

Calibration and evaluation of a machine learning algorithm for β^+ brain imaging using an intracerebral micro probe

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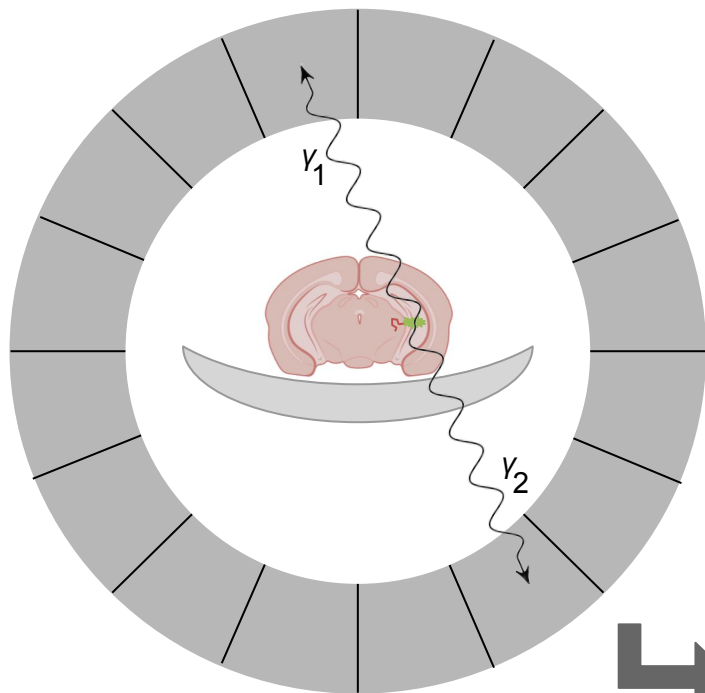
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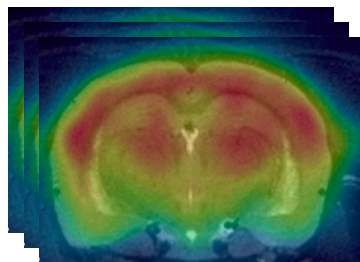


Context: Preclinical neuroimaging with micro-PET



micro-Positron Emission Tomography (micro-PET):

- Use injected β^+ radioisotopes
- Detects gamma rays from β^+ /e- annihilation
- High sensitivity (pmol)
- **Requires anesthesia**
 - What is the effect of the **anesthesia**?
 - Perform **simultaneous behavior** studies and real time **neuroimaging**



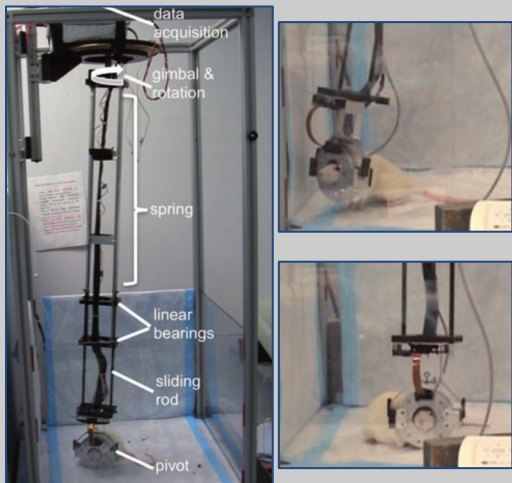


Context: Neuroimaging in awake and freely moving small animals

Stakes:

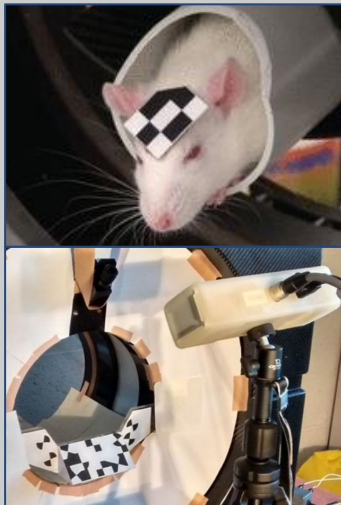
- Understand **anesthesia** effects on neuroimaging
- Perform **simultaneous behaviour** and **neuroimaging**

