Brain Perfusion Imaging -Performance and Accuracy

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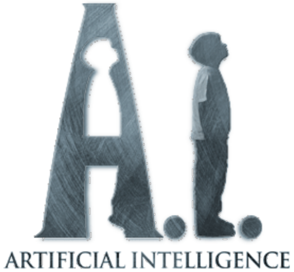
Outline

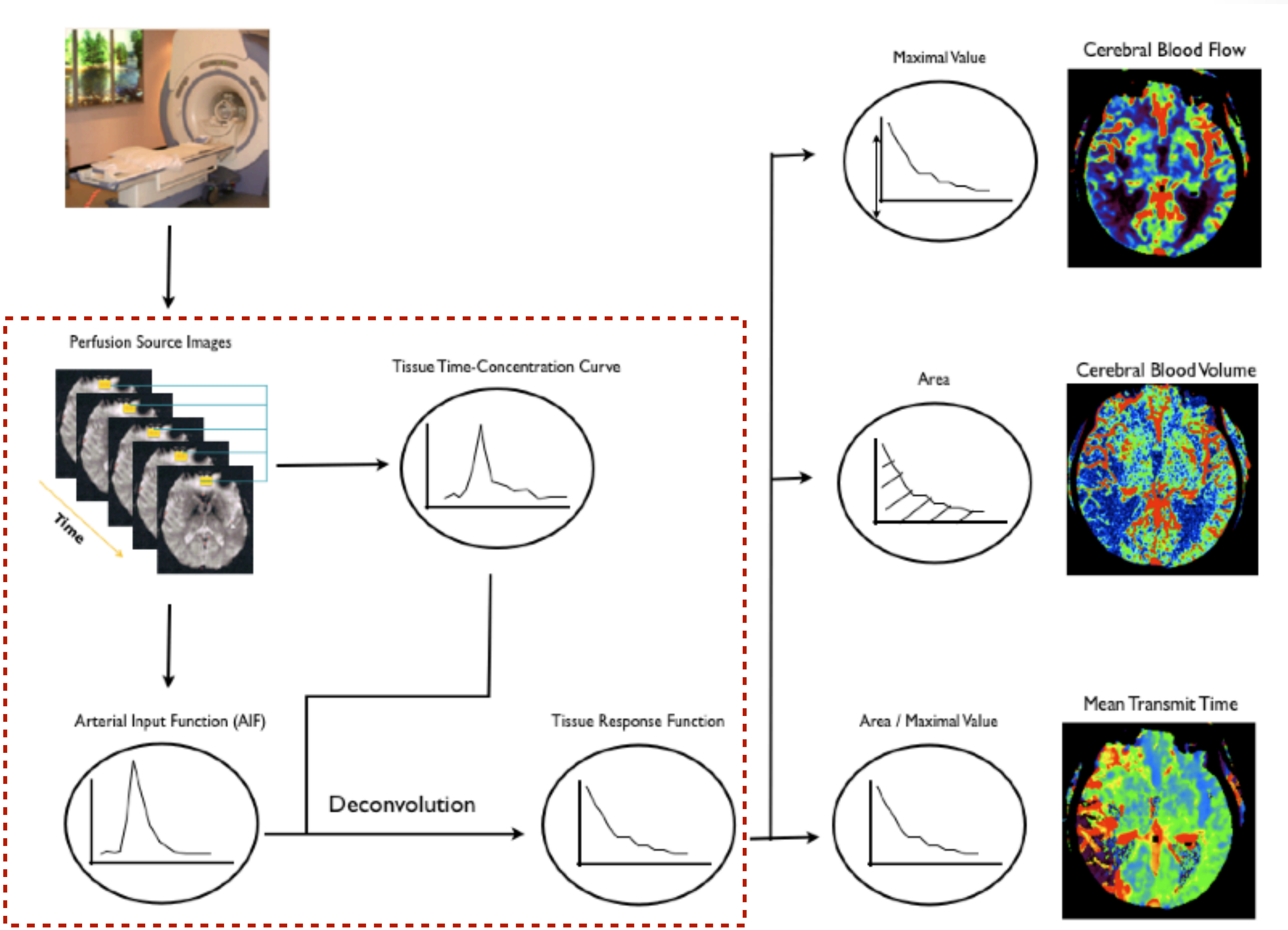
- My PhD



PhD Project

- Brain Perfusion Imaging
  - Performance speed up using GPGPU
  - Noise reduction using Gaussian process regression
  - Automatic lesion area detection

What is Perfusion Imaging



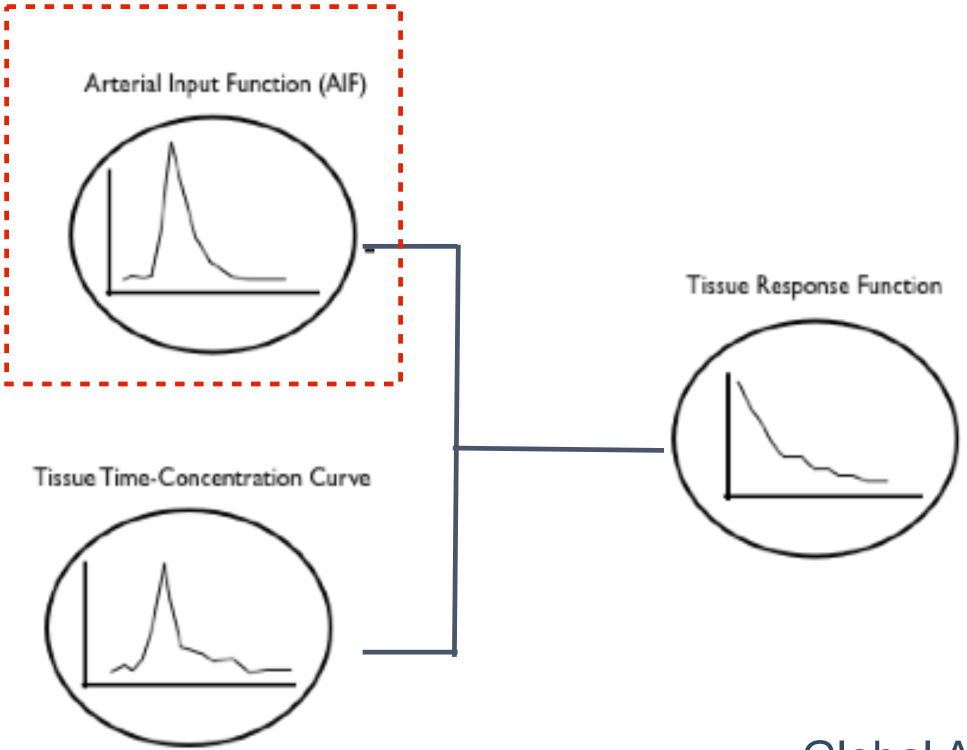
Performance in Perfusion Imaging Processing

Time is brain!

