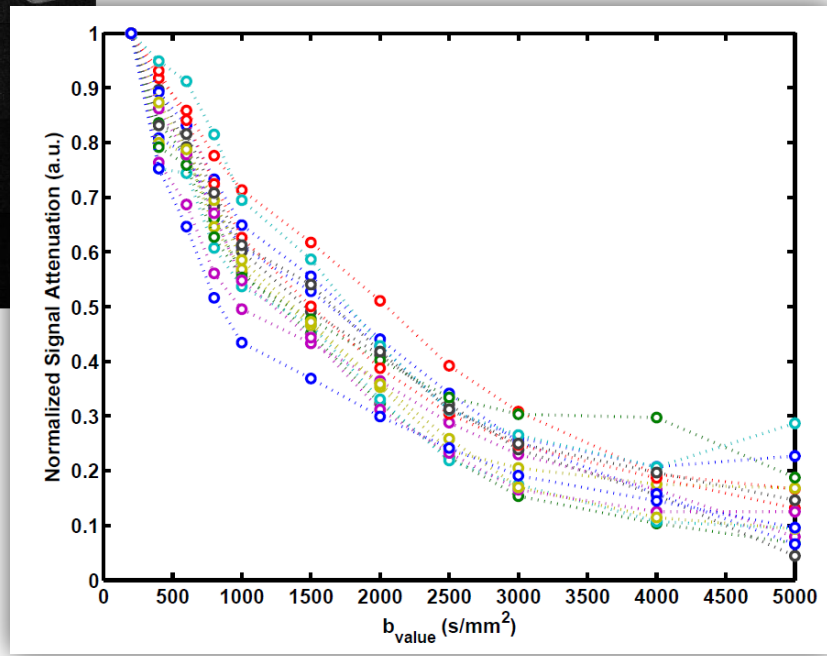
128x128 pixel image

x

number of slice (~10-40)

x

number of diffusion gradient directions (≥ 15)



Cumulant expansion approach: kurtosis tensor measurement

$$S(b) \propto e^{-D_{app} b + \frac{1}{6} K_{app} [D_{app} b]^2 + \dots}$$



$$S(b) = S(0) \exp \left[-b \sum_{i,j} n_i n_j D_{ij} + \frac{1}{6} b^2 \left(\frac{1}{3} \sum_i D_{ii} \right)^2 \sum_{i,j,k,l} n_i n_j n_k n_l W_{ijkl} + O(b^3) \right]$$

$N \geq 15$ independent measures to get W_{ijkl}

$$K(\mathbf{n}) = \frac{\bar{D}^2}{[D(\mathbf{n})]^2} \sum_{i,j,k,l=1}^3 n_i n_j n_k n_l W_{ijkl}.$$



$$MK = \frac{1}{N} \sum_{i=1}^N K(\mathbf{n}_i)$$

$$\begin{aligned}\bar{K} = & F_1(\lambda_1, \lambda_2, \lambda_3)\tilde{W}_{1111} + F_1(\lambda_2, \lambda_1, \lambda_3)\tilde{W}_{2222} \\ & + F_1(\lambda_3, \lambda_2, \lambda_1)\tilde{W}_{3333} + F_2(\lambda_1, \lambda_2, \lambda_3)\tilde{W}_{2233} \\ & + F_2(\lambda_2, \lambda_1, \lambda_3)\tilde{W}_{1133} + F_2(\lambda_3, \lambda_2, \lambda_1)\tilde{W}_{1122},\end{aligned}$$

$$K_{\parallel} = \frac{(\lambda_1 + \lambda_2 + \lambda_3)^2}{9\lambda_1^2} \tilde{W}_{1111},$$

$$\begin{aligned}K_{\perp} = & G_1(\lambda_1, \lambda_2, \lambda_3)\tilde{W}_{2222} + G_1(\lambda_1, \lambda_3, \lambda_2)\tilde{W}_{3333} \\ & + G_2(\lambda_1, \lambda_2, \lambda_3)\tilde{W}_{2233},\end{aligned}$$

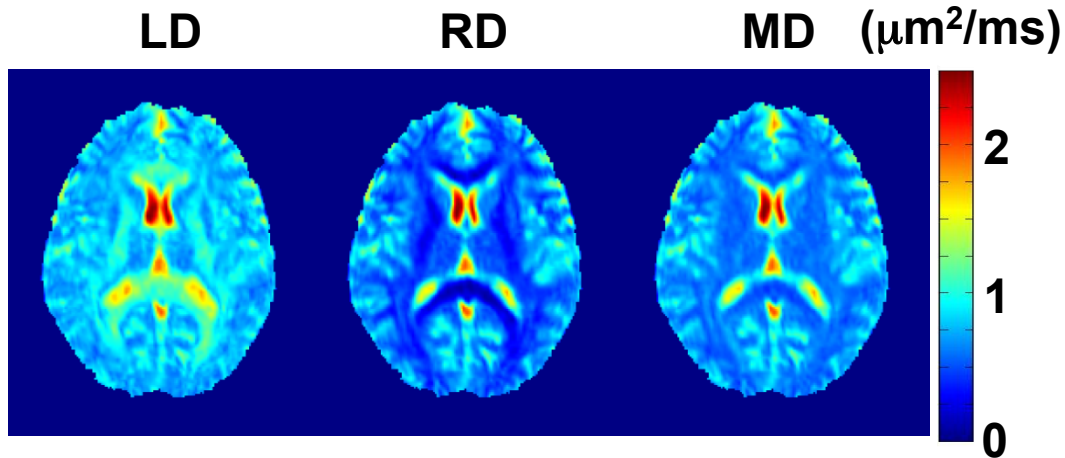
$$G_1(\lambda_1, \lambda_2, \lambda_3) = \frac{(\lambda_1 + \lambda_2 + \lambda_3)^2}{18\lambda_2(\lambda_2 - \lambda_3)^2} \left(2\lambda_2 + \frac{\lambda_3^2 - 3\lambda_2\lambda_3}{\sqrt{\lambda_2\lambda_3}} \right),$$

