

A high-throughput stream-oriented GPU environment for simultaneous processing and visualization of EEG measurements

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High resolution EEG imaging

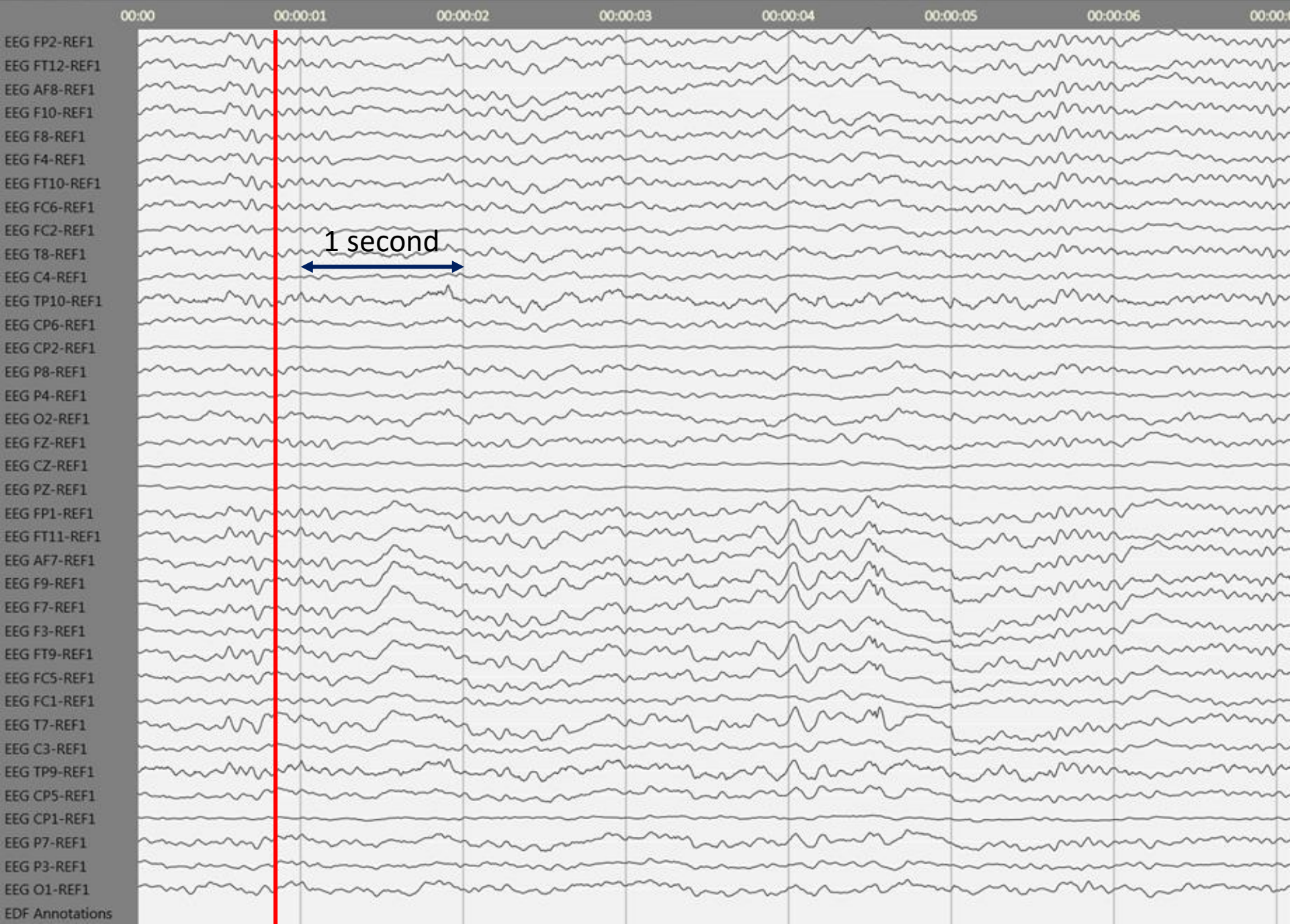
EEG fundamentals

- Cortical neurons as current sources
- The electrical field generates potentials on the scalp

Primary tool in

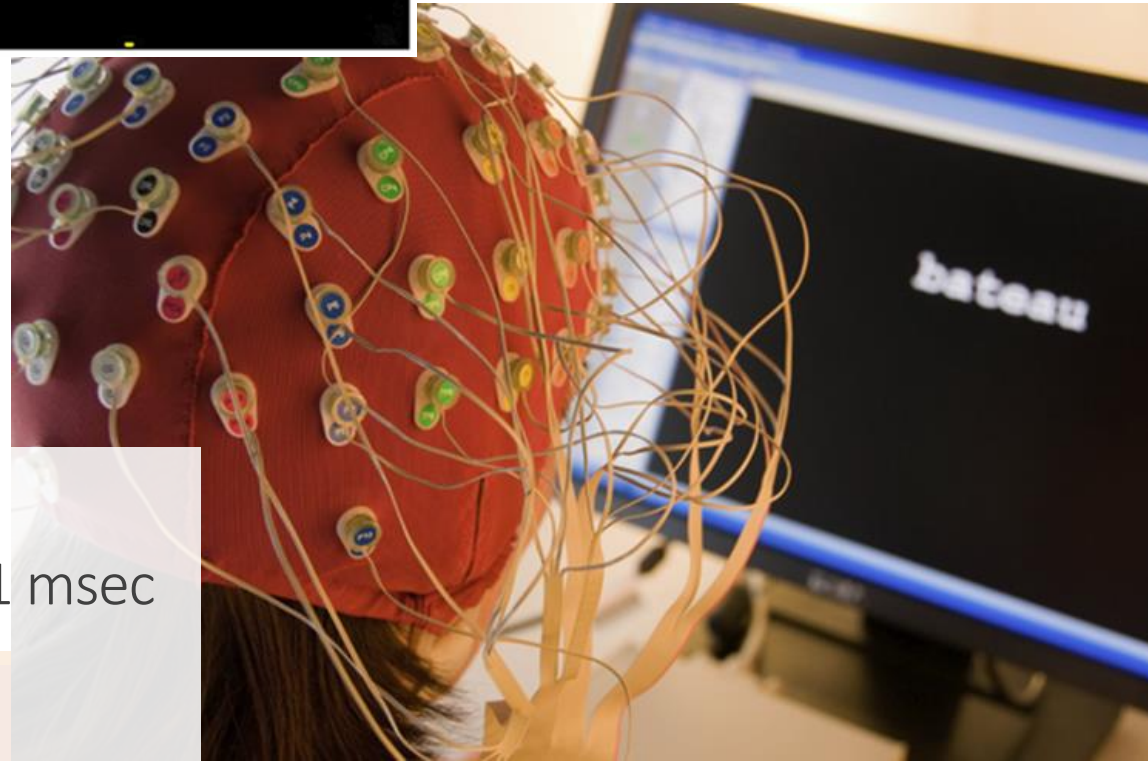
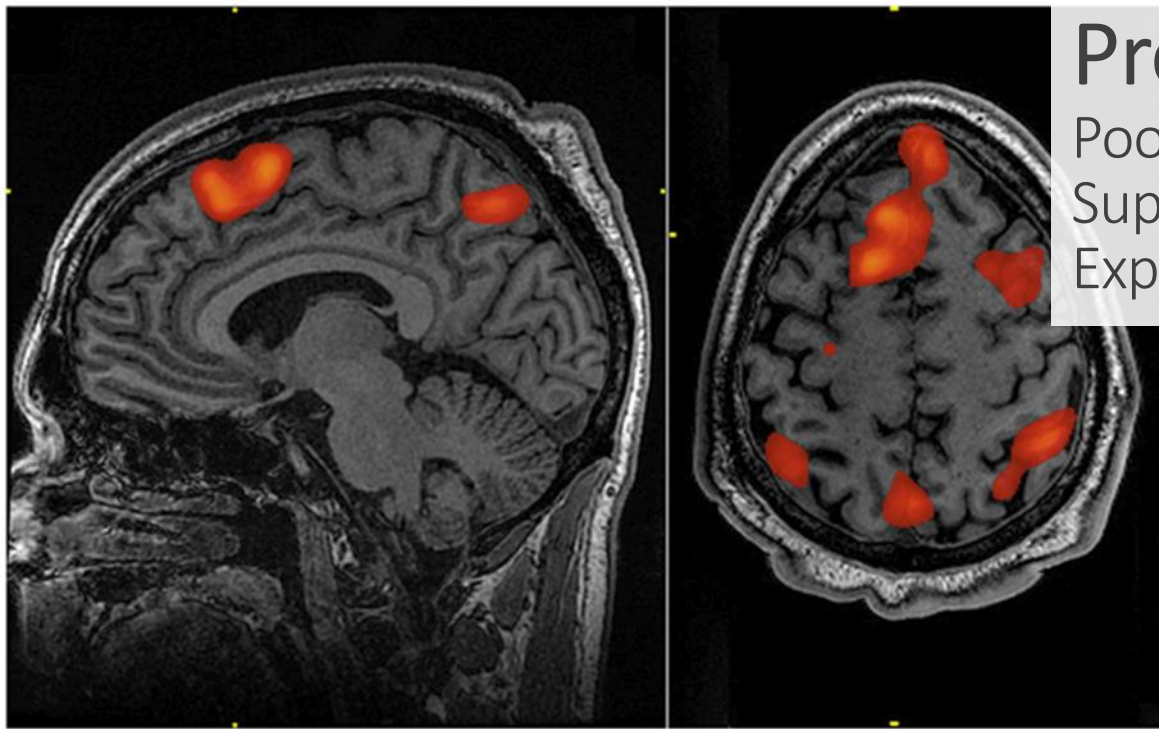
- epilepsy diagnosis and treatment,
- neurocognitive studies