Time is Brain!

	Neurons Lost	Synapses Lost	Myelinated Fibers Lost	Accelerated Ageing
Per Second	3.2×10^4	2.3×10^8	0.2 km	8.7 h
Per Minute	1.9×10^6	1.4×10^{10}	12 km	3.1 wk
Per Hour	1.2×10^8	8.3×10^{11}	714 km	3.6 y
Per Stroke	1.2×10^9	8.3×10^{12}	7140 km	36 y

Arterial Input Function



$$\text{AIF} \otimes \text{IRF} = \text{VOF}$$

Global AIF

Local AIFs

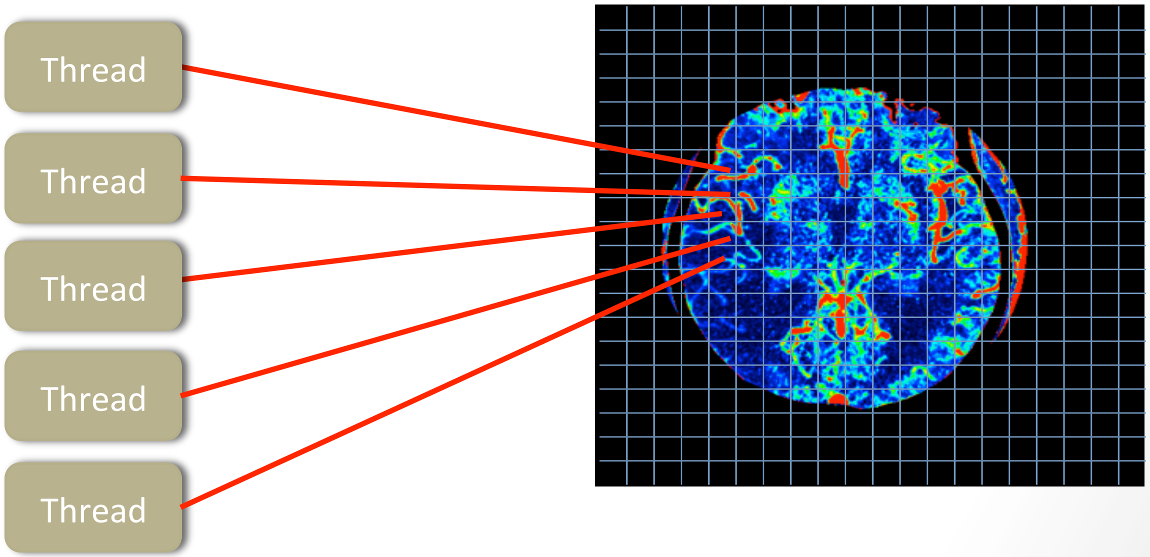
< 10 seconds

> 35 minutes

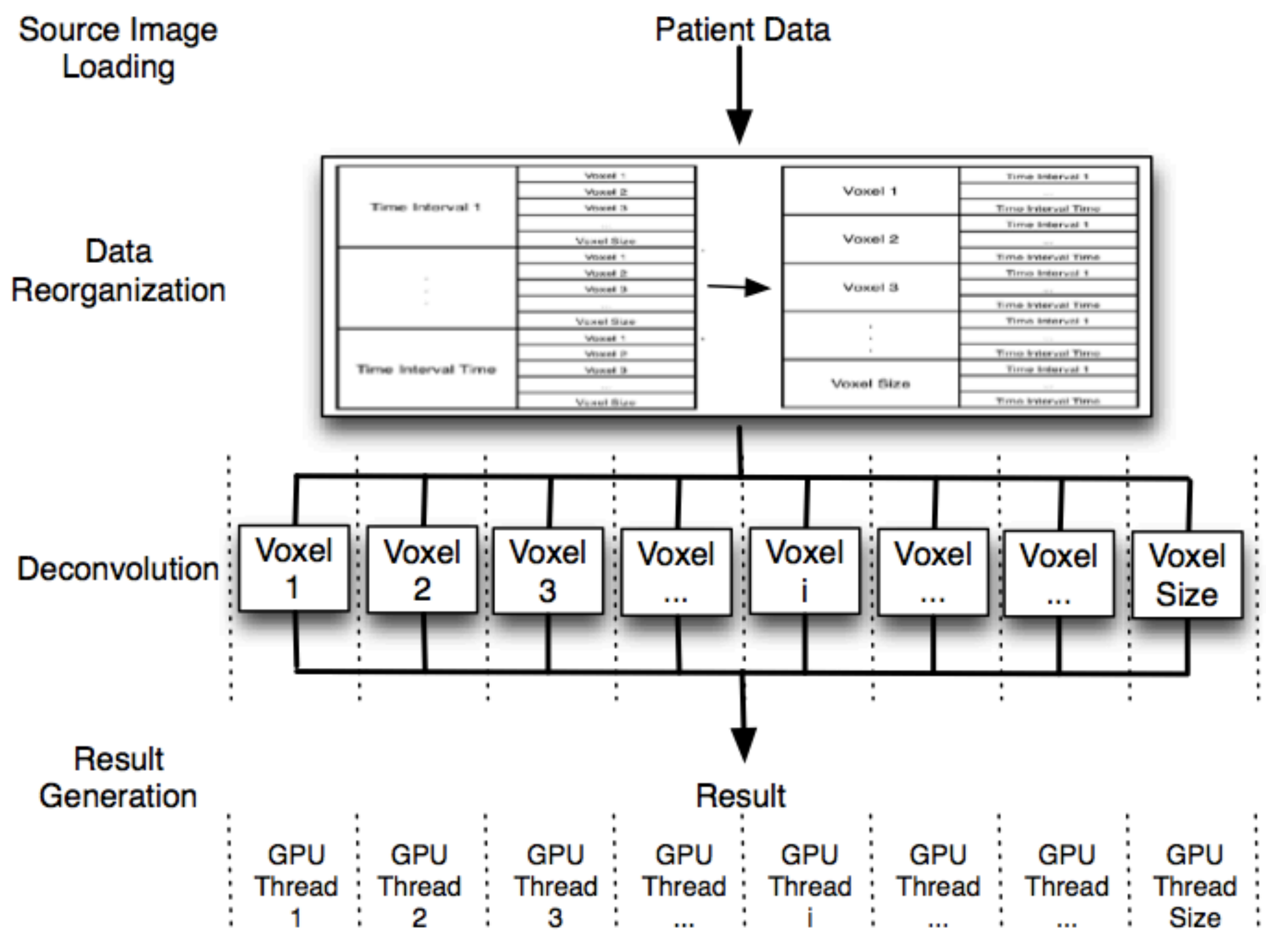
How Parallelization Works

- Tens of Thousands of voxels
  - Ideally Parallel when deconvolution using data parallelism
- Accelerate the process without any quality loss

