Study of pulse-coupled neural networks for glioma segmentation.

Brad Niepceron, Ahmed Nait-Sidi-Moh and Filippo Grassia. University of Picardie Jules Vernes

Speaker: Brad Niepceron. brad.niepceron@etud.u-picardie.fr

01

CONTEXT

Towards lighter diagnosis solutions

- High interest for computer aided diagnosis
- Deep Learning as a solution for medical image analysis
 - Training models is **time** consuming
 - Need for expensive dedicated hardware
 - High energy cost
- Rise of biologically plausible solutions
- Image processing using Pulse-coupled neural networks

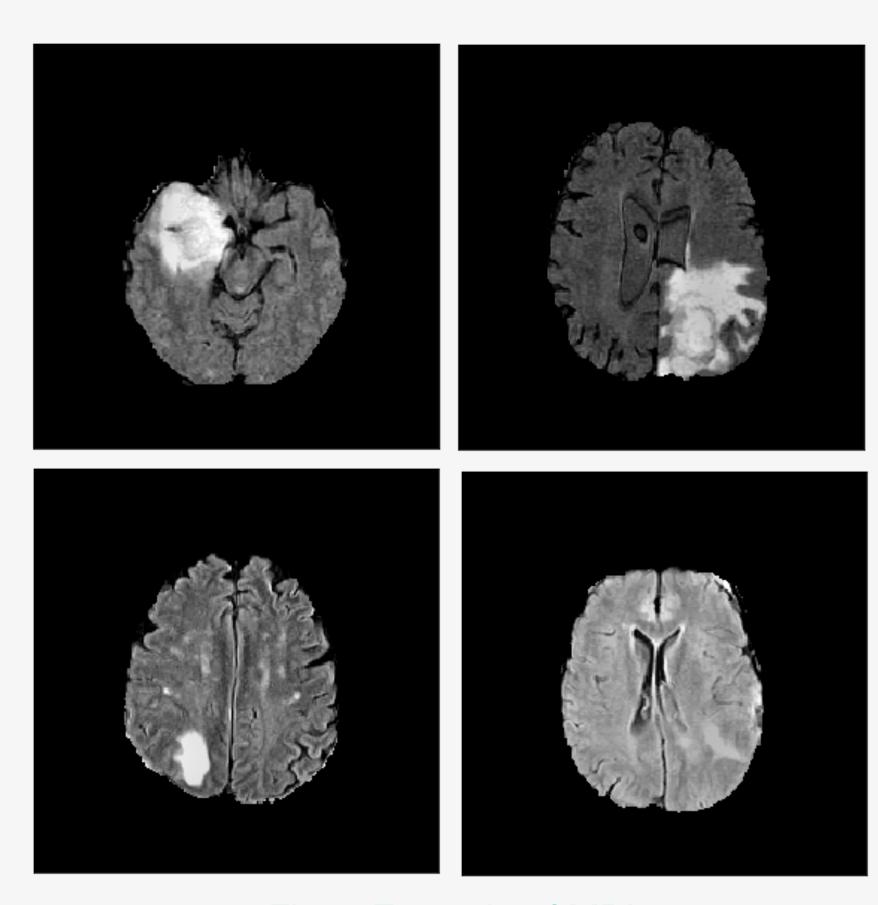


Fig 1. Example of MRI

Dataset info:

- Pre-operative MRI scans
- Manually segmented by 1-4 raters
- Four MRI sequences: Flair, T2, T1, T1C
- Contains 3 unhealthy cell labels
- Focused on segmentation and overall survival