Properties of fMRI

Poor temporal resolution $> \text{sec}$
Superb spatial resolution $\sim 1 \text{ mm}$
Expensive



Properties of EEG

Superb temporal resolution $< 1 \text{ msec}$
Poor spatial resolution $> 2 \text{ cm}$
Inexpensive

Main goals

Use for imaging processing and visualization

Fast execution how fast?

High spatial resolution close to MRI/fMRI

Functional mapping classify activation source

Novel architecture dataflow/stream processing –
high throughput

Fundamentals – Head model

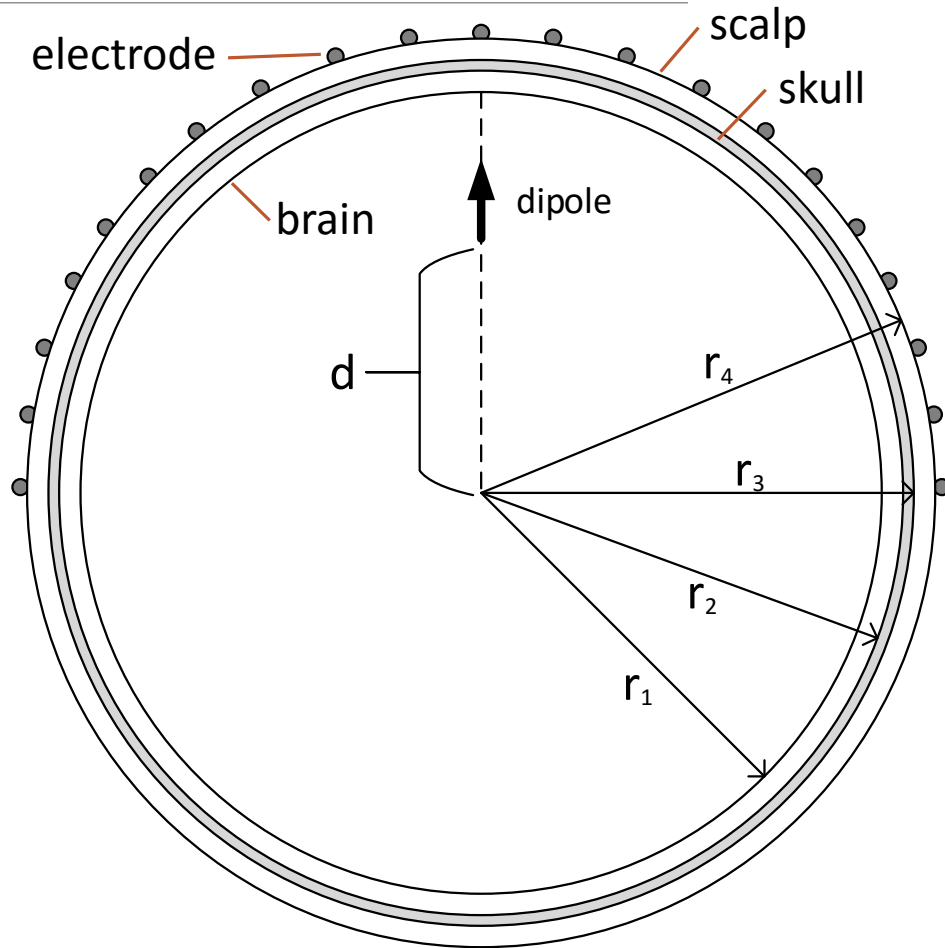
Simplified head geometry for computation

Various head models known

- Spherical, elliptical
- Realistic (segmented from MRI)
- 3, 4 or 5 layers (brain, skull, scalp)

Various forward solvers

- analytical (spherical model)
- BEM, FEM (realistic models)



EEG imaging

Generate maps of potential and derived values on the scalp or on the cortex

Image on scalp

- Volume conduction of skull blurs the source image
- Requires large number of electrodes
- **Laplacian** can increase spatial resolution (high-resolution EEG)

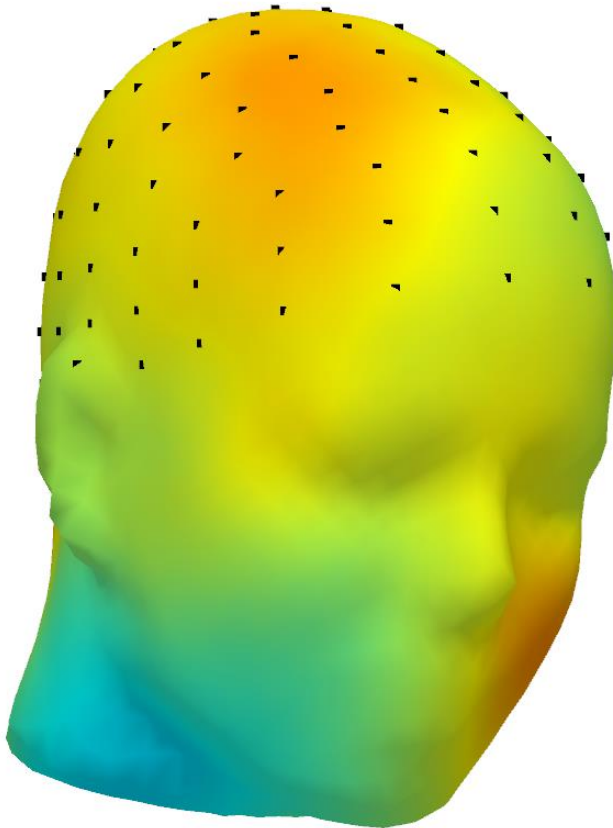
Image on the cortex

- Cortical imaging (back projection from scalp potential image)
- Intracranial electrodes (electrodes placed on cortex – invasive /ouch!/))
- Source localisation (determine sources from measured potential – **inverse problem**)