RatCAP



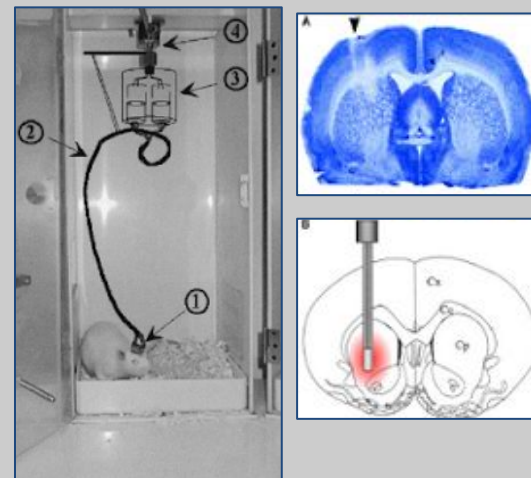
Schulz et al., Nature methods, 2011.

Motion tracking



Spangler-Bickell et al., Phys. Med. Biol., 2016.

Beta Microprobe



Pain et al., PNAS, 2002.



MAPSSIC Project

Goals

To develop a pixelated β^+ sensitive imaging device

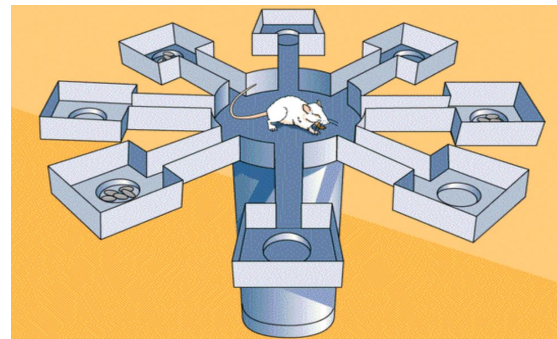
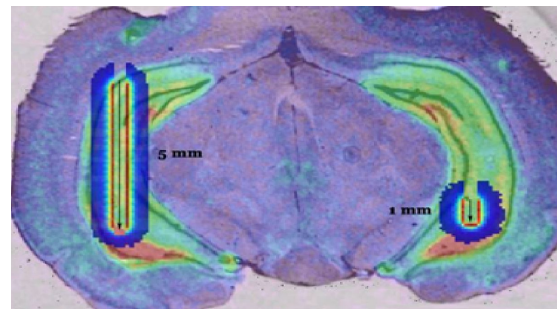
Direct detection of short range β^+

To give a real **autonomy** to the rat

Constrains

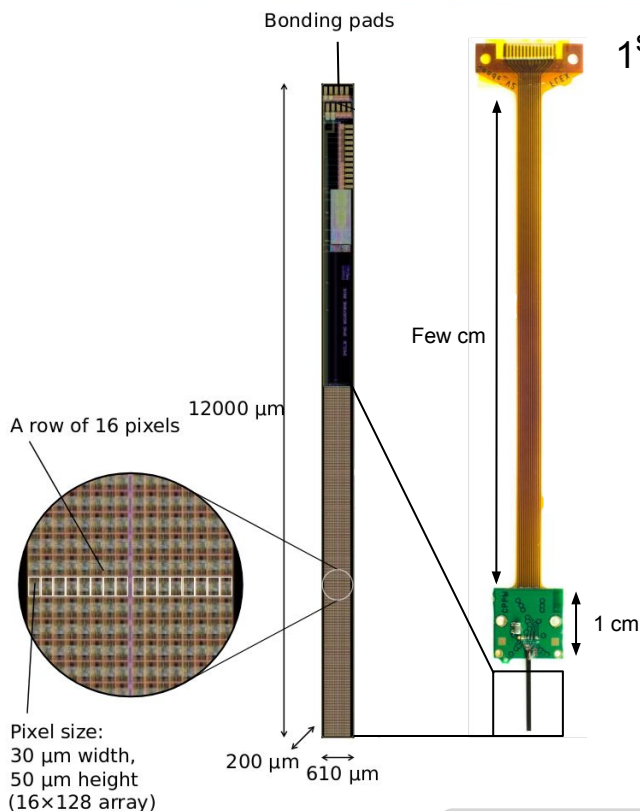
Weight limit: 10% of the animal \approx 35g