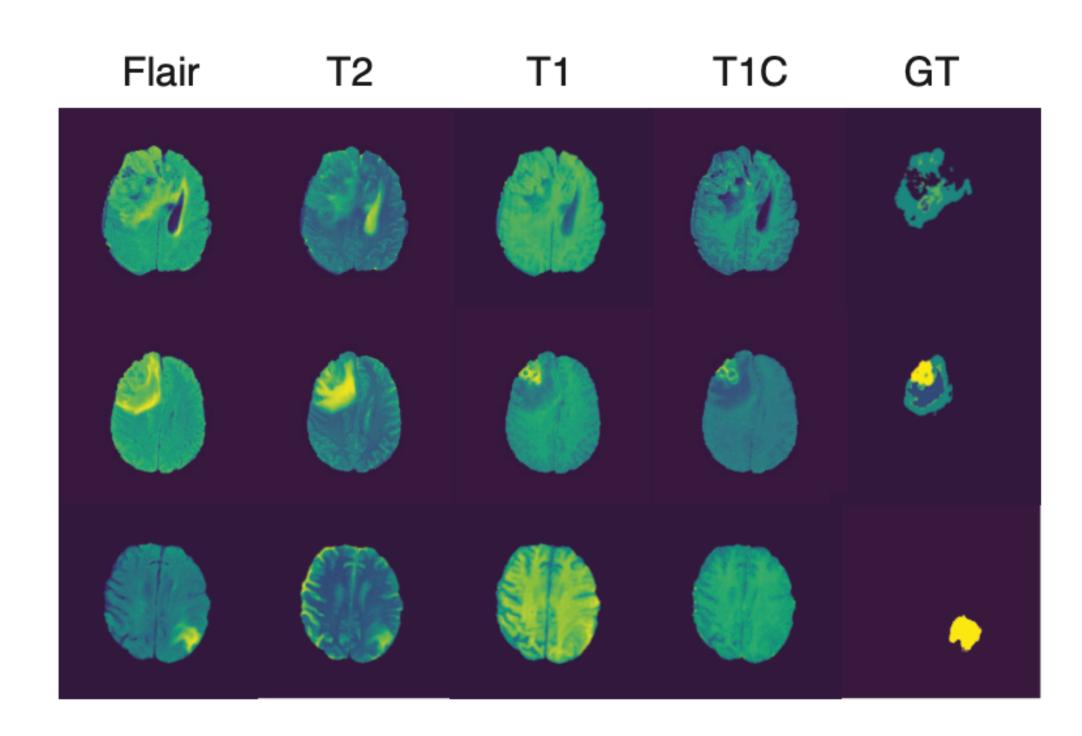


Fig 2. MRI cases taken from the BRaTS Dataset

Pixel intensity normalization and histogram matching applied

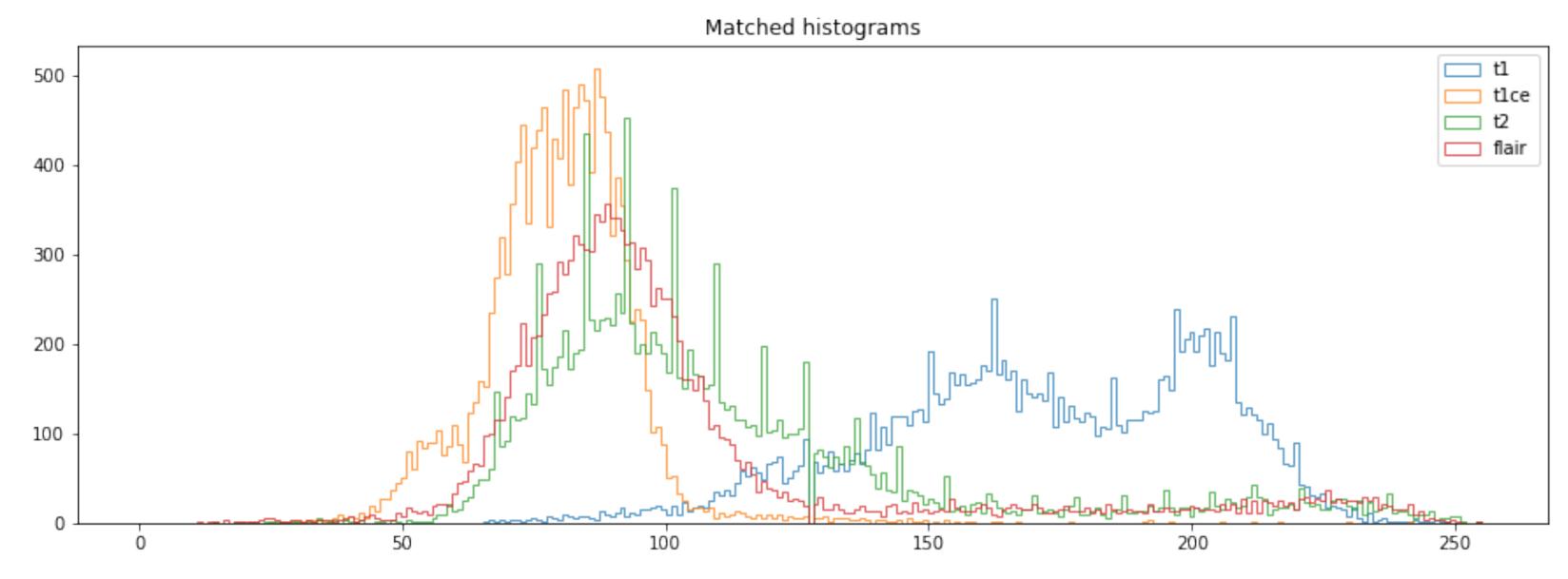


Fig 3. MRI sequence histogram matching