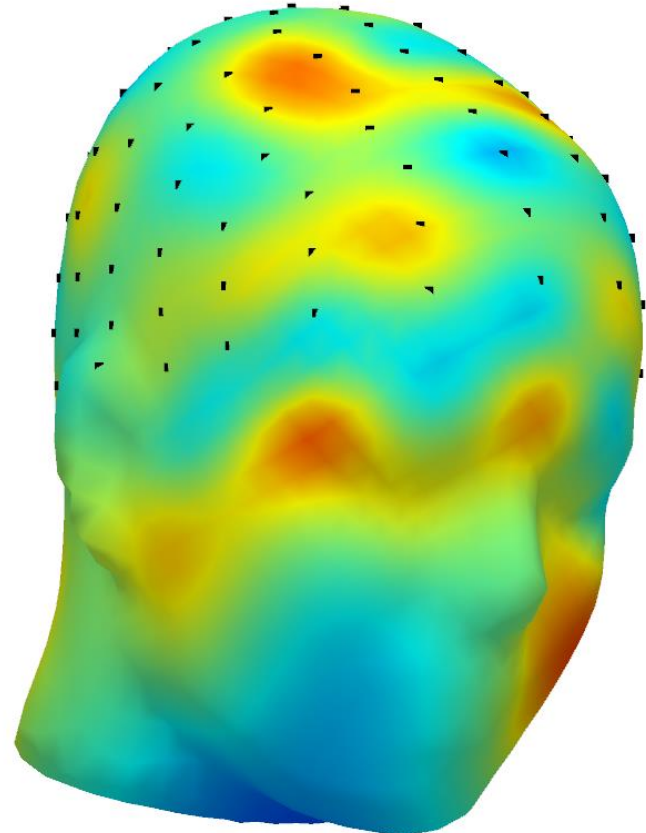
Surface Laplacian

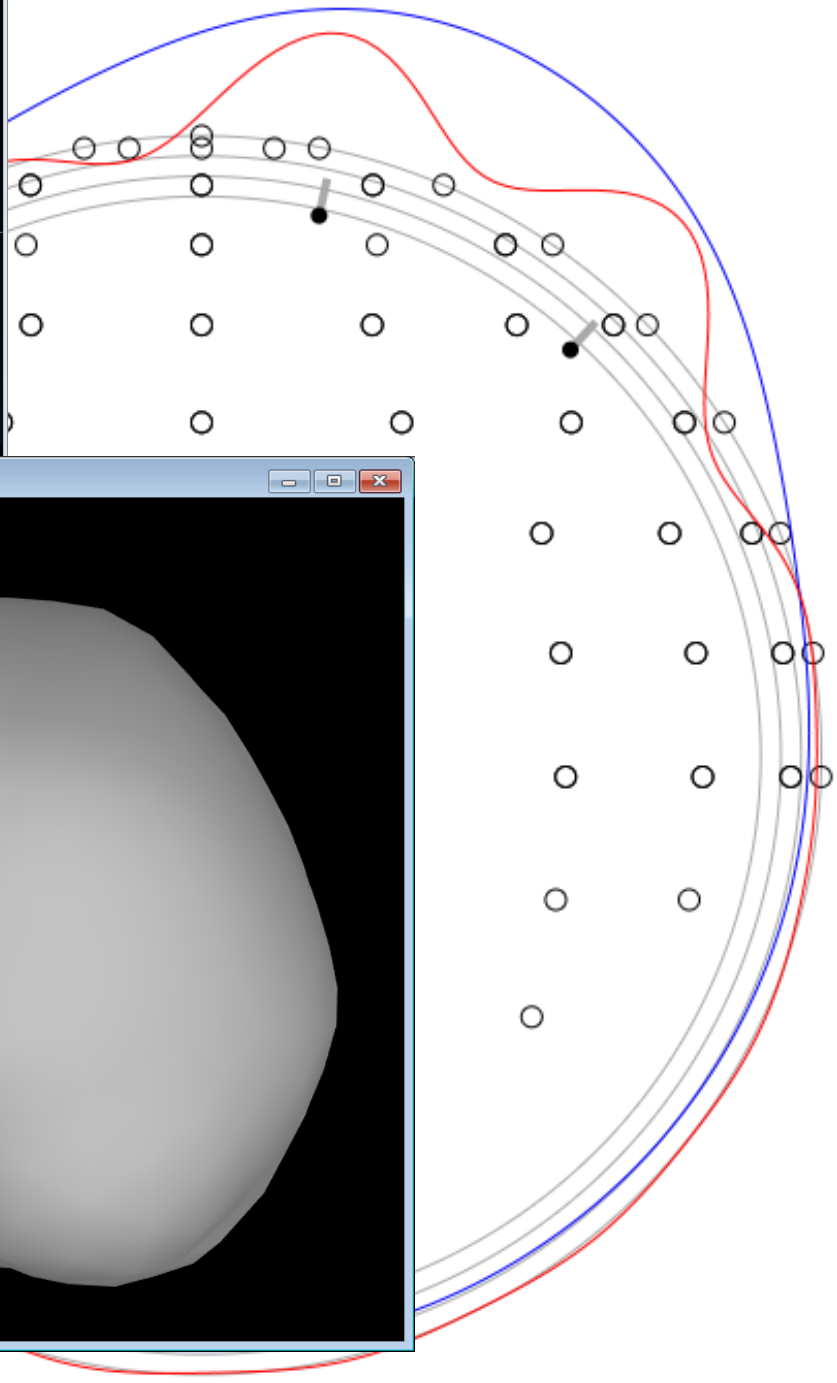
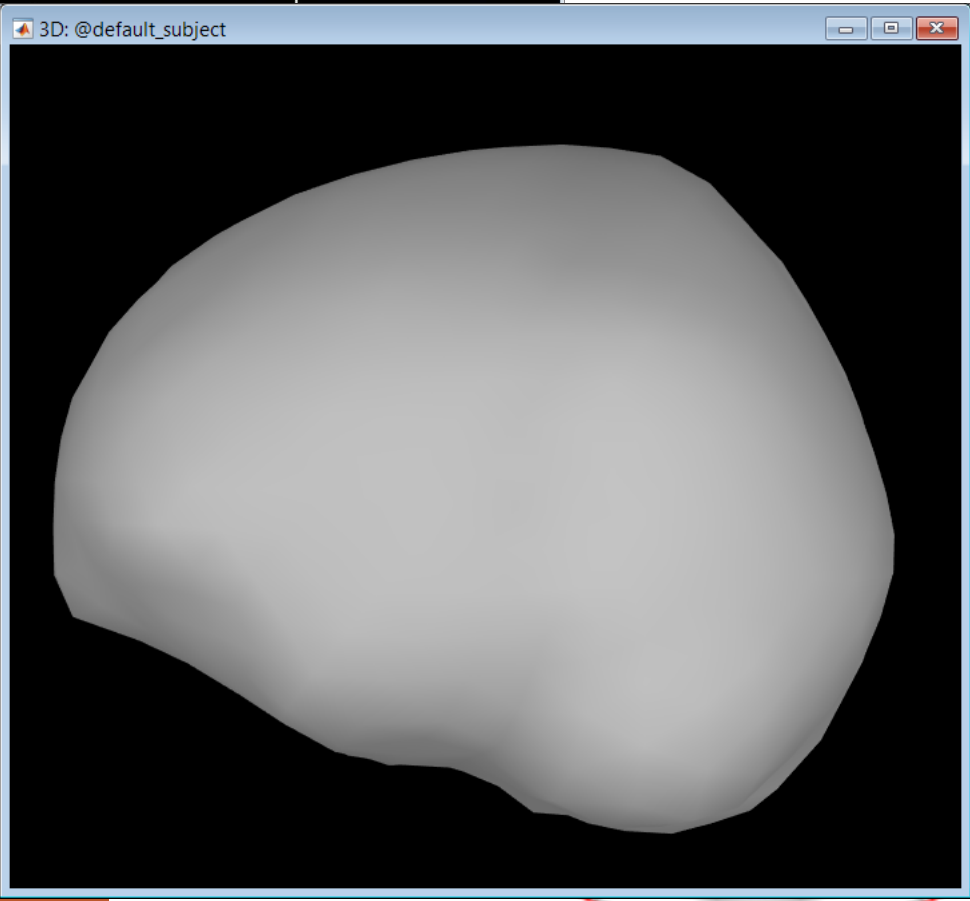
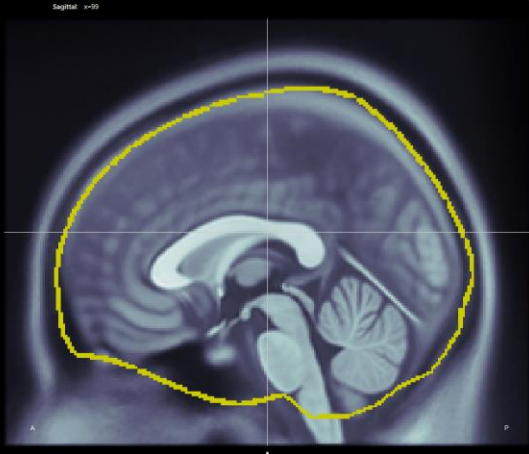
Normally computed at the electrode positions only