$$G_2(\lambda_1, \lambda_2, \lambda_3) = \frac{(\lambda_1 + \lambda_2 + \lambda_3)^2}{3(\lambda_2 - \lambda_3)^2} \left(\frac{\lambda_2 + \lambda_3}{\sqrt{\lambda_2\lambda_3}} - 2 \right).$$

$$F_1(\lambda_1, \lambda_2, \lambda_3) \equiv \frac{(\lambda_1 + \lambda_2 + \lambda_3)^2}{18(\lambda_1 - \lambda_2)(\lambda_1 - \lambda_3)} \left[\frac{\sqrt{\lambda_2\lambda_3}}{\lambda_1} R_F\left(\frac{\lambda_1}{\lambda_2}, \frac{\lambda_1}{\lambda_3}, 1\right) + \frac{3\lambda_1^2 - \lambda_1\lambda_2 - \lambda_2\lambda_3 - \lambda_1\lambda_3}{3\lambda_1\sqrt{\lambda_2\lambda_3}} R_D\left(\frac{\lambda_1}{\lambda_2}, \frac{\lambda_1}{\lambda_3}, 1\right) - 1 \right],$$

and

$$F_2(\lambda_1, \lambda_2, \lambda_3) \equiv \frac{(\lambda_1 + \lambda_2 + \lambda_3)^2}{3(\lambda_2 - \lambda_3)^2} \left[\frac{\lambda_2 + \lambda_3}{\sqrt{\lambda_2\lambda_3}} R_F\left(\frac{\lambda_1}{\lambda_2}, \frac{\lambda_1}{\lambda_3}, 1\right) + \frac{2\lambda_1 - \lambda_2 - \lambda_3}{3\sqrt{\lambda_2\lambda_3}} R_D\left(\frac{\lambda_1}{\lambda_2}, \frac{\lambda_1}{\lambda_3}, 1\right) - 2 \right].$$



Conventional DTI

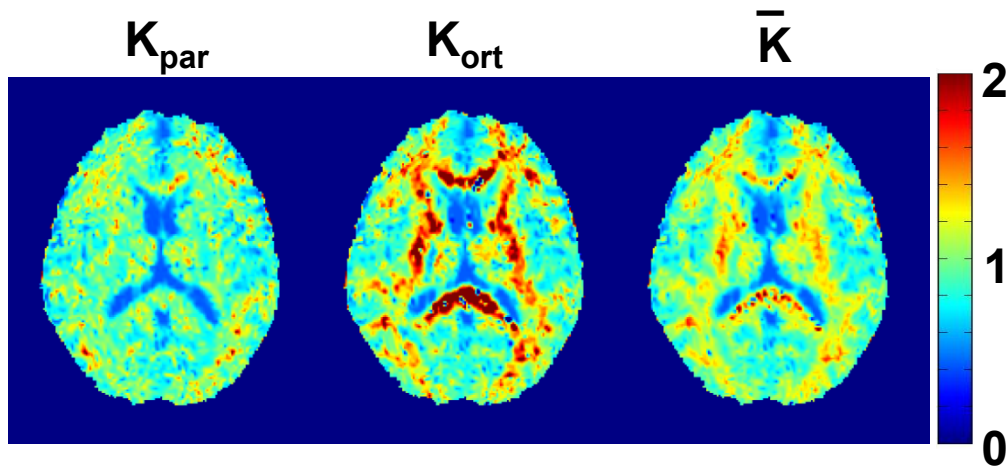
$128 \times 128 \times 32 \times 15$

=

$7.864320 \cdot 10^6$

linear systems to solve

~ **15 s** on CPU*



Kurtosis tensor imaging

$128 \times 128 \times 32 \times 15$

=

$7.864320 \cdot 10^6$

non-linear fit to perform

~ **7200 s** on CPU*

* 8 threads on an Intel Xeon E5-2609 CPU at 2.4 GHz

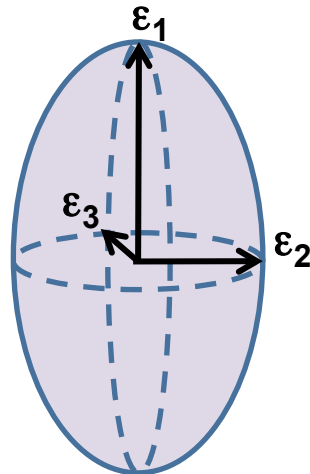
Stretched exponential model

$$S(b) = S(0)e^{-A_1 (b_1^*)^{\gamma_1} - A_2 (b_2^*)^{\gamma_2} - A_3 (b_3^*)^{\gamma_3}}$$