Low electrical consumption



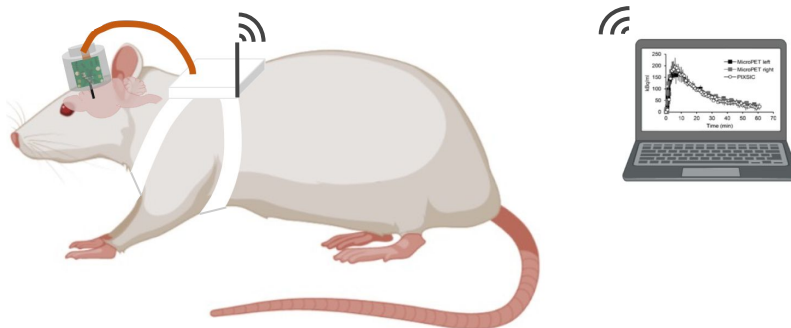


Context: Neuroimaging in awake and freely moving rats



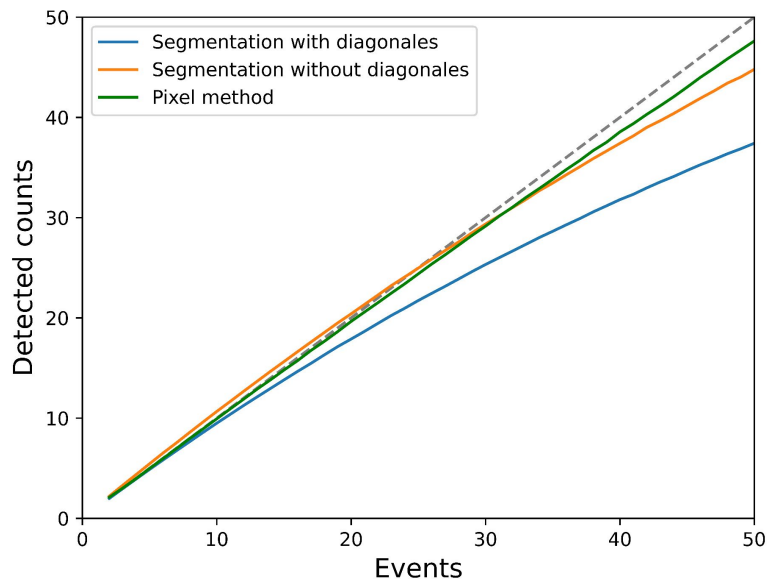
1st digital sensor prototype (IMIC-1, 2018):

- Based on **MAPS technology**
- Sensitive thickness: 18 μm
- Pixel digitation: **1 bit**
- Probe made with 2 sensors glued back to back
- **Rolling-shutter** + microcontroller, 500 ms integration time
- **Expecting 100 counts/s** max at in vivo use



Consequence : **Pile up** occurs at high count rates

Activity	
Low	High



→ **Best method so far** : Cluster size method.