Scalp potential map



Scalp surface Laplacian –
current source density

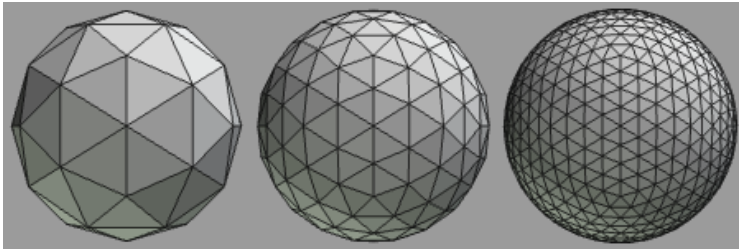




Cortical image spatial resolution

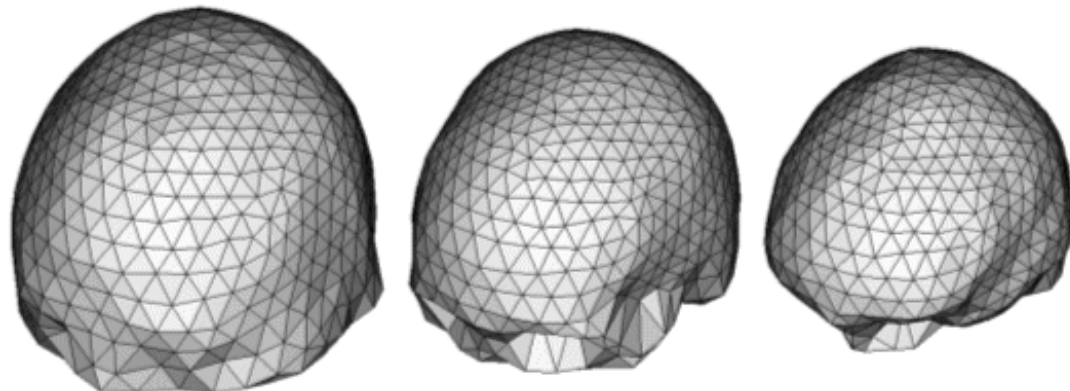
Polygon mesh: required vertex count vs spatial resolution

Icosphere mesh, $r=80\text{mm}$



| ICOSPHERE LEVEL | VERTEX COUNT | AVG PATCH AREA [mm ²] | APPROX PATCH DIAMETER [mm] |
|-----------------|--------------|-----------------------------------|----------------------------|
| 2 | 936 | 85.92 | 10.460 |
| 3 | 3816 | 21.08 | 5.180 |
| 4 | 15336 | 5.24 | 2.584 |
| 5 | 61416 | 1.31 | 1.291 |
| 6 | 245736 | 0.33 | 0.646 |

Realistic mesh



Scalp

Outer skull

Inner skull

| VERTEX COUNT | AVG PATCH AREA [mm ²] | APPROX PATCH DIAMETER [mm] |
|--------------|-----------------------------------|----------------------------|
| 362 | 222.17 | 16.819 |
| 812 | 99.05 | 11.230 |
| 1082 | 74.33 | 9.728 |
| 1922 | 41.84 | 7.299 |
| 2432 | 33.07 | 6.489 |
| 3242 | 24.81 | 5.620 |
| 5762 | 13.96 | 4.216 |
| 7292 | 11.03 | 3.747 |
| 10242 | 7.85 | 3.162 |
| 12962 | 6.20 | 2.811 |

Spherical surface Laplacian pseudo code

compute A^{-1}

for each time sample K

compute coefficients \mathbf{C}

for each surface point S

for each electrode E_i

$lap \leftarrow lap + c_i h(\cos(S, E_i))$

...

$$LAP(S) = \sum_{i=1}^n c_i h(\cos(S, E_i))$$

$$\mathbf{GC} + \mathbf{T}c_0 = \mathbf{Z} \quad \mathbf{Z} = \text{potentials}$$

$$\mathbf{T}'\mathbf{C} = 0$$

$$\begin{bmatrix} \mathbf{G} & \mathbf{T} \\ \mathbf{T}' & 0 \end{bmatrix} \begin{bmatrix} \mathbf{C} \\ 0 \end{bmatrix} = \begin{bmatrix} \mathbf{Z} \\ 0 \end{bmatrix} \rightarrow \mathbf{Ax} = \mathbf{b}$$

$$\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$$

gives \mathbf{C} for each \mathbf{Z}

$$h(x) = -\frac{1}{4\pi} \sum_{n=1}^{\infty} \frac{(2n+1)}{n^{m-1}(n+1)^{m-1}} P_n(x)$$

$$g(x) = \frac{1}{4\pi} \sum_{n=1}^{\infty} \frac{(2n+1)}{n^m(n+1)^m} P_n(x)$$

Pseudo code

FORWARD STEP

```
for each time sample  $k$  in  $K$  do           //  $N$   
    for each electrode  $e$  in  $E$  do           // 128  
        for each dipole  $d$  in  $D$  do         // approx. 10K  
             $pot \leftarrow pot + \text{compute potential at } e \text{ generated by } d$ 
```