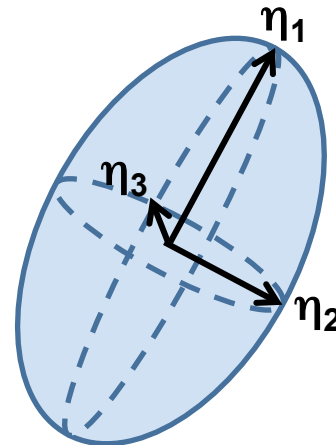
$$b_i^* = \vec{b} \cdot \vec{\eta}_i$$

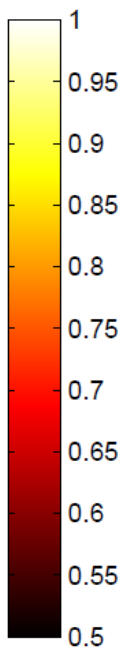
**Anomalous diffusion
reference frame**

**DTI
reference frame**



**Anomalous Diffusion
reference frame**

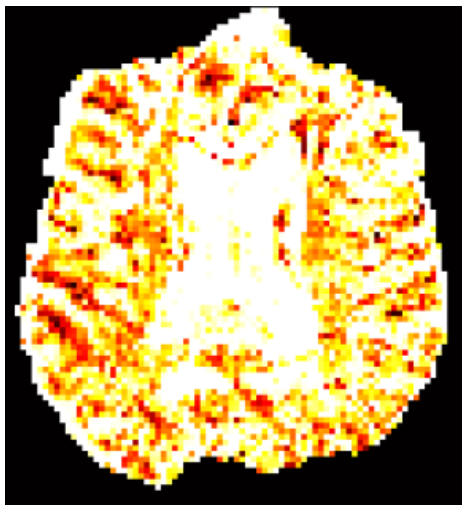




M_γ



γ_{par}



γ_{ort}



Conventional DTI

$128 \times 128 \times 32 \times 15$

=

$7.864320 \cdot 10^6$

linear systems to solve

~ 15 s on CPU*

Stretched exponential imaging

$128 \times 128 \times 32 \times 15$

=

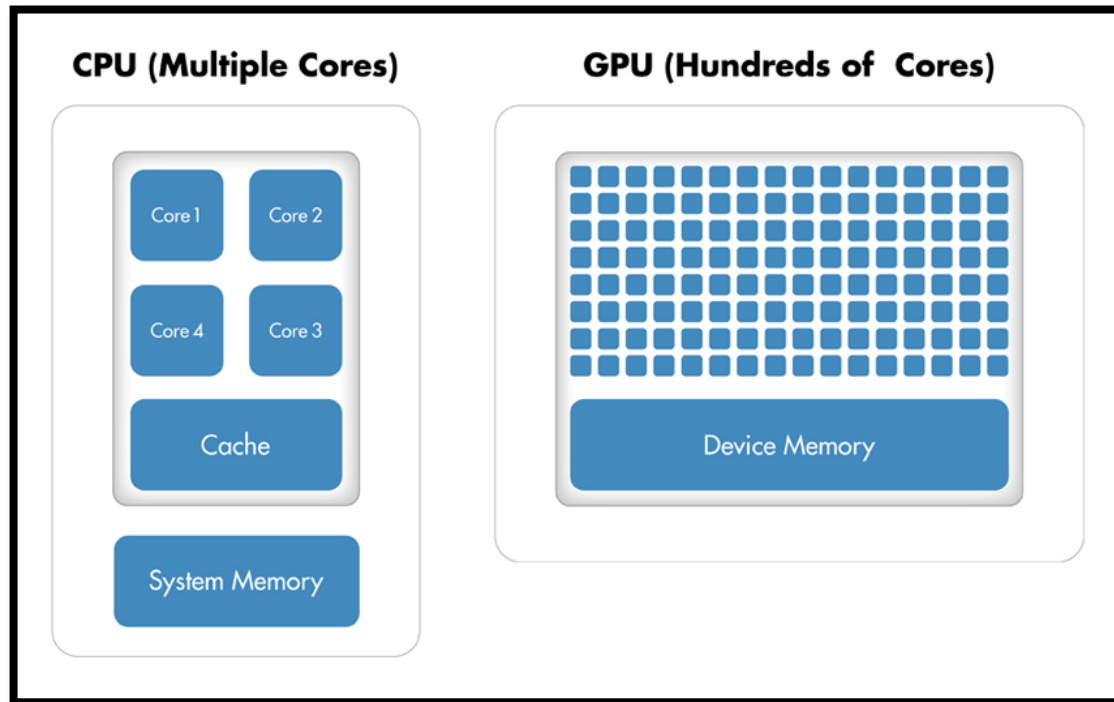
$7.864320 \cdot 10^6$

non-linear fit to perform

~ 6600 s on CPU*

* 8 threads on an Intel Xeon E5-2609 CPU at 2.4 GHz

When GPU can accelerate an application



- **Computationally intensive** — The time spent on computation significantly exceeds the time spent on transferring data to and from GPU memory.
- **Massively parallel** — The computations can be broken down into hundreds or thousands of independent units of work.