- GPGPU
  - Weak cores.
  - Much higher number of cores



Parallelization Workflow



Code Segment 1

```
/***** Example code segment for parallel reorganization *****/
__global__ void reorganization( DATATYPE *d_input,
                                DATATYPE *d_output,
                                int time)
{
        int idx = blockIdx.x*blockDim.x + threadIdx.x;
        int i = idx % time;
        int j = idx / time;
        d_output[j*time+i] = d_input[i*time+j];
}
```

Thread number = (Number of voxels) * (Number of sampling time points)

Code Segment 2

```
/***** Example code fragment for parallel deconvolution *****/
__global__ void deconvolution( INPUT *input, OUTPUT *output)
{
        int idx = blockIdx.x*blockDim.x + threadIdx.x;
        int *localmemory = find_and_pass_some_free_global_memory(idx);
        matrix_decomposition(intput, output, idx);
        other_matrix_operations(input, output, idx);
}
```

Thread number = Number of voxels

Performance Improvement

Serial

GPU Parallel

CPU Parallel

Data Size ($Dim1 \times Dim2 \times Dim3 \times time$)	Serial Running Time (s)	GPGPU Running Time (s)	OpenMP Running Time (s)	MPI Running Time (s)
$128 \times 128 \times 22 \times 80$ (MRI Image Size)	2114	564 Speedup Factor = 3.75	956 Speedup Factor = 2.21	619 Speedup Factor = 3.42
$128 \times 128 \times 11 \times 44$ (CT Image Size)	360	65 Speedup Factor = 5.56	159 Speedup Factor = 2.26	94 Speedup Factor = 3.84

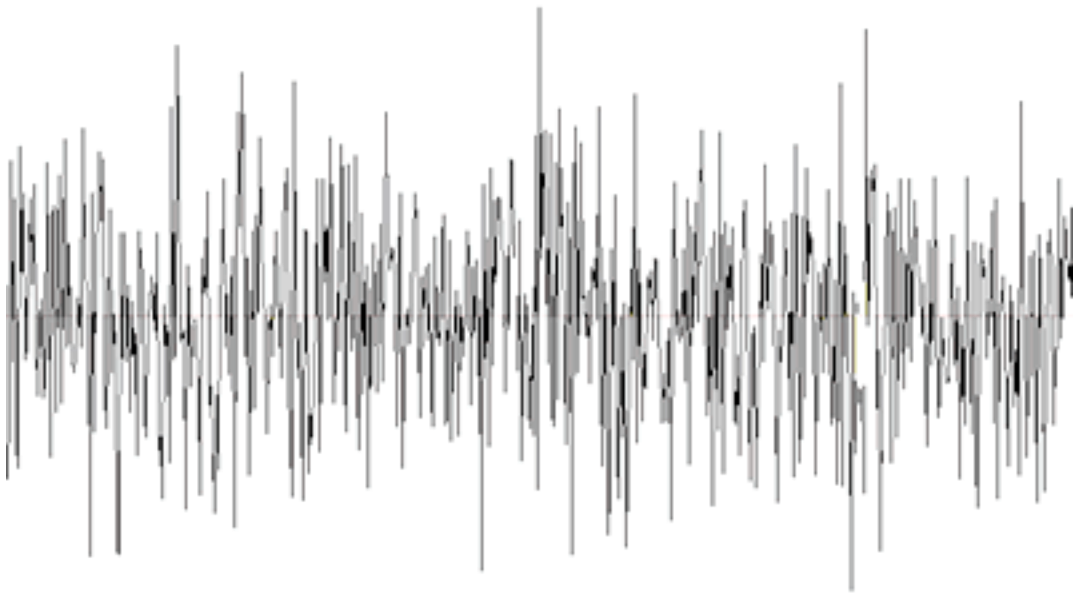
One Tesla C1060 GPU

- 240 GPU cores
- 1.44 GHz each core
- 1.0 GB global memory
- 4 KB shared memory
- 1.036 TFLOPS

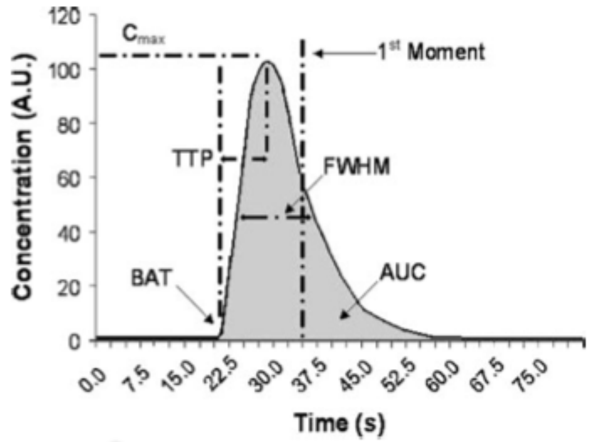
Two Intel(R) Xeon(R) E5620 CPUs

- Dual cores each
- 3.0 GHz each core
- 8.0 GB global memory
- 4 MB cache each

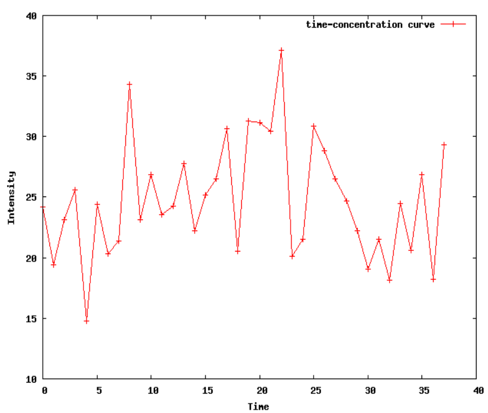
Noise Reduction in Perfusion Source Images