INVERSE STEP

```
find single dipole source using optimisation (location and moment)  
or  
find weights of a set of fixed dipoles using linear MNE
```

Baseline execution time results per sample

| | Matlab 1-core | Java – CPU |
|----------------------------|---------------|-------------|
| Spherical Laplacian | | |
| • 512 vertices | 23.03 sec | 77.22 msec |
| • 1024 vertices | 23.15 sec | 144.84 msec |
| • 5 120 vertices | 24.40 sec | 719.25 msec |
| • 32 768 vertices | - | 4.56 sec |
| Forward solver (spherical) | | |
| • 10 dipoles | 0.95 sec | 25.40 msec |
| • 100 dipoles | 7.22 sec | 28.60 msec |
| • 1 000 dipoles | 70.03 sec | 174.51 msec |
| • 10 000 dipoles | 698.26 sec | 1.42 sec |

x 2048 for one second

CPU – intel Core i7-3820QM 2.7 GHz

CUDA implementation

Alternatives

- OpenACC, OpenMP 4
- Parallel libraries
- OpenCL

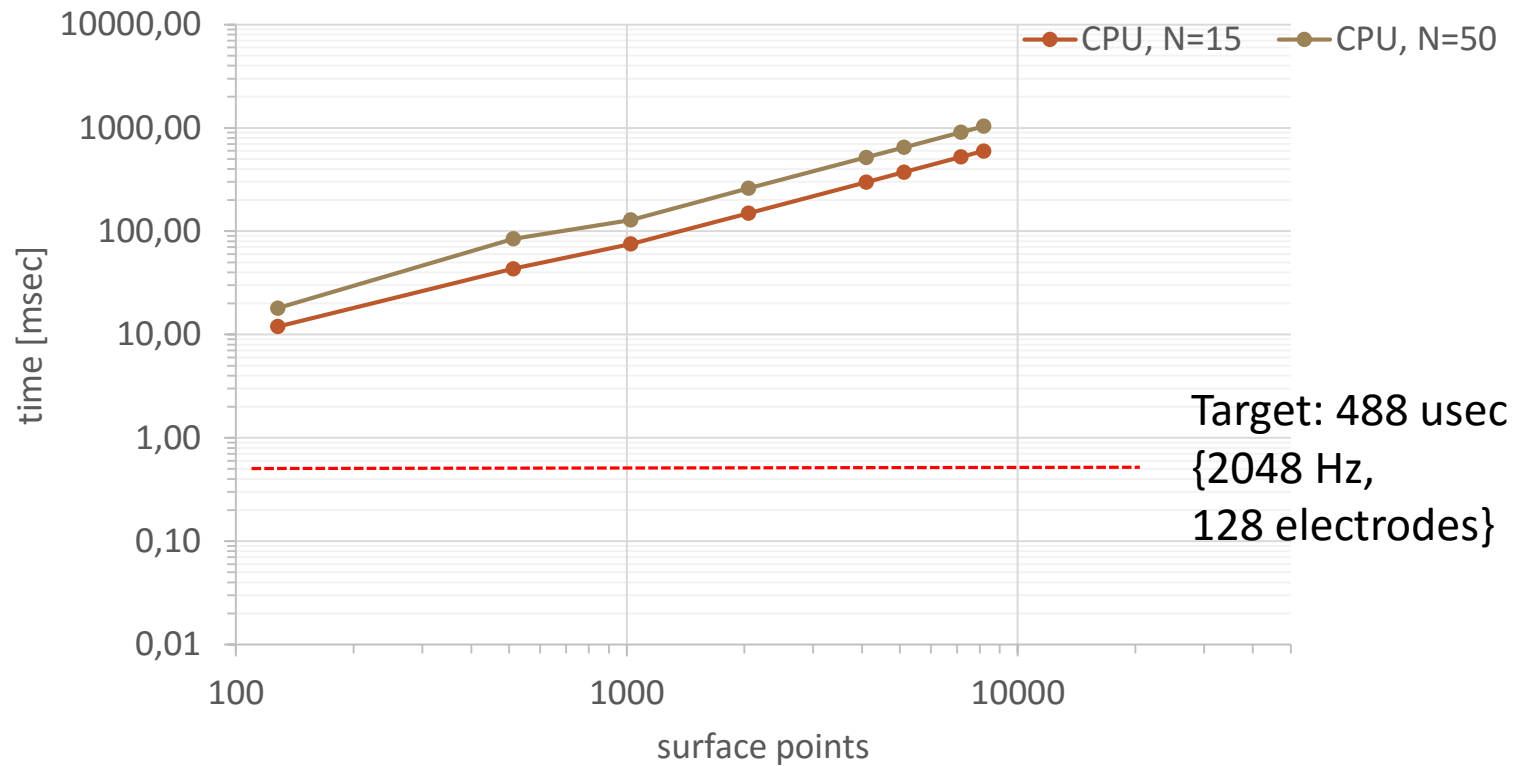
CUDA – maximum freedom, ability to match architecture and algorithm, maximize performance, use advanced optimization tricks

C and various GPU algorithm variations,

C/GPU heterogeneous solution

CPU, Java, double precision, 1 core

Laplace execution time [msec]



Target: 488 usec
{2048 Hz,
128 electrodes}

for each time sample K

compute coefficients \mathbf{C}

for each surface point S

for each electrode E_i

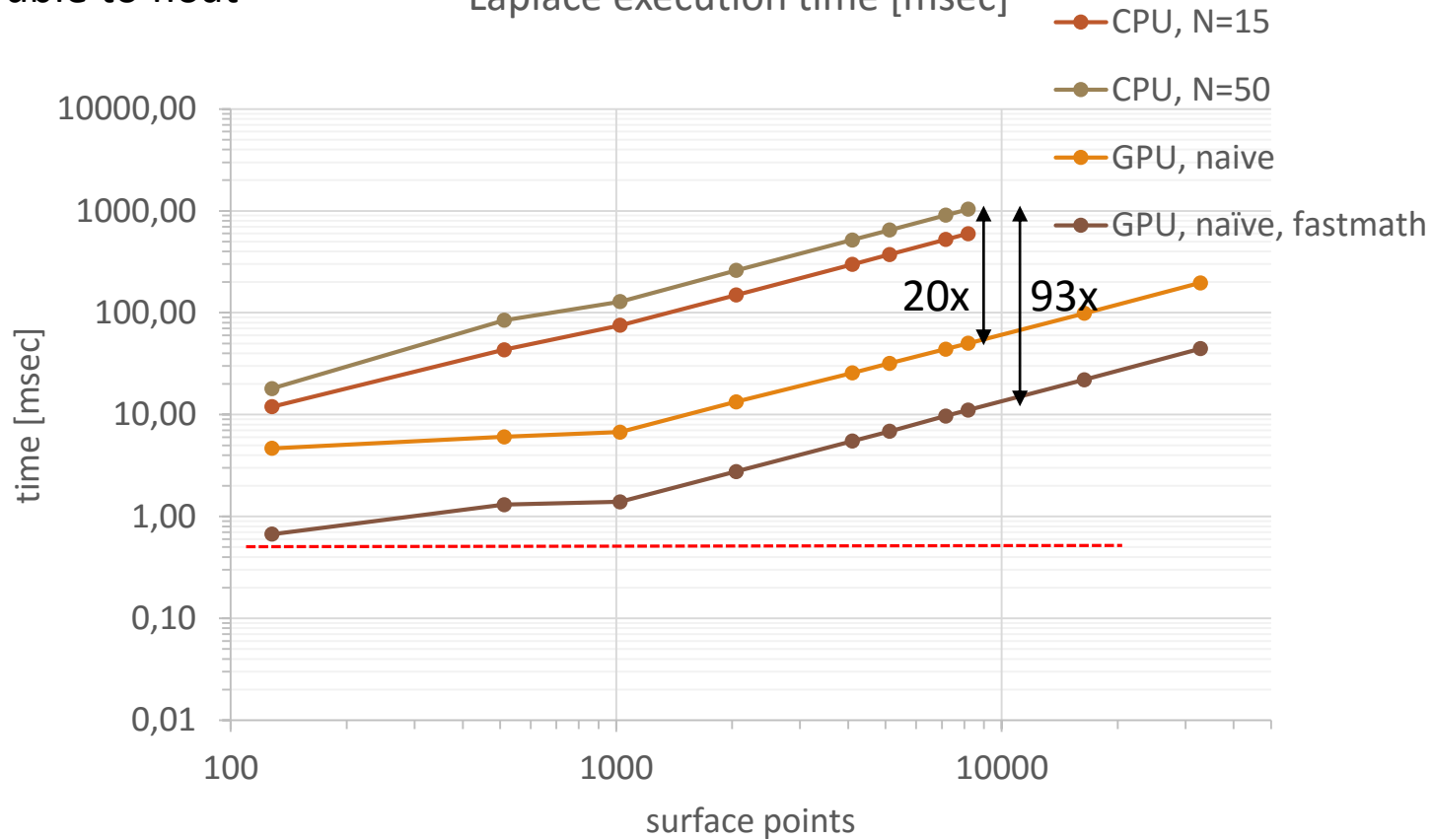
$lap \leftarrow lap + c_i h(\cos(S, E_i))$