Computationally intensive

Kurtosis tensor imaging

non-linear fit

~7 ms per pixel

vs

~ 10-80 ns to read data
from memory

Stretched exponential imaging

non-linear fit

~6 ms per pixel

vs

~10-80 ns to read data from
memory

Massively parallel

Kurtosis tensor imaging

~ 10^6 - 10^7 independent non-
linear fit

Stretched exponential imaging

10^6 - 10^7 independent non-
linear fit

- Non-conventional NMR image processing algorithms code optimization;

Algorithms porting on GPU

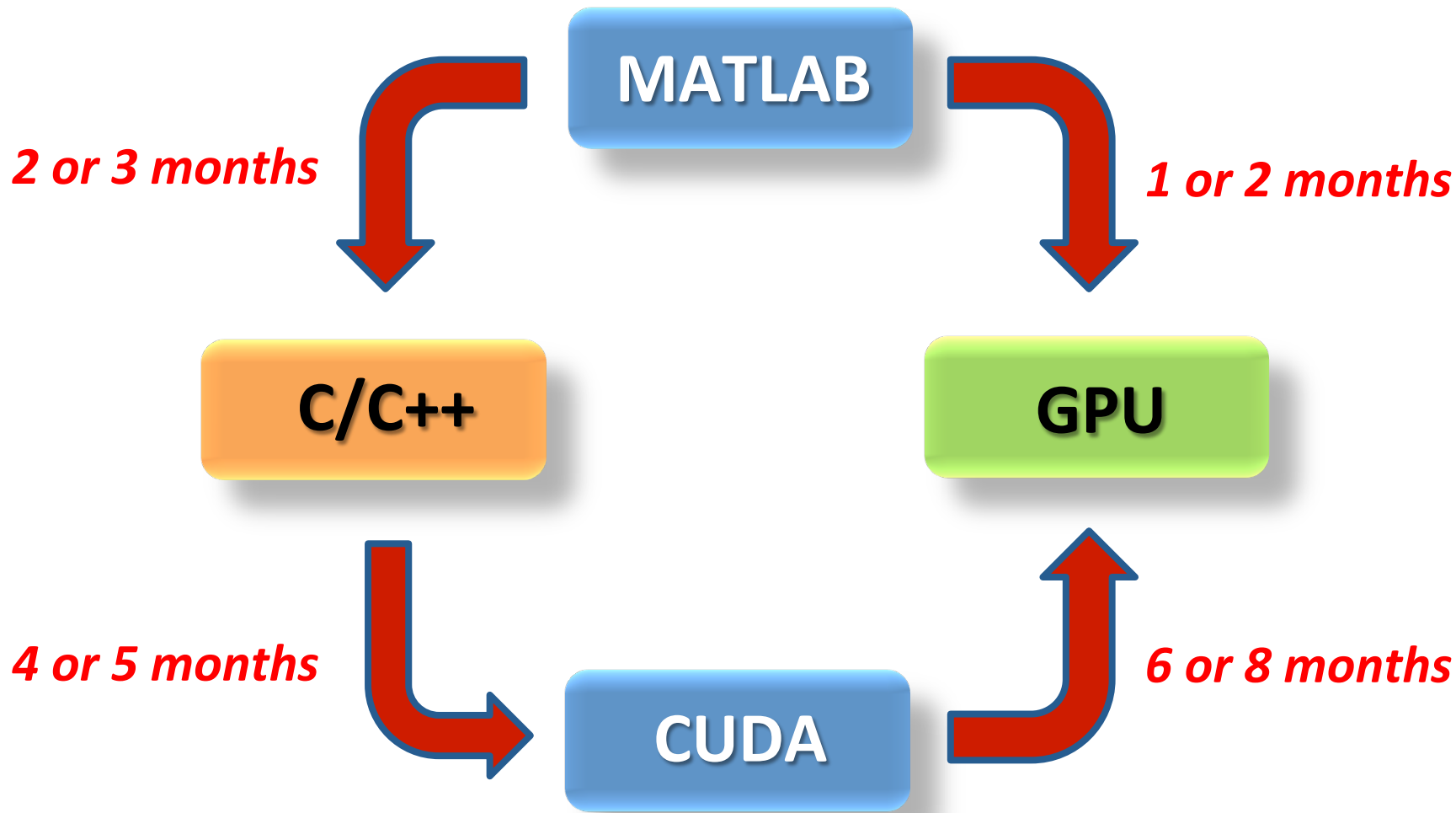
MATLAB



CUDA

- Easier and faster (all our codes are written for Matlab)
- Bypass the study of the specific hardware architecture
- Only a single GPU can be used

- Slower (all our codes are written for Matlab)
- Require the study of the specific hardware architecture
- Multiple GPUs can be used



Completed Steps to achieve our goals

(0) Configuring gap01 server for NMR imaging applications:

1. New license for MATLAB R2013b server usage by multiple accounts (2 simultaneous users) bought;
2. Matlab Parallel Toolbox; Matlab Image Processing Toolbox and Matlab Optimization Toolbox bought;

(00) Recruitment and training of new people to involve in the Project

1. One new PhD Student and one new Graduating Student recruited and under training for DW-NMR image processing and related numerical simulations

(i) Fast-implementation: using of available Matlab custom script.

1. Optimization of available Matlab custom script for DKI and SEM analysis for usage on GPU by means of the Matlab Parallel Toolbox: feasibility study by means of numerical simulations.