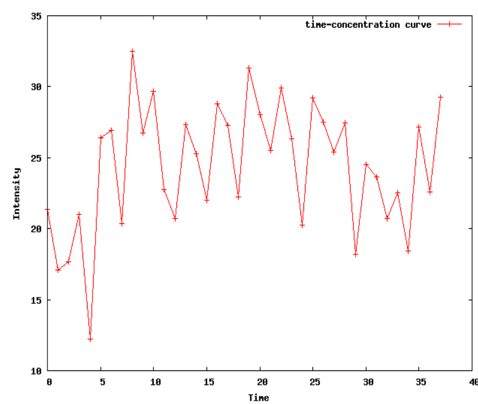


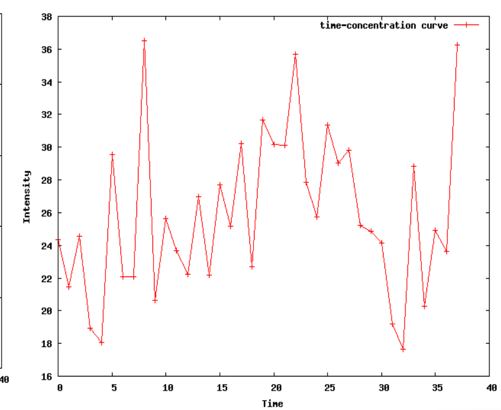
The Need for Denoising



Only a dream :-(

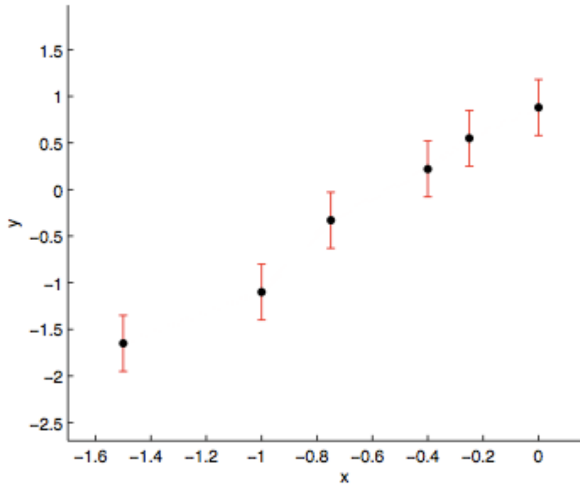


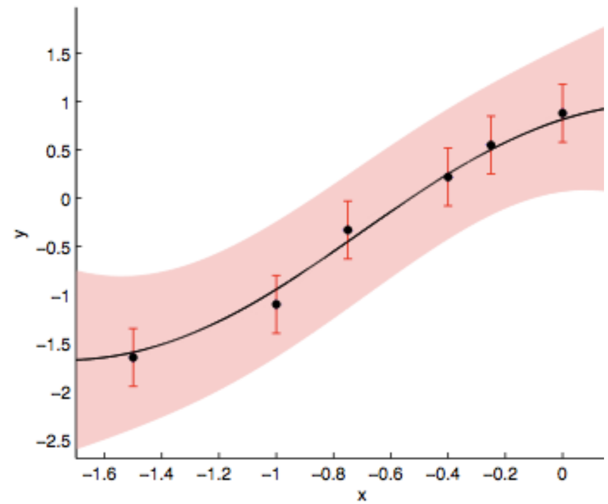




Bloody Reality

Gaussian Process Regression





$$k(t_p,t_q) = \mu_f^2 exp(-\frac{1}{2l^2}(t_p - t_q)^2) + \mu_n^2 \delta_{pq}$$

$$K(T,T) = \begin{bmatrix} k(t_1,t_1) & k(t_1,t_2) & \cdots & k(t_1,t_n) \\ k(t_2,t_1) & k(t_2,t_2) & \cdots & k(t_2,t_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(t_n,t_1) & k(t_n,t_2) & \cdots & k(t_n,t_n) \end{bmatrix}$$

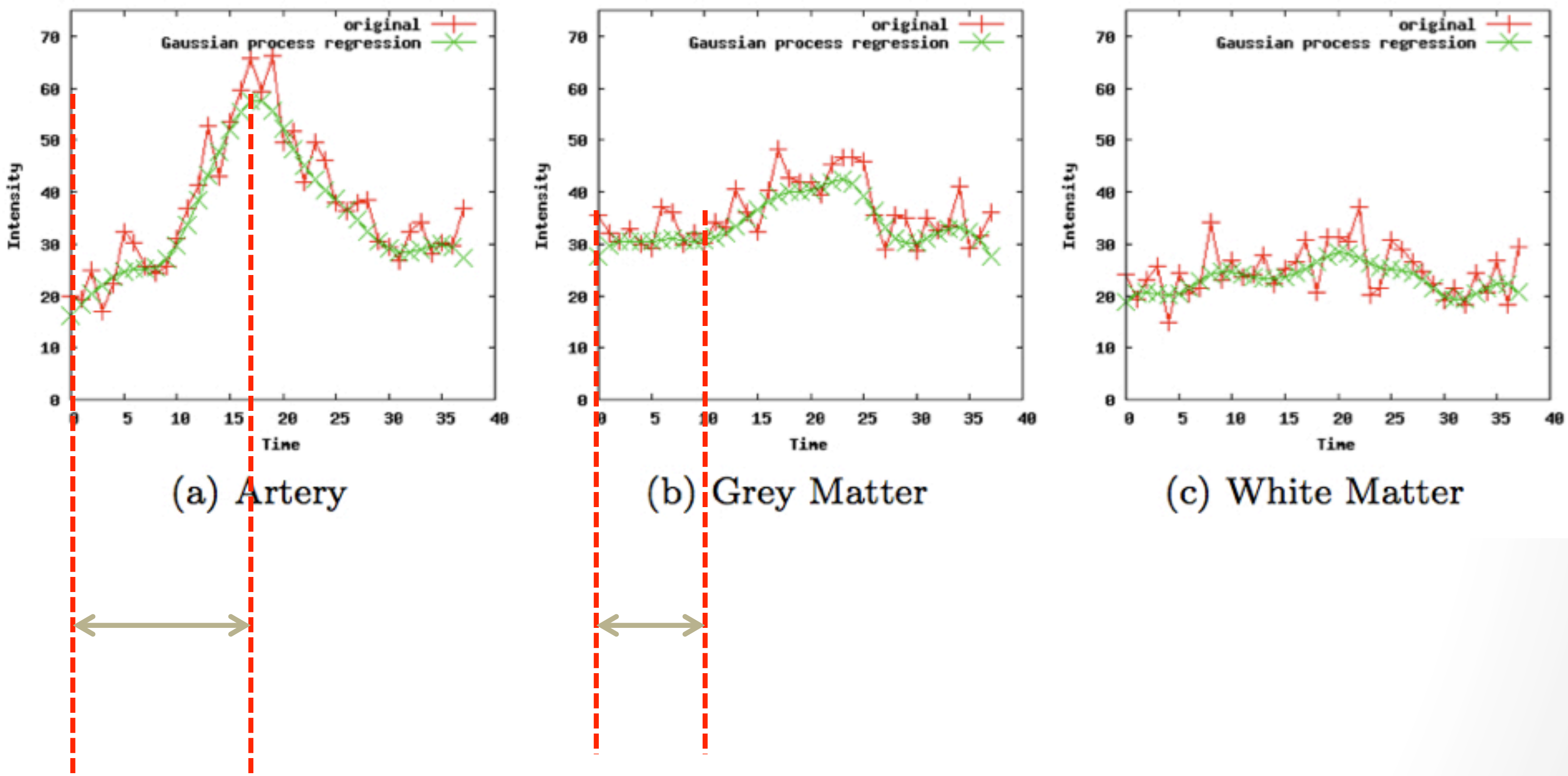
$$f'(t_x) = \begin{bmatrix} k(t_x,t_1) & k(t_x,t_2) & \cdots & k(t_x,t_n) \end{bmatrix} \begin{bmatrix} k(t_1,t_1) & k(t_1,t_2) & \cdots & k(t_1,t_n) \\ k(t_2,t_1) & k(t_2,t_2) & \cdots & k(t_2,t_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(t_n,t_1) & k(t_n,t_2) & \cdots & k(t_n,t_n) \end{bmatrix}^{-1} \begin{bmatrix} f(t_1) \\ f(t_2) \\ \vdots \\ f(t_n) \end{bmatrix}$$