CUDA thread

$$h(x) = -\frac{1}{4\pi} \sum_{n=1}^{\infty} \frac{-(2n+1)}{n^{m-1}(n+1)^{m-1}} P_n(x)$$

From double to float

Laplace execution time [msec]



for each time sample K

compute coefficients \mathbf{C}

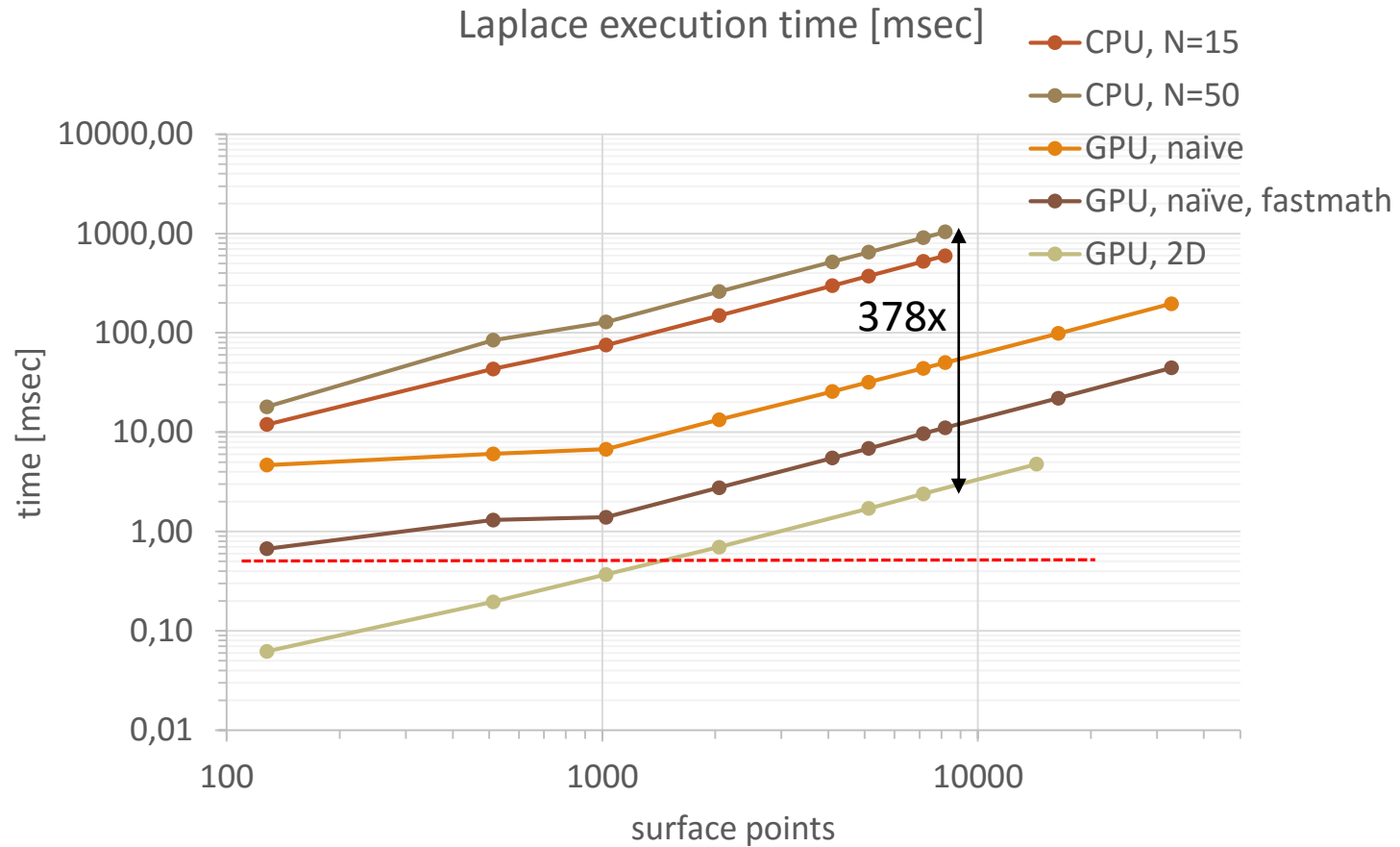
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for each time sample K