METHODS BRaTS 2020 Dataset

Fusion strategy using Discrete Wavelet Transform

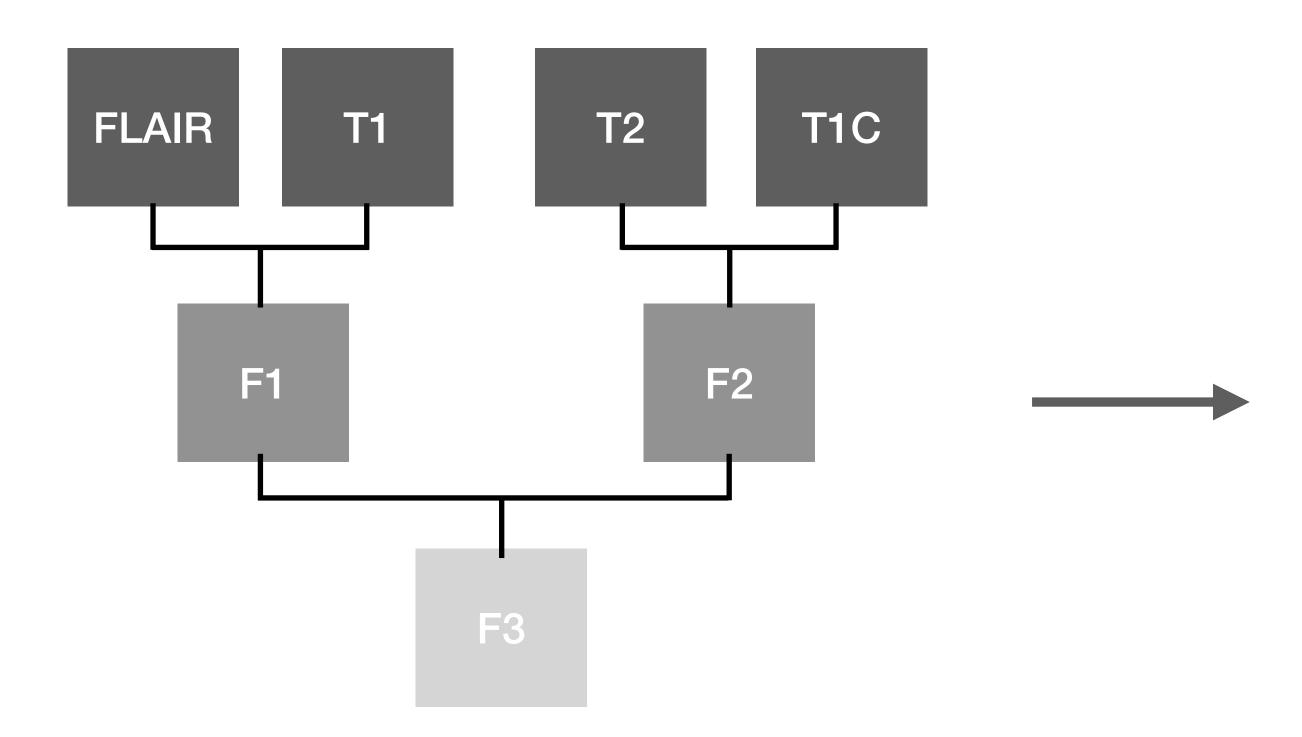


Fig 4. DWT computation tree

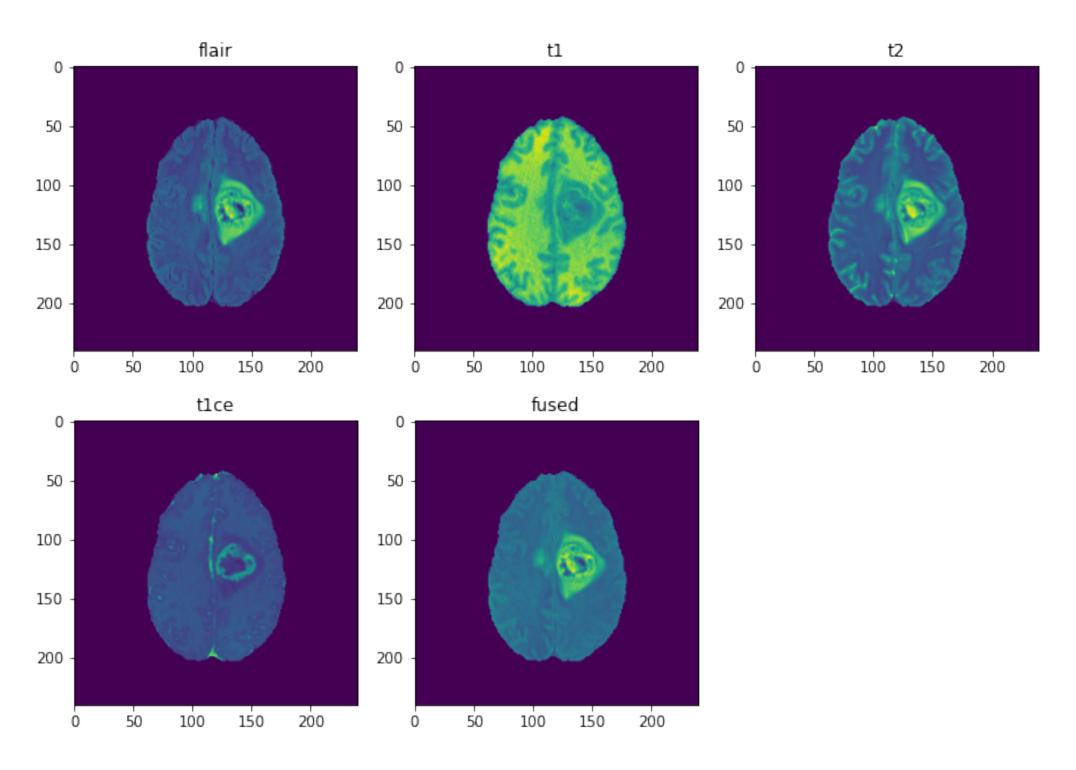


Fig 5. Sequences and fused image

Standard PCNN:

- Laterally-connected neurons
- 2D input image
- Feeding: Computes voltage with input stimulus
- Linking: Updates neuron's internal activity
- Pulse: Fire if membrane potential exceeds threshold