$$K(T_*,T) = \begin{bmatrix} k(t_*,t_1) & k(t_*,t_2) & \cdots & k(t_*,t_n) \end{bmatrix}$$

Filter Equations

$$K(T_*,T_*) = [k(t_*,t_*)]$$

Result of Using GPR



(a) Artery (b) Grey Matter (c) White Matter

Time to Peak

Baseline Period

Contrast-to-Noise Ratio

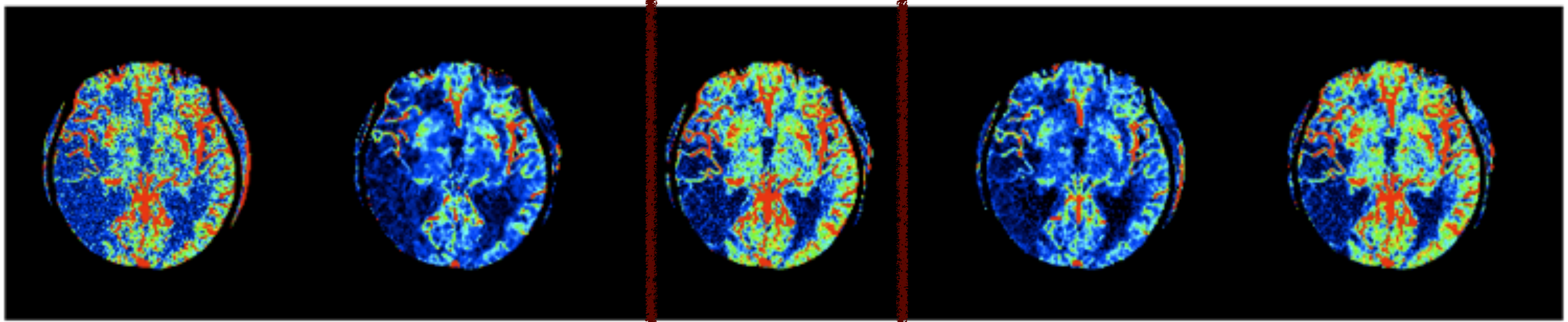
CNR = SNR + Bias Removal

	Age	Gender	Time to Imaging (hh:mm)
Subject 1	74	Male	01:54
Subject 2	77	Male	05:30
Subject 3	78	Female	04:05
Subject 4	88	Female	01:50
Subject 5	83	Male	01:45
Subject 6	84	Female	02:40
Subject 7	82	Female	01:30
Subject 8	82	Male	01:30
Subject 9	51	Female	03:45
Subject 10	47	Female	04:40
Average	**75**	**M=4, F=6**	02:17

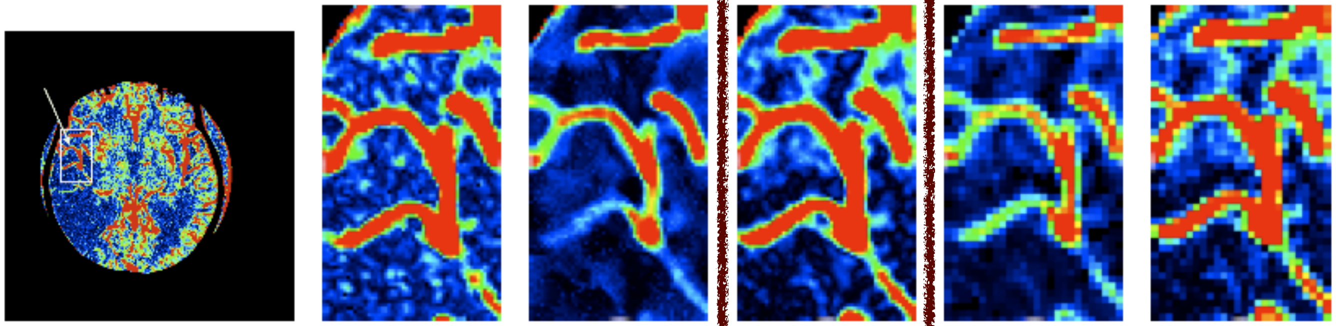
	Raw	GPR
Subject 1	1.58	3.70
Subject 2	1.32	3.09
Subject 3	2.16	3.29
Subject 4	1.28	1.93
Subject 5	1.80	4.32
Subject 6	2.10	5.44
Subject 7	2.04	3.60
Subject 8	1.36	3.51
Subject 9	1.14	1.35
Subject 10	1.07	1.76

Optimized results	Original	GPR
Mean	1	1.99
Standard Deviation	-	0.516

Parametric Maps



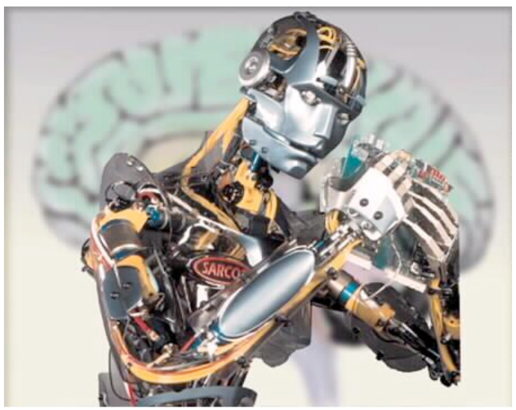
(a) Raw CBF (b) TIPS CBF (c) GPR CBF (d) MEAN & GPR CBF (e) MGPR CBF