(ii) Implementation of numerical simulations supporting experimental data analysis: Monte Carlo and Finite Elements Method (FEM) on GPU

1. Implementation of a parallelized version of available Monte Carlo and FEM algorithms to numerically simulate DW-MRI signal attenuation in complex restricting/hindering geometries for usage on GPU by means of the Matlab Parallel Toolbox;

NMR simulation of diffusion weighted NMR images reconstruction

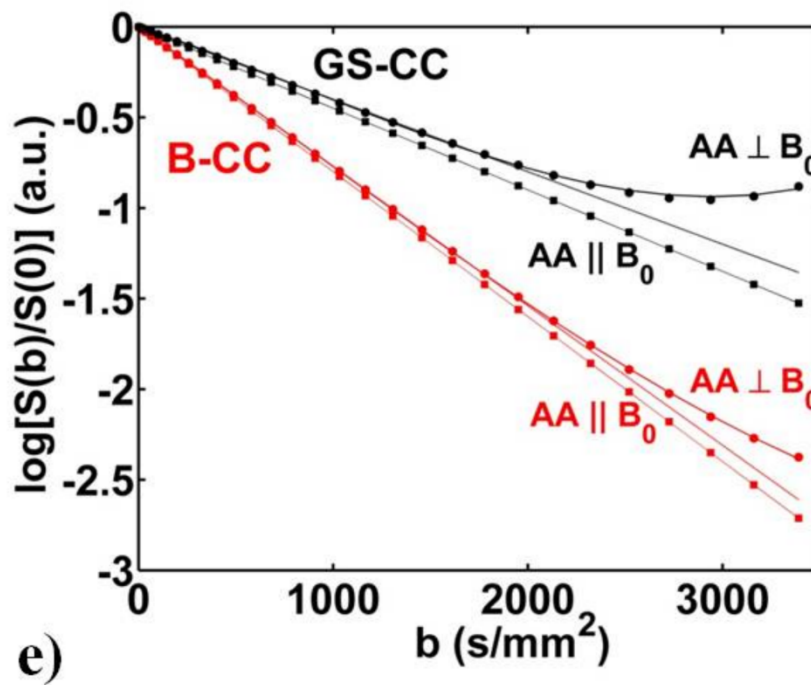
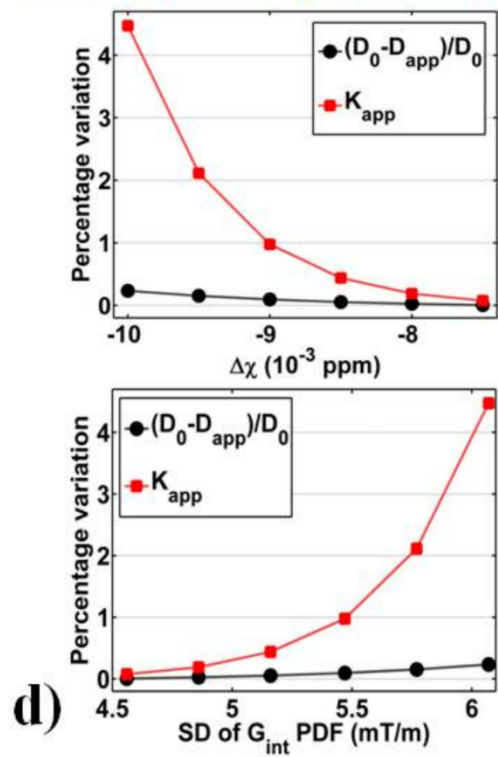
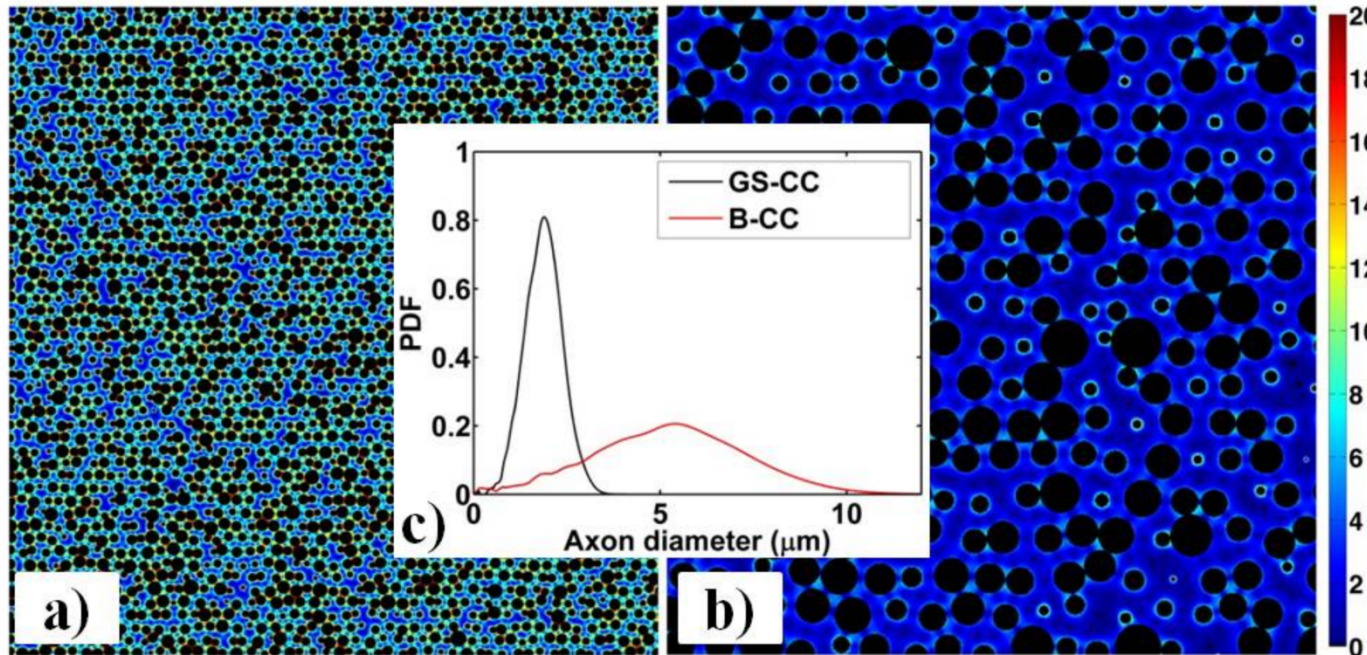
Simulated system: **500 μm^2** in plane resolution images of different human brain White Matter regions (Genu, Splenium and Body of Corpus Callosum), comprised of about **2x10³ axons**;