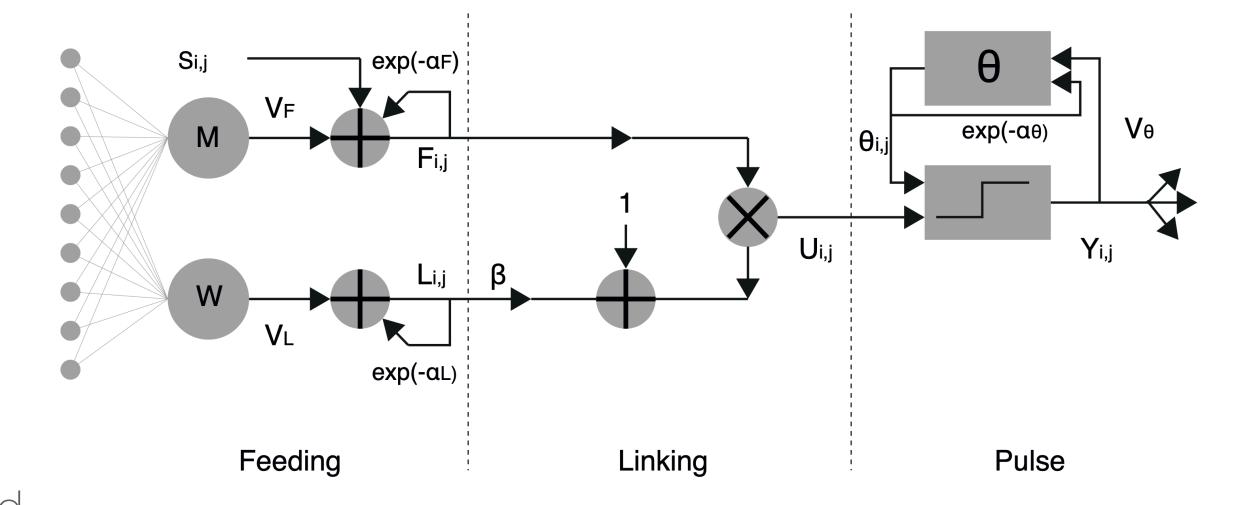


Fig 6. Standard PCNN

Unit-linking

- Simplified version of PCNN
- Reduced computational cost
- Reduced parameters

Changes

- Feeding: Now equal to the intensity of a pixel
- Linking: Allows a neuron to fire when one or more neighbors fired

Fast-linking

- Uses Spiking cortical neurons
- Fast linking synapses
- Neurons fire faster

Changes

- Feeding: As for Unit-linking
- Pulse: Combines stimulus and synaptic modulation to charge the membrane



Parameters settings:

- Differential Evolution for optimization
- Dice Score as loss function $\frac{2|Y\cap Y|}{|Y|+|\hat{Y}|}$
- Iteration number constrained to 10

Model	Standard PCNN	ULPCNN	FLSCM
$\overline{\beta}$	0.47	0.47	0.44
$lpha_{ heta}$	0.0125	0.015	_
$lpha_F$	0.96	_	_
$lpha_L$	0.81	_	_
$V_{ heta}$	20	20	20
V_F	0.21	_	_
V_L	0.36	-	-
W	3x3 gaussian kernel	_	-
M	\mathbf{W}	_	-
$lpha_U$	-	-	0.49

Table 1. Parameters used for our experiments

- Segmentation evaluated with Dice Score
- Iteration can be stopped if best dice score has been found.
- Fast-linking average running time: 17 seconds
- Unit-linking average running time: 17 seconds
 - PCNN average running time: 60 seconds

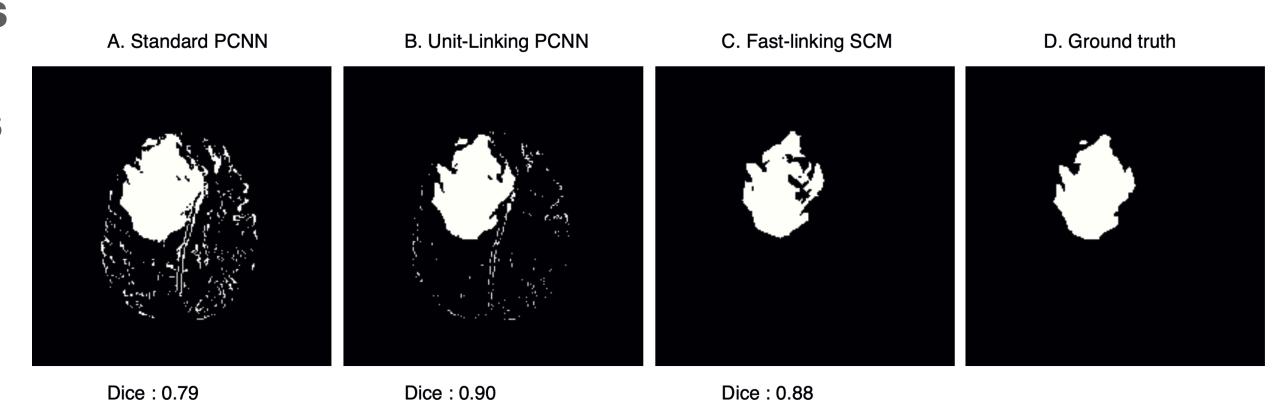


Fig7. Results of PCNN based segmentation

CONCLUSION

- Experiments proved the efficiency of PCNN models
- Fast computation makes PCNN a perfect fit for diagnosis tasks
- Differential Evolution coupled with Dice Loss appeared efficient for segmentation parameters optimization

- Multi-channel versions could be use for semantic segmentation
- PCNN can be coupled with a spiking classifier

Thank you.

Brad Niepceron, Ahmed Nait-Sidi-Moh and Filippo Grassia. University of Picardie Jules Vernes

Speaker: Brad Niepceron. brad.niepceron@etud.u-picardie.fr