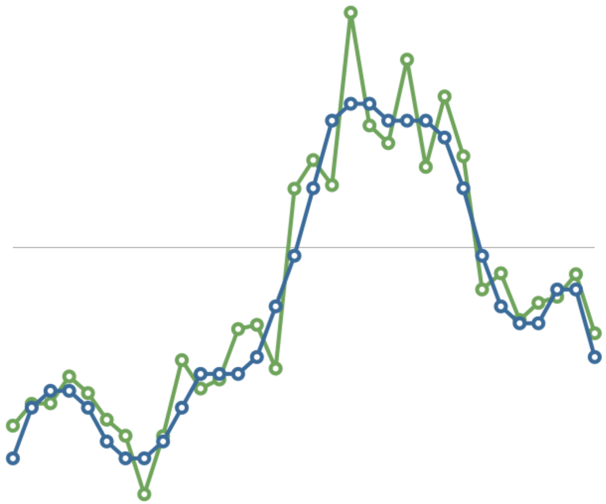


(a) Zoom In Area (b) Raw (c) TIPS (d) GPR (e) MEAN & GPR (f) MGPR

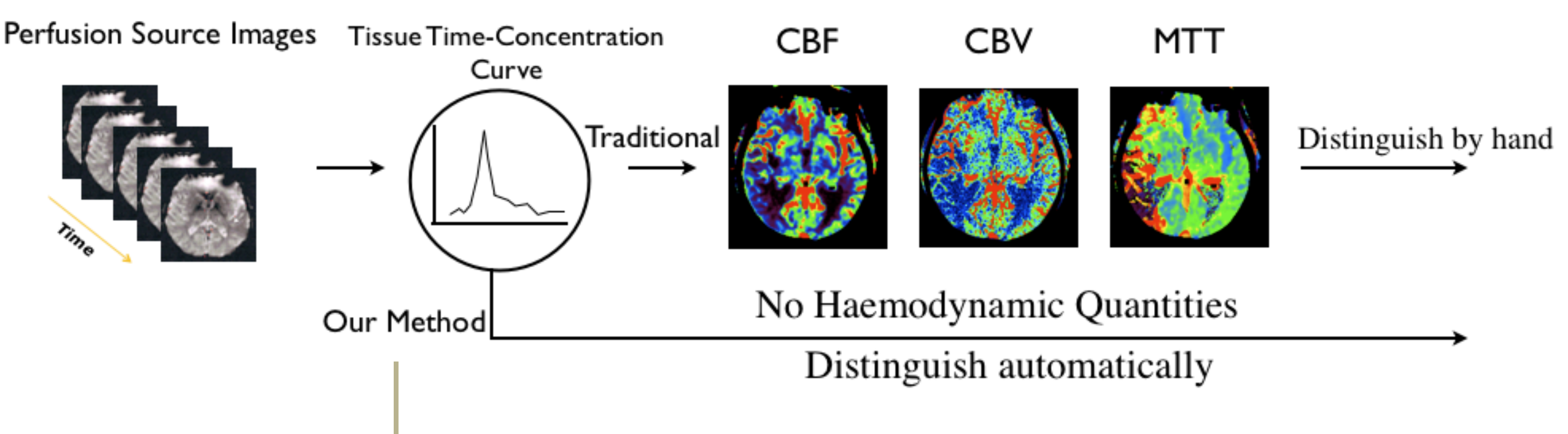
Automatic lesion area detection

Blue = Healthy
Green = ?





Pattern Recognition using Correlation Test



Using pattern recognition

Pattern Recognition using Correlation Test (con.)

ALGORITHM 1 - AUTOMATIC LESION AREA DETECTION

For $count \leftarrow 0$ **to** $sizeof(image) - 1$ {
    $image[count] \leftarrow Preprocessing(image[count])$
    $image[count] \leftarrow remove\_head\_end(image[count], 2)$
    }

$ref \leftarrow generate\_ref()$

For $count \leftarrow 0$ **to** $sizeof(image) - 1$ {
    ρ *or* $r \leftarrow correlation\_test(image[count], ref)$
    $color[count] \leftarrow translate(\rho \text{ or } r)$
    $bitmap[count] \leftarrow Student\ t\ test(\rho \text{ or } r)$
    }

return *color*[ ] and *bitmap*[ ]

Noise reduction to enhance the pattern

Pattern generation (reference)

Pattern recognition

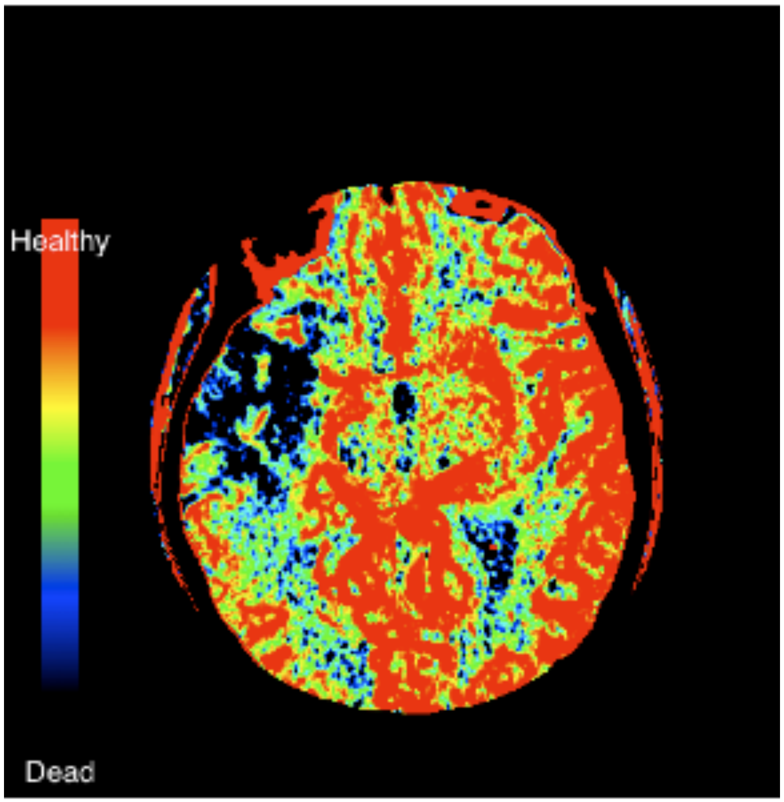
Correlation Equations

$$r = \frac{\operatorname{cov}(X,Y)}{\sigma_X \cdot \sigma_Y} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