Advantage : Allows a limited loss in sensitivity

Drawback : **No event localization**

Previously explored methods¹ :

1. Simple segmentation = contouring (with/without diagonals)
2. Cluster size method: Estimate counts number using the number of activated pixels over the mean number of activated pixels per clusters:

$$\text{Cluster number} = \frac{\text{\# activated pixels}}{\text{mean \# of pixels per cluster}}$$

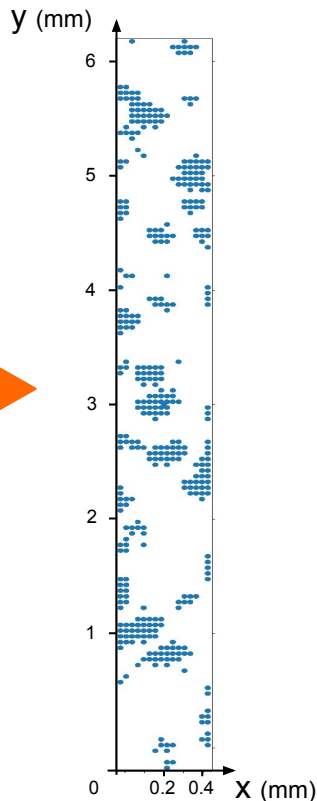
1. Luis Ammour. Développement d'une sonde intracérébrale à pixels actifs pour l'imagerie bêta du cerveau du rat libre de ses mouvements. Université Paris Saclay (COmUE), 2018. Français.



Frame



Coordinates



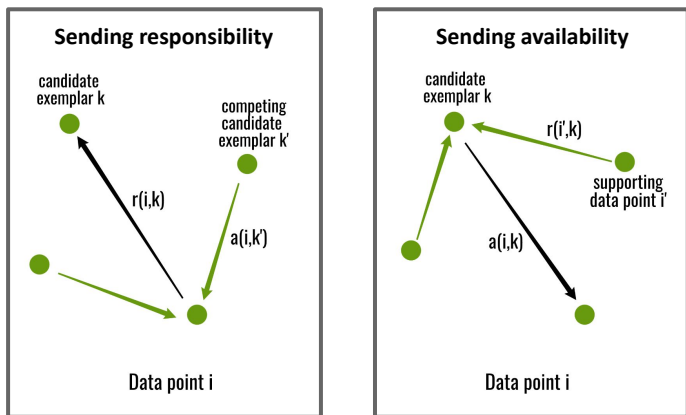
AFFINITY PROPAGATION algorithm² :

- Based on iterative message passing between Data points
- Implemented in Scikit-Learn

2. Brendan J. Frey and Delbert Dueck, "Clustering by Passing Messages Between Data Points", Science Feb. 2007



AFFINITY PROPAGATION algorithm² :

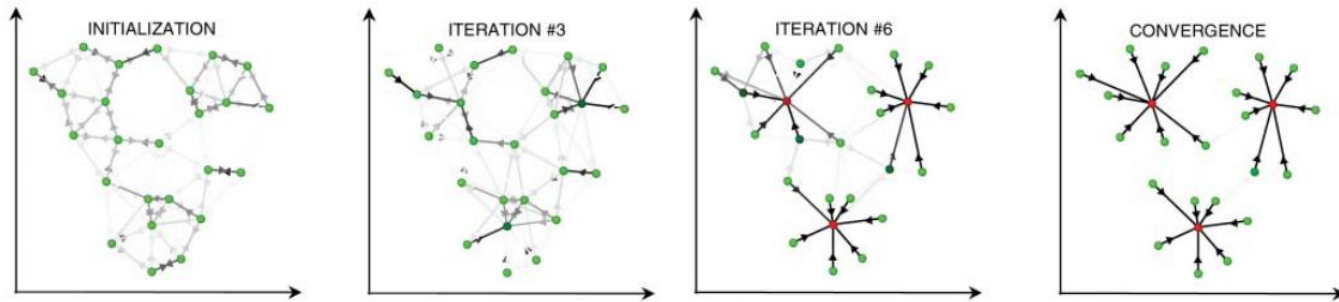


- Based on iterative message passing between Data points
- Implemented in Scikit-Learn
- 2 types of passing messages:
 - *responsibility* $r(i,k)$:
 - *availability* $a(i,k)$:
- Determine the **number** and the **position** of clusters
- **No cluster number needed as input**
- Each cluster is composed by an *exemplar* (which better represents the distribution) and targets (points associated to an exemplar)