compute coefficients C

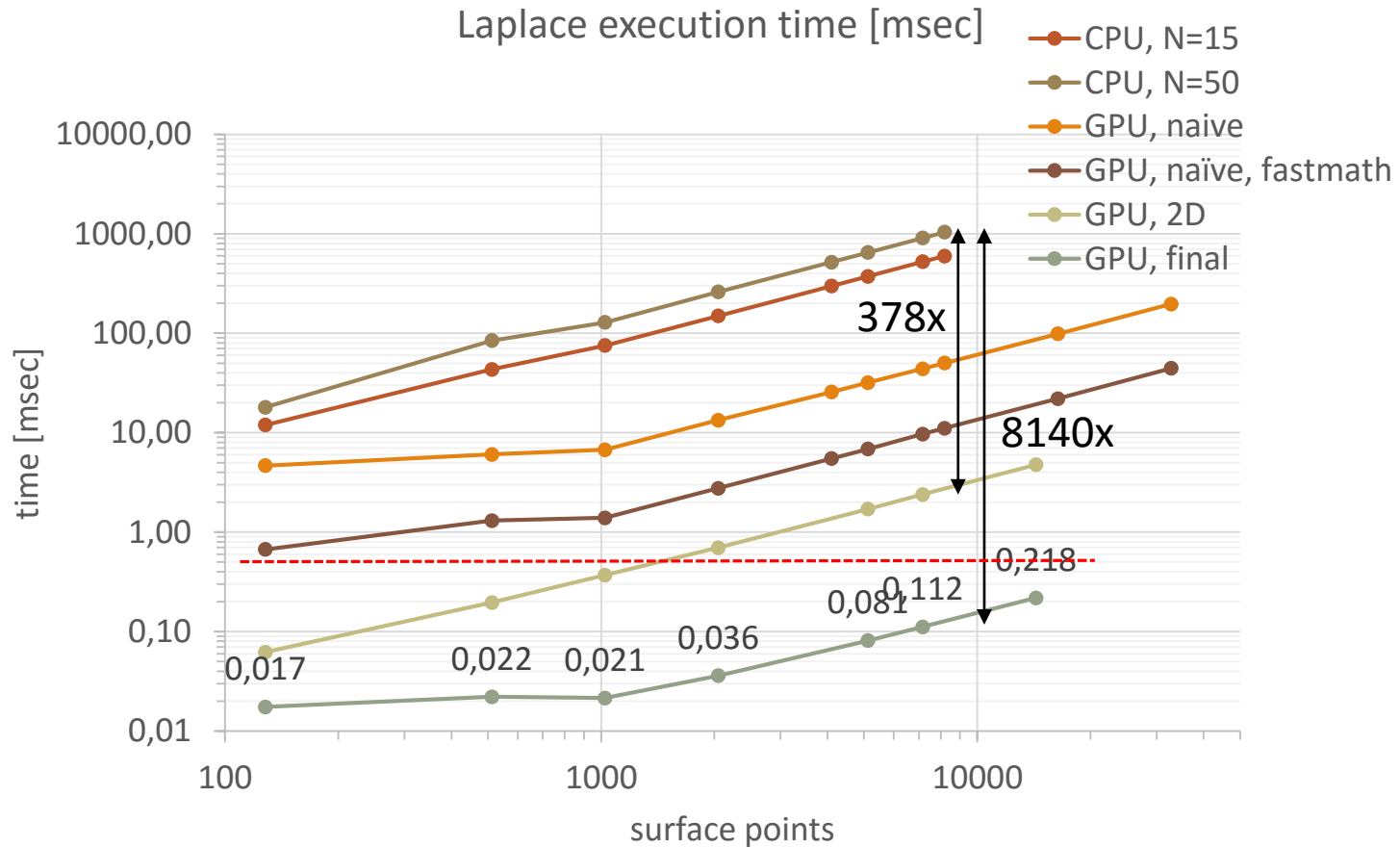
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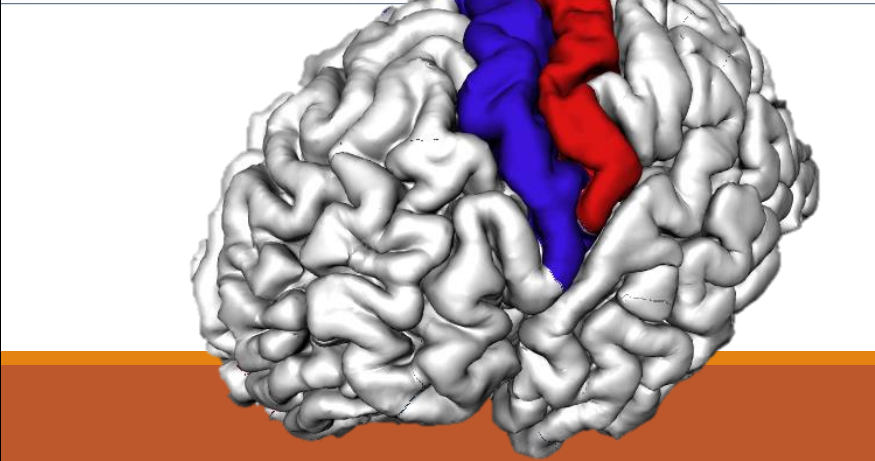
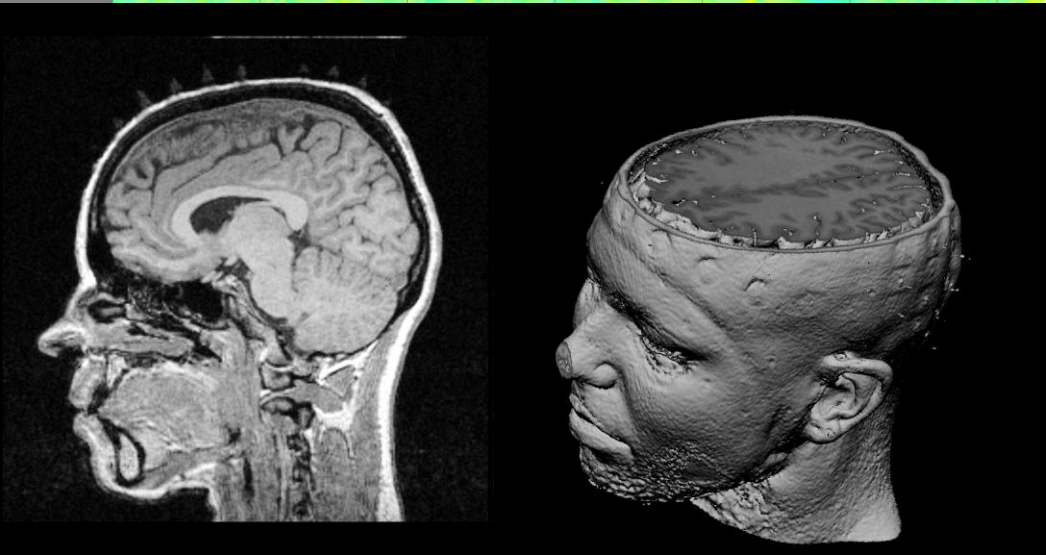
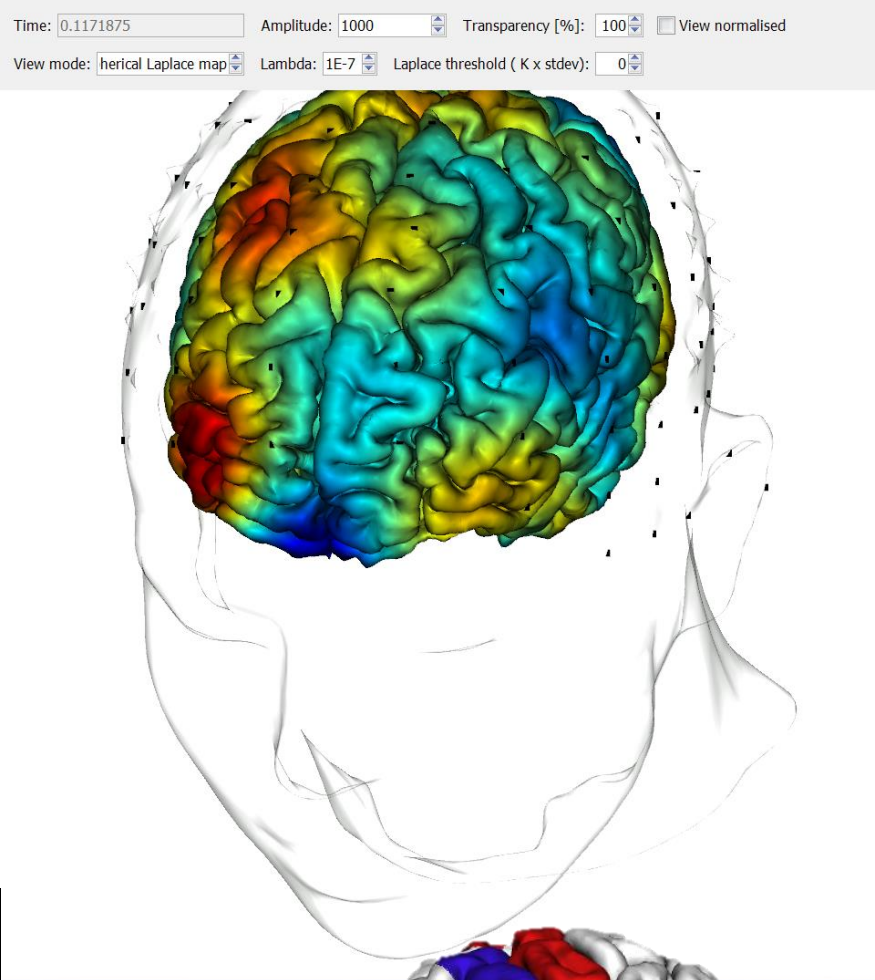
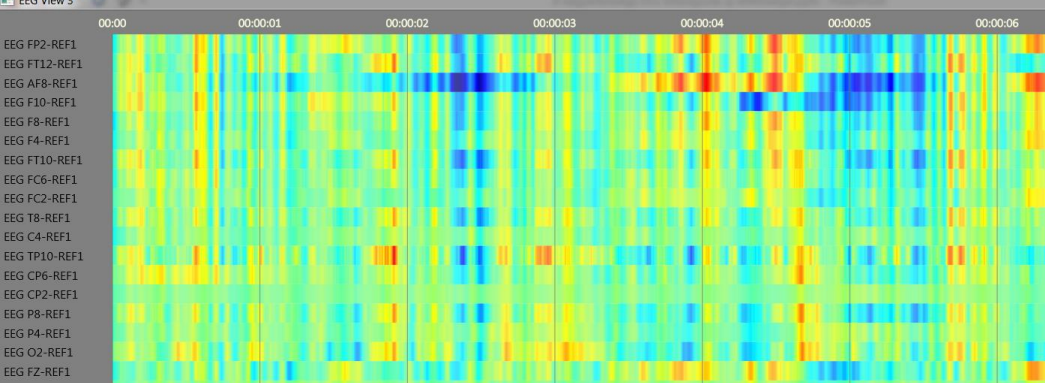
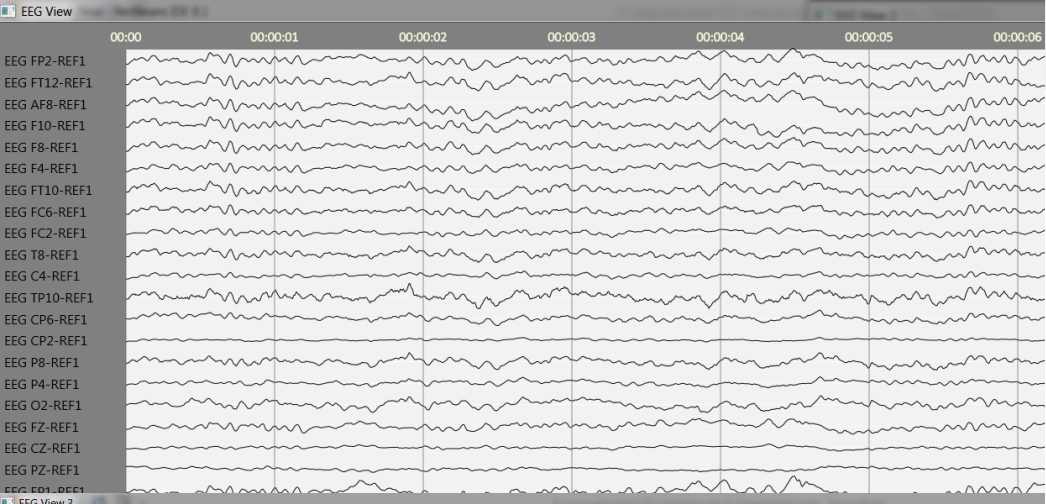
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CUDA thread