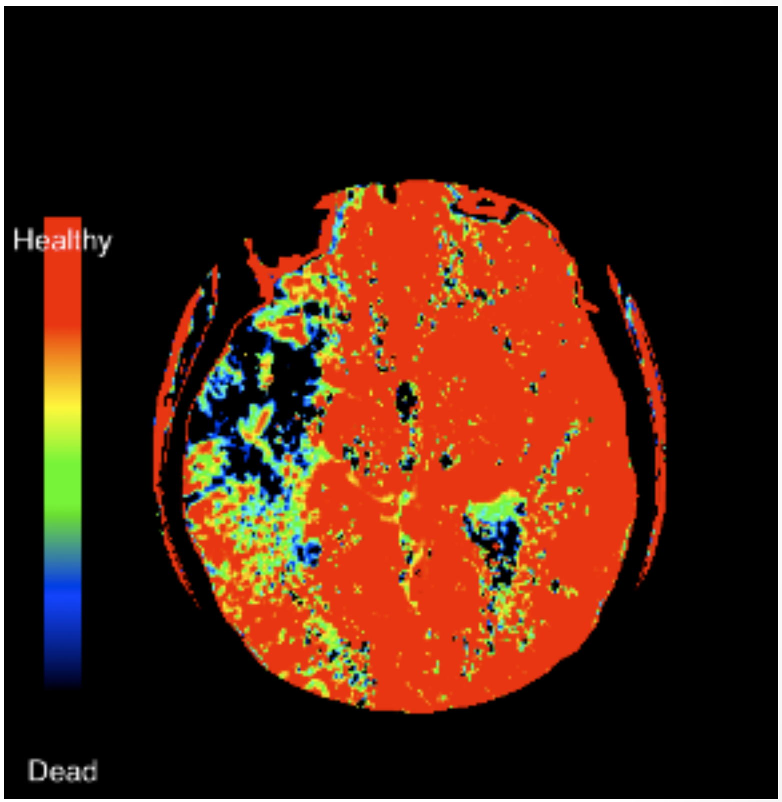
$$\rho = \frac{\sum_i (x'_i - \bar{x}')(y'_i - \bar{y}')}{\sqrt{\sum_i (x'_i - \bar{x}')^2 \sum_i (y'_i - \bar{y}')^2}}$$

$$t = r\sqrt{\frac{N-2}{1-r^2}} \quad or \quad t = \rho\sqrt{\frac{N-2}{1-\rho^2}}$$

Raw Vs. Denoised



Raw

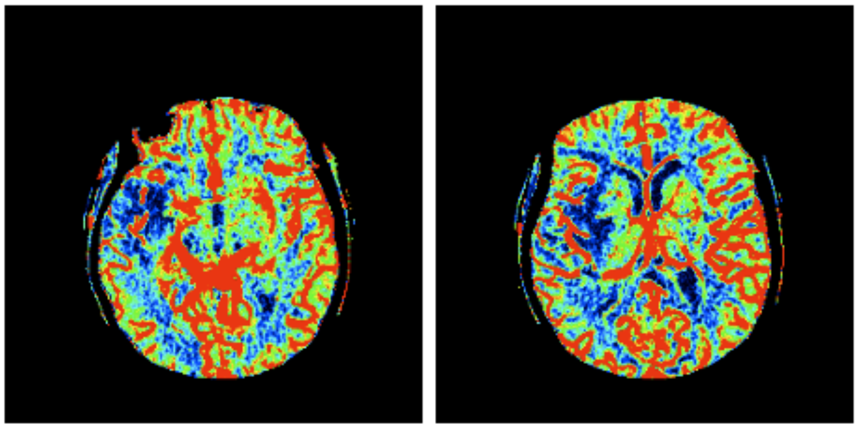


Denoised

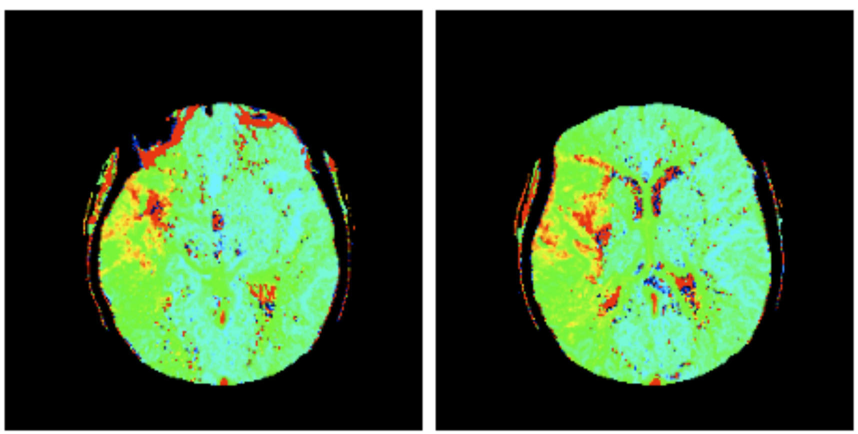
Results

Red = Healthy
Black = Dead

Brainstem
(Healthy)