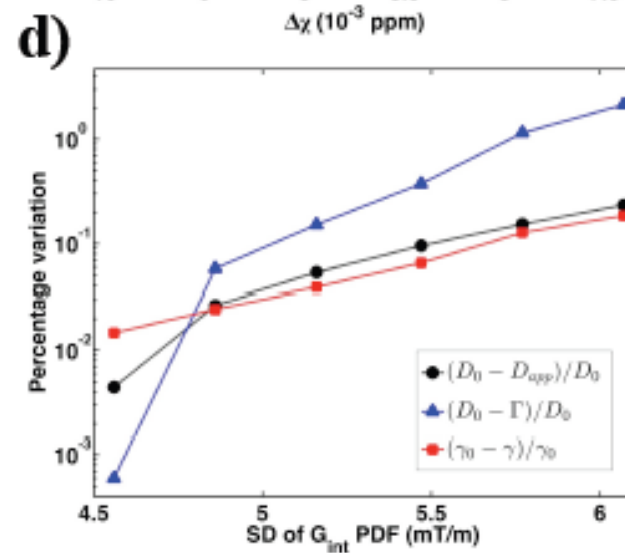
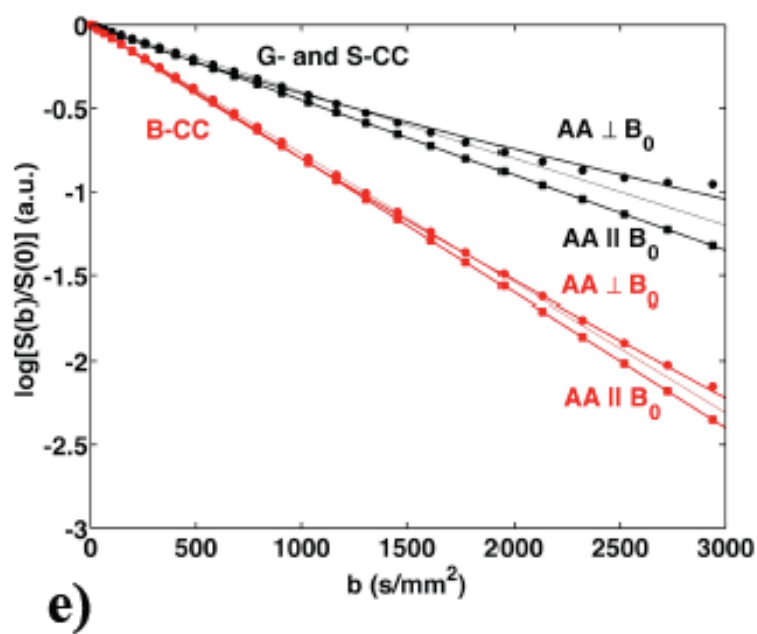
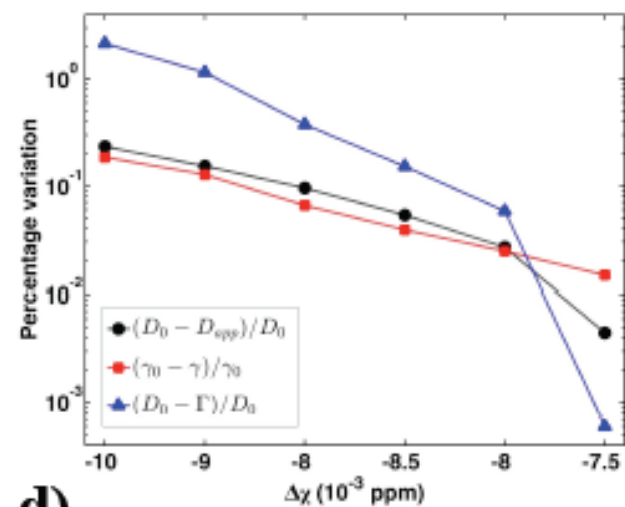
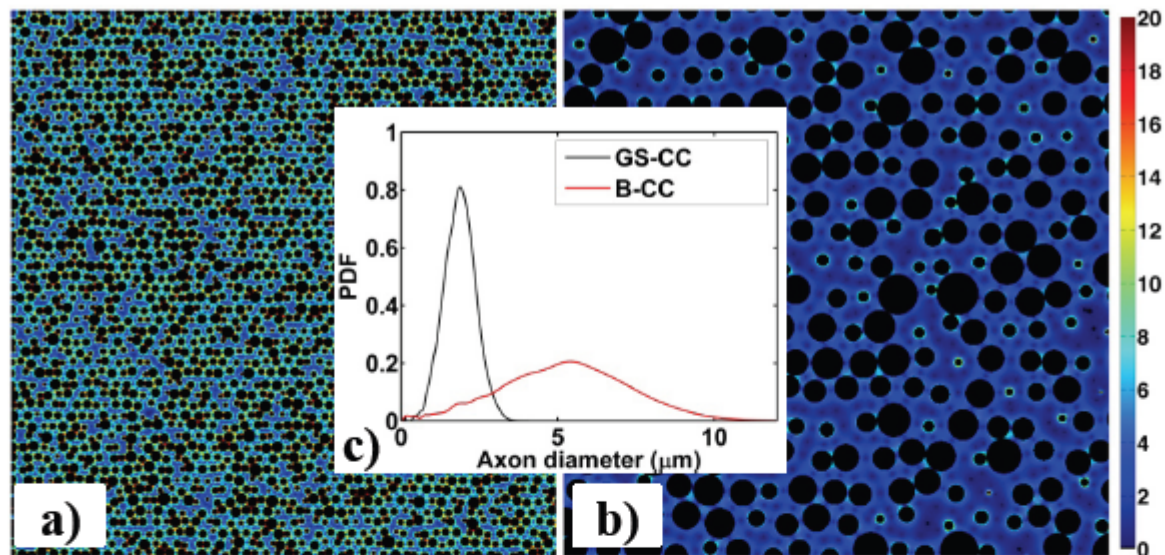
Matrix dimension: from **32x32** to **2048x2048**;