2. Brendan J. Frey and Delbert Dueck, "Clustering by Passing Messages Between Data Points", Science Feb. 2007



Affinity propagation algorithm



Brendan J. Frey and Delbert Dueck, "Clustering by Passing Messages Between Data Points", Science Feb. 2007

- Influence parameter :
 - **Preference** : Calculated number of clusters is **directly influenced** by the *preference* value

→Need for **calibration** of the algorithm : Search for the optimal *preference* value for AP clustering on frames containing from 1 to 100 clusters



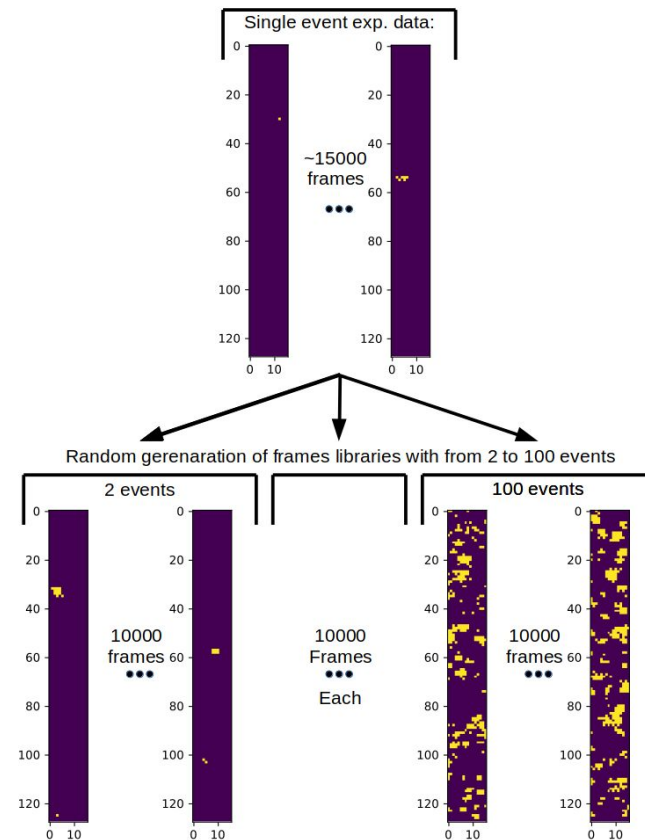
Data generation

Data generation:

- From **experimental frames** ($N \approx 15\,000$)
 - Obtained with **^{18}F source**
→ (liquid source in contact with the sensor)
 - Containing exactly 1 cluster
- **Random generation** of 1 to 100 clusters frames
($N = 2$ million)

Calibration frames (50 %)

Validation frames (50 %)

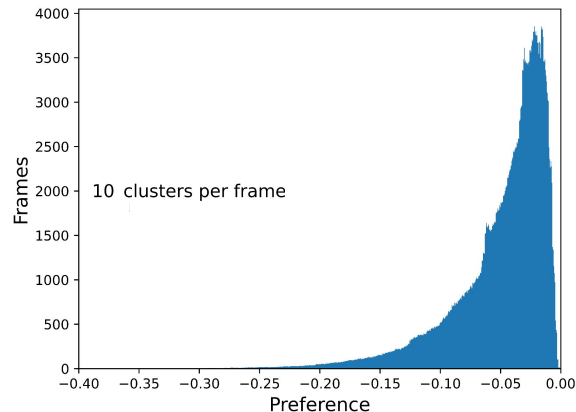
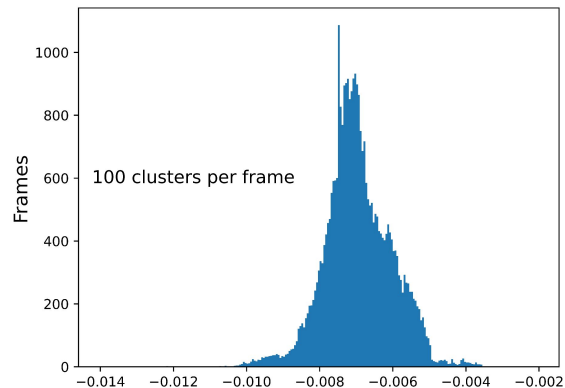