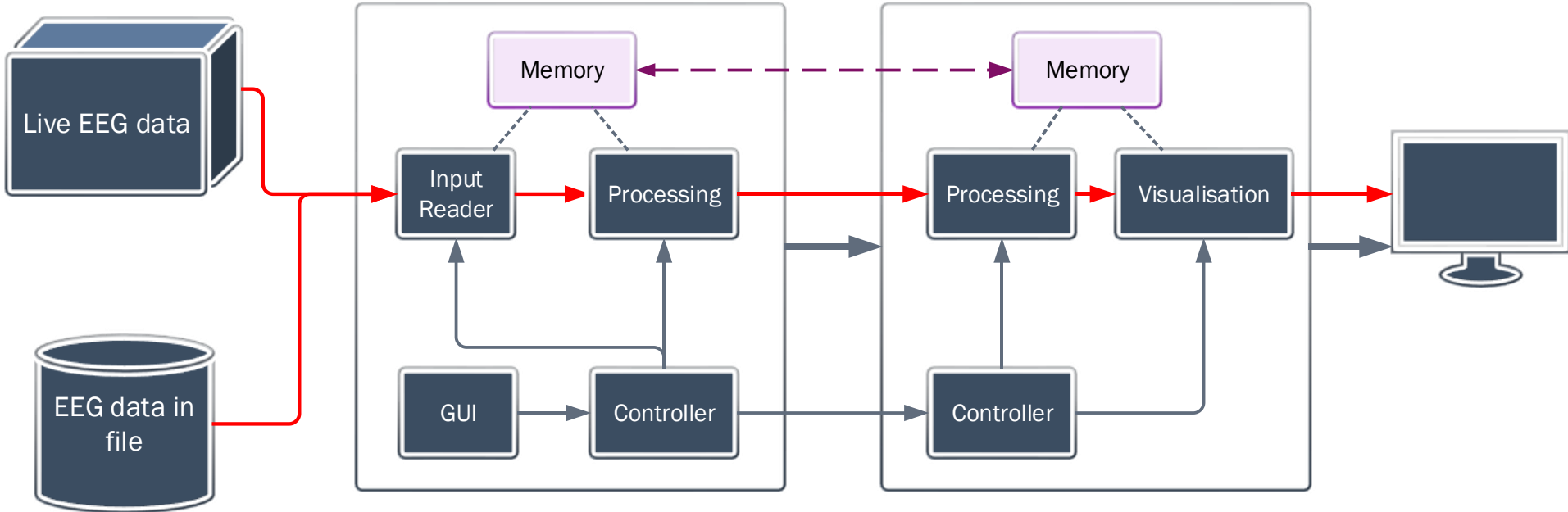
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Stream processing architecture: a high-level view

Compute and visualise; optimised end-to-end processing sequence
CPU (4-10 gigaflops) GPU (4-20 teraflops)



— Control flow —>

← Memory data transfer →

— Data flow —>

— Hardware interface connection —>



Summary

Real-time EEG imaging is possible **3 teraflops sustained performance**

Requires careful tuning and exploiting architecture features

Future work

Implementing further algorithms

- Independent Component Analysis
- Short-time FFT, Wavelet transform
- Functional mapping, connectivity
- Statistics, machine learning

Multi-GPU environments

Application for arbitrary real-time data processing tasks (sensor data, audio, video, etc)