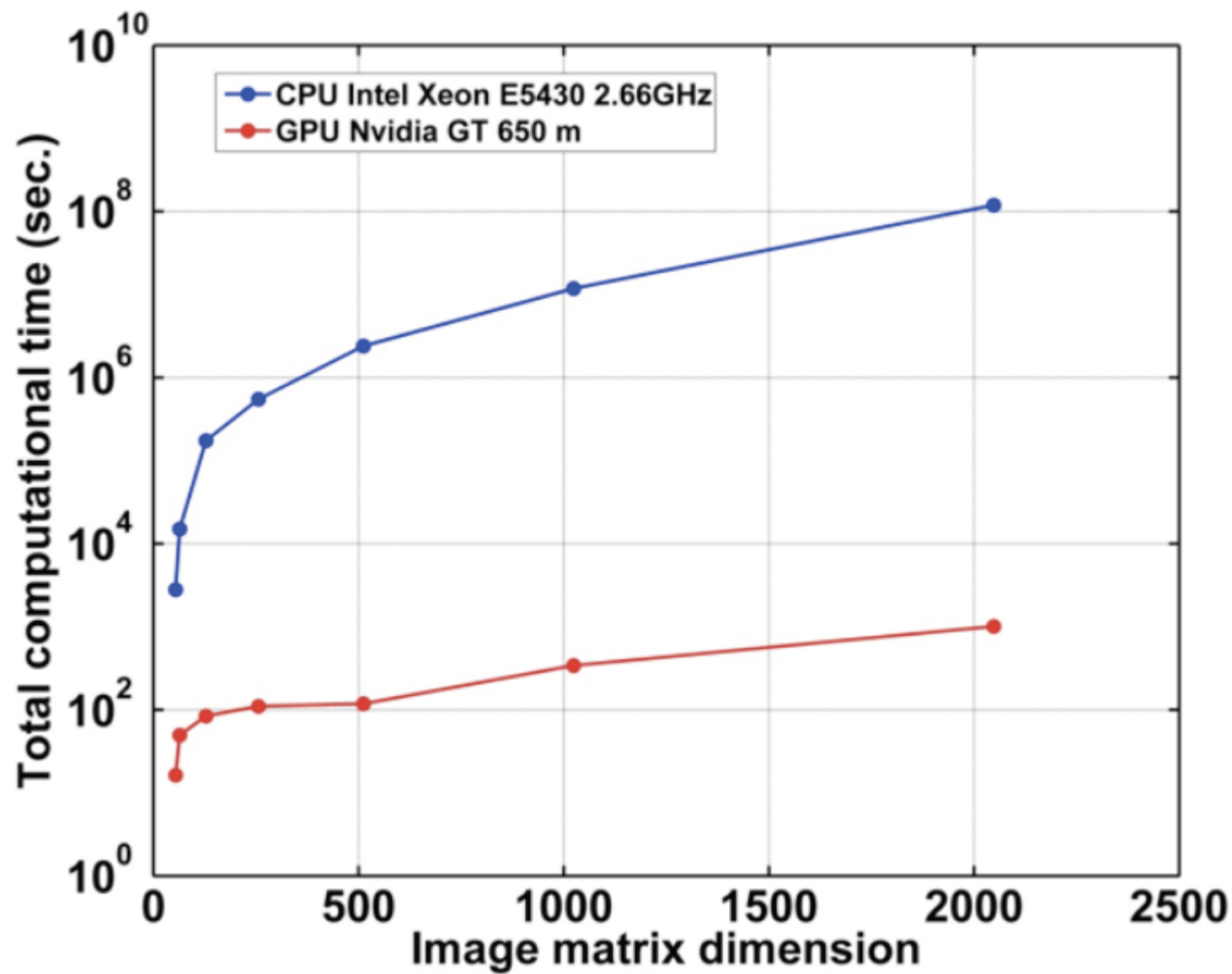
30 values of b: from **0** to **5000 s/mm²**;