Data processing from AP calibration runs:

- Determination of the optimal *preference*:
 - AP runs on calibration frames **scanning** the previously determined **preference range**
 - **Mean** and **Mode** of the distribution *preference* values leading to the **smallest error** between calculated and actual cluster number for a given frame
 - Gaussian draw of a new *preference* value if the previous does not converge to an answer (400 times maximum)

Distribution of preference values giving the smallest error

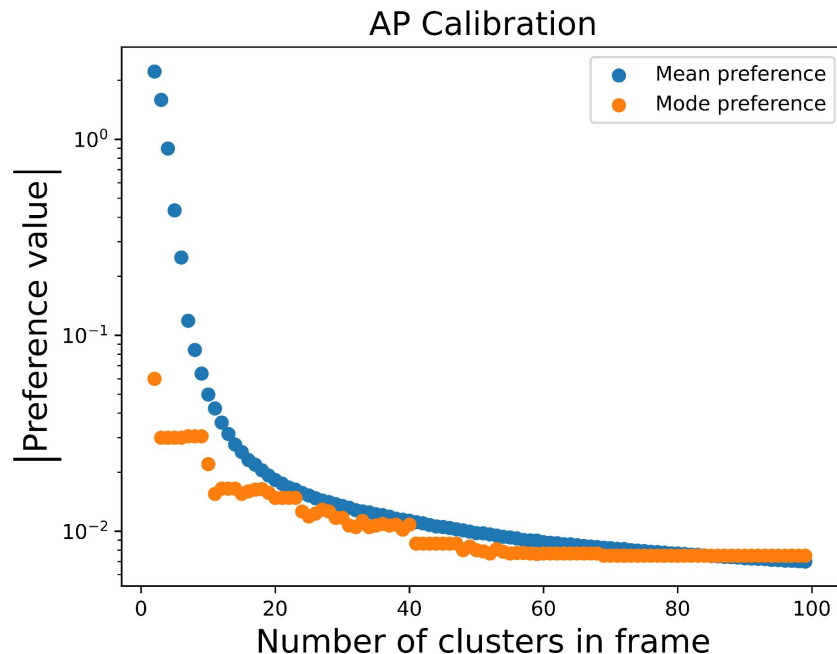




Affinity propagation algorithm - Validation

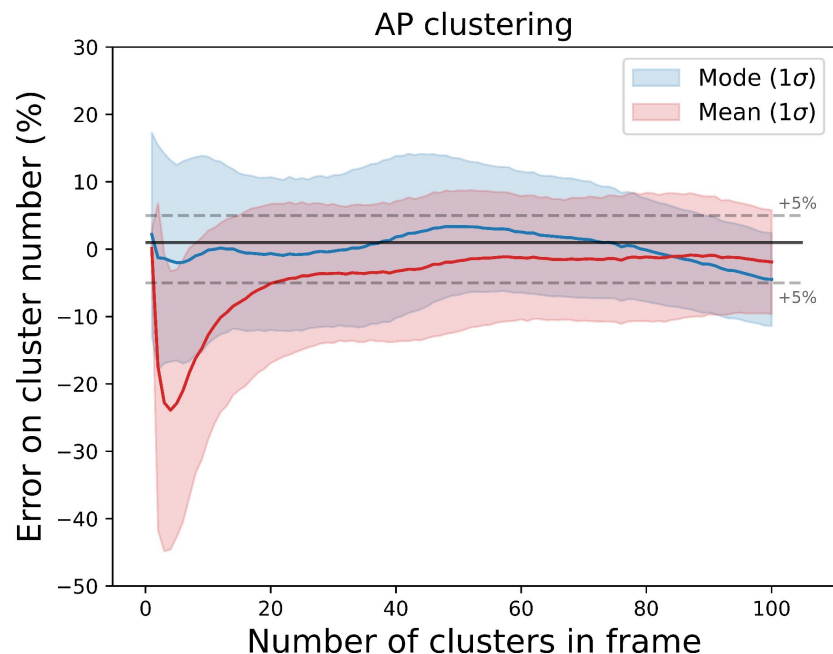
Run of AP algorithm on the validation data set with both mean and mode *preference* values :

- Actual operating conditions
- **No a priori** on the cluster number per frame.
→ **Rough estimation** of the cluster number based on the number of activated pixels
- Run of AP algorithm with the selected *preference* values according to the estimated cluster number (taking into account the estimation bias).





Affinity propagation algorithm - Validation



Results on validation frames:

- ≥ 50 clusters/frame, the mode *preference* performed better than the mean *preference*
- ≤ 50 clusters/frame, mean *preference* shows a drop in accuracy
- Using the mode *preference* gives an error not greater than 5% no matter the number of clusters per frame

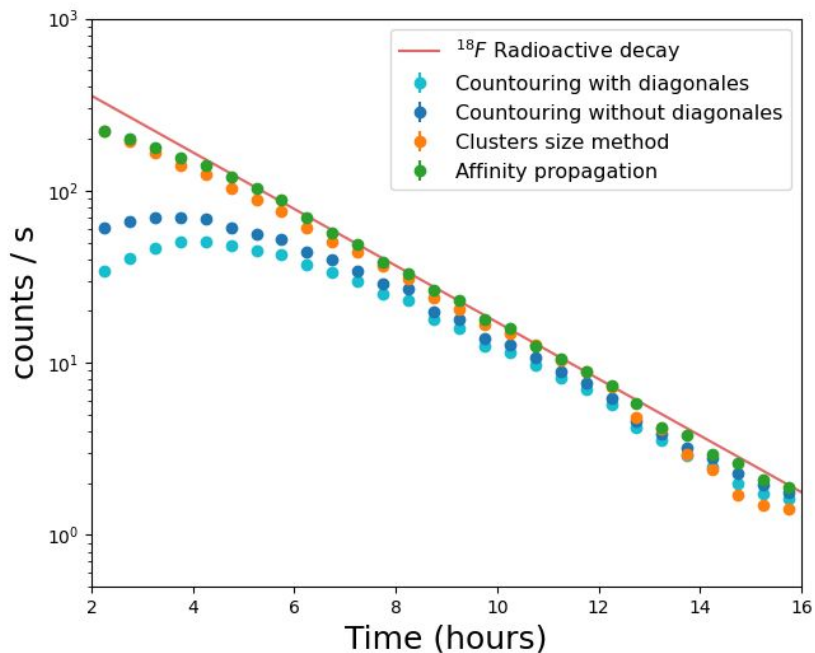


Mix of AP algorithm with mean and mode preference values according to the estimation



Affinity propagation algorithm - Validation

AP algorithm **performed on experimental Data** from ^{18}F radioactive decay measurement:



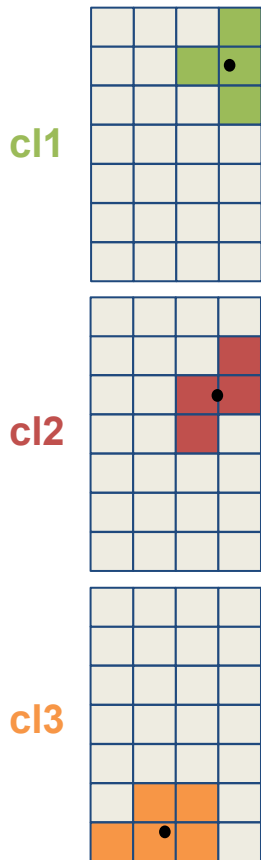
- **Achieved linearity** for the expected count rates for *in vivo* measurements
- Calculation time varies from **few milliseconds** to 0.5 seconds per frame



Results compatible with *in vivo* measurements



Affinity propagation algorithm - Spatial performances

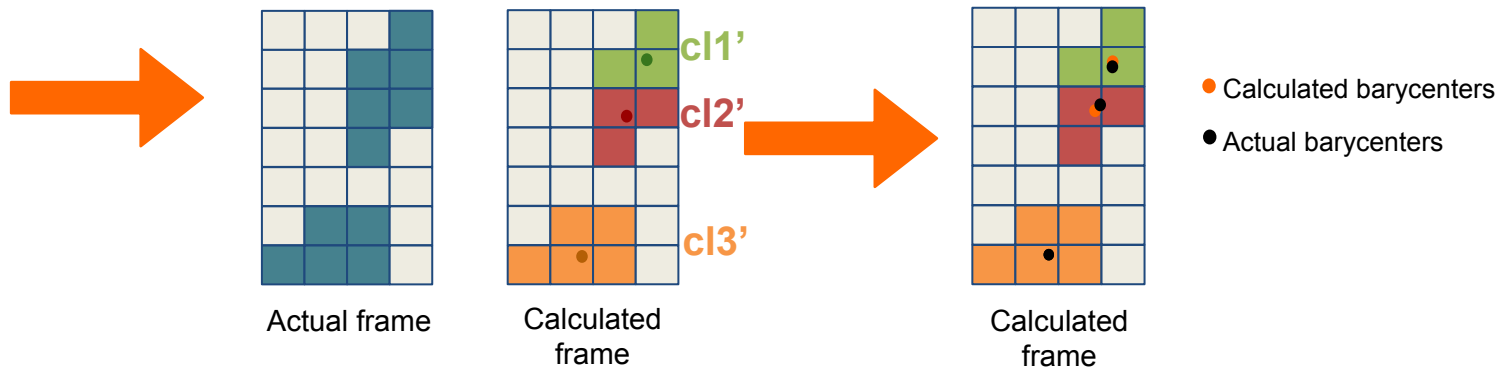


- Determination of the barycenter for each real cluster
- Determination of the barycenter for each calculated cluster
- Error on **weighted average barycenters**

$$cl1_{err} = (cl1 - (3 \times cl2' + 1 \times cl1' + 0 \times cl3'))/4$$

$$cl2_{err} = (cl2 - (1 \times cl2' + 3 \times cl1' + 0 \times cl3'))/4$$

$$cl3_{err} = (cl3 - (0 \times cl2' + 0 \times cl1' + 5 \times cl3'))/5$$

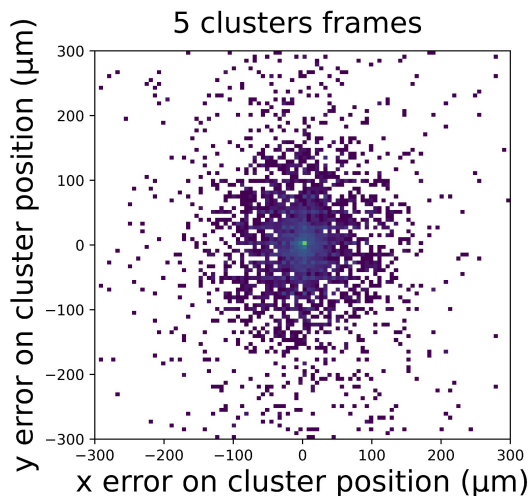