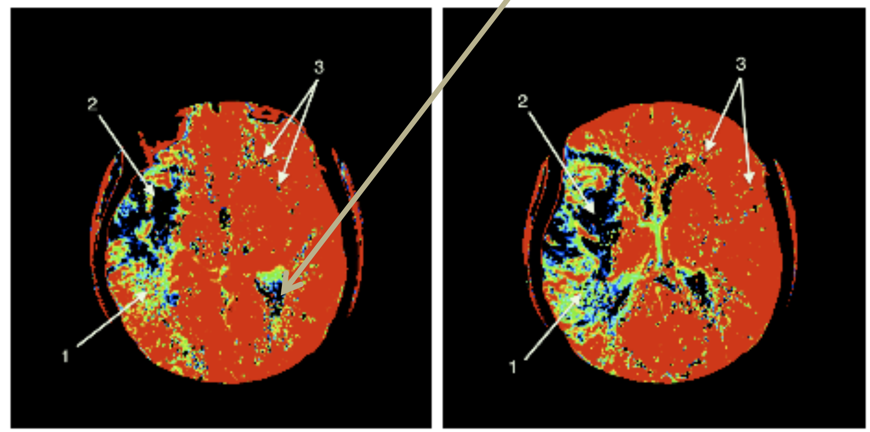


(a) Slice 1 - CBF (b) Slice 2 - CBF

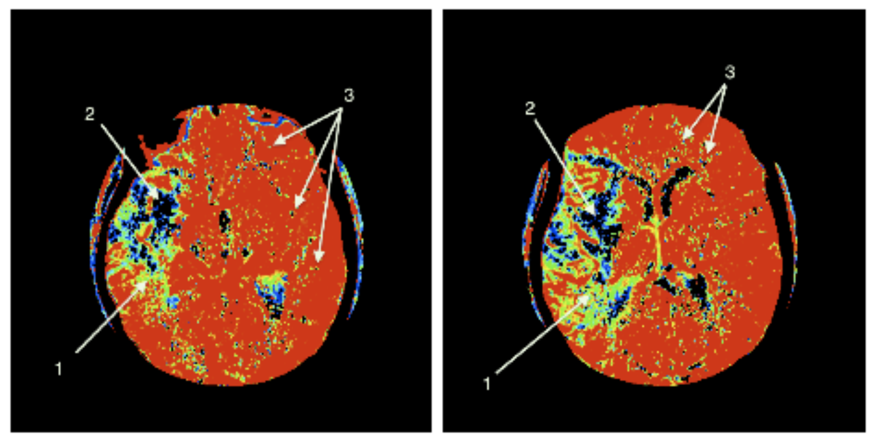


(c) Slice 1 - TTP (d) Slice 2 - TTP

Hemodynamic quantity maps



(a) Pearson's Correlation Coefficient 1 (b) Pearson's Correlation Coefficient 2



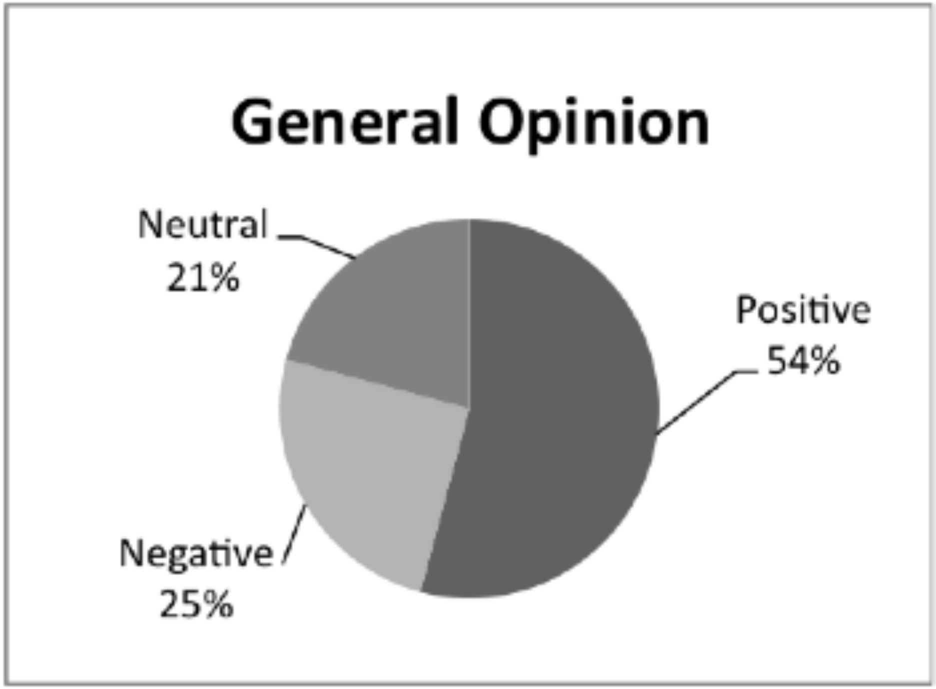
(c) Spearman's Rank Correlation Coefficient 1 (d) Spearman's Rank Correlation Coefficient 2

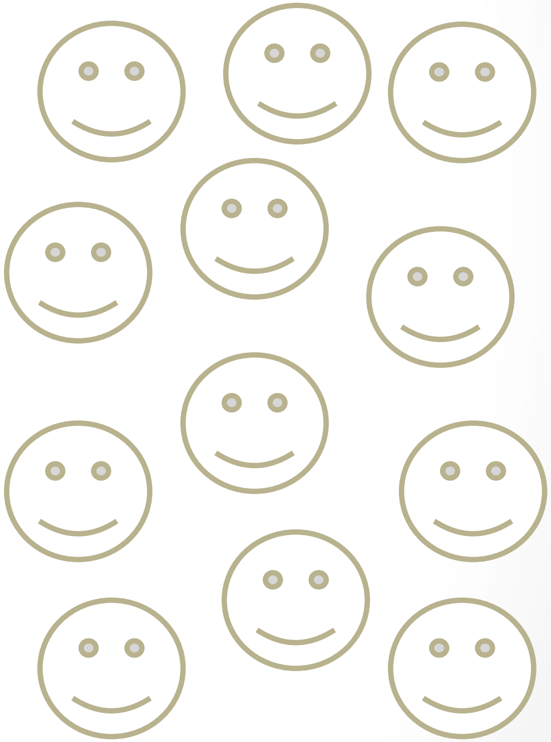
Automatic segmentations

Experts' Opinions

✖ Ground truth (noise free diagnosis result)

✔

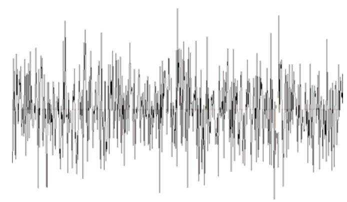




Summary

Performance

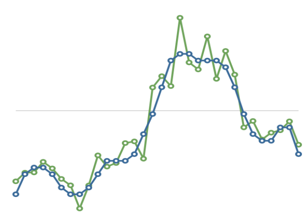
3.75X – 5.56X



Noise Reduction

CNR ↑99%

Better images



Automatic Detection

54% positive opinion

Additional information

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  - Dr. Trevor Carpenter
  - Prof. Joanna Wardlaw

edinburgh data-intensive research

cisa | Centre for Intelligent Systems and their Applications

THE UNIVERSITY of EDINBURGH informatics

ORSAS Overseas Research Students Awards Scheme

BRAIN RESEARCH IMAGING CENTRE Edinburgh

SINAPSE Scottish Imaging Network - A Platform for Scientific Excellence

Scottish Funding Council

NHS Lothian