Bloch-Torrey equation:

$$\frac{\partial M_{xy}(\vec{r}, t)}{\partial t} = -i\gamma(\vec{r} \cdot \vec{G})M_{xy}(\vec{r}, t) + D\nabla^2 M_{xy}(\vec{r}, t)$$





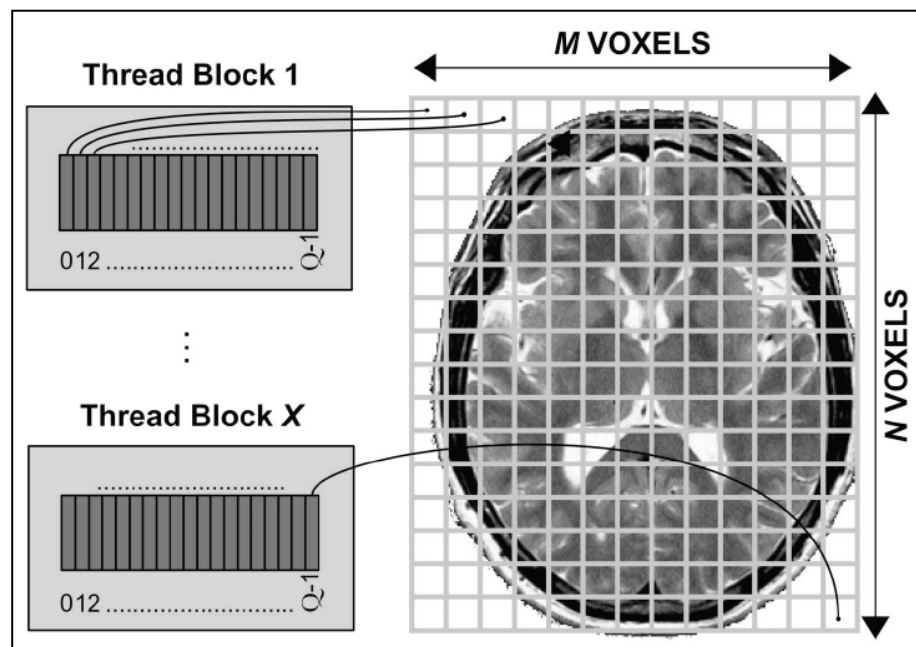


Preliminary estimation of time gain by using GPU in NMR imaging

- **Typical dimensions** of NMR images are maximum **512x512 pixels**.
- The **estimated gain** in terms of computing time ranges from **10^2** (for images at low resolution) to **10^4** (for 512x512 pixels resolution images).
- In **practical applications** it is necessary to iteratively employ **optimization algorithm based on the minimization of non-linear functions** (from 40 to 400 iterations). The effective gain in terms of computing time is expected to be from **40 to 400 times lower**.
- The **real gain** in computing time for DW-NMR image analysis with non-Gaussian diffusion models is expected to be **20 -100 for 128x128 pixels resolution images**.

Non-Gaussian diffusion model based DW-MRI reconstruction by GPU

- The Levenberg-Marquardt algorithm is based on an iterative numerical optimization procedure that minimizes the sum of squared model residuals.
- The CUDA kernel performs the Levenberg-Marquardt algorithm. This kernel maps each CUDA thread to a voxel, and it launches as many threads as voxels contained in a particular slice.
- Because processing of different voxels is totally independent, the threads do not need to synchronize.
- It is noteworthy that each thread must compute all steps of the Levenberg-Marquardt algorithm using large intermediate structures (the size of the structures depends on the number of parameters to fit and the number of diffusion-sensitising gradient directions K of the input dataset).



Next Steps to achieve our goals

(i) Fast-implementation: using of available Matlab custom script (3 months).

1. Implementation of a parallelized version of the Levenberg-Marquadt algorithm for usage on GPU by means of the Matlab Parallel Toolbox;
2. Optimization of available Matlab custom script for DKI and SEM analysis for usage on GPU by means of the Matlab Parallel Toolbox.

(ii) Slow-implementation: translating available Matlab custom script in CUDA language (6 months).

1. Implementation of a parallelized version of the Levenberg-Marquadt algorithm for usage on GPU by means of CUDA platform;
2. Translation of available Matlab custom script for DKI and SEM analysis for usage on GPU by CUDA platform.

(iii) Implementation of numerical simulations supporting experimental data analysis: Monte Carlo and Finite Elements Method (FEM) on GPU (3 months)

1. Translation of parallelized version of Monte Carlo and FEM algorithms to numerically simulate DW-MRI signal attenuation for usage on GPU by CUDA platform.

People involved

- ❑ **Dr. Silvia Capuani** (Physics Dep. Sapienza University of Rome and CNR-IPCF UOS Rome): involved in **all topics**;
- ❑ **Dr. Marco Palombo** (Physics Dep. Sapienza University of Rome and CNR-IPCF UOS Rome): involved in **all topics**;
- ❑ **PhD Student in Biophysics Stella Caporale** (Physics Dep. Sapienza University of Rome): involved in **DW-NMR image reconstruction by means of non-Gaussian diffusion models using GPU**;
- ❑ **Graduating Student in Physics Ruggero Lo Sardo** (Physics Dep. Sapienza University of Rome): involved in **NMR Numerical Simulation on GPU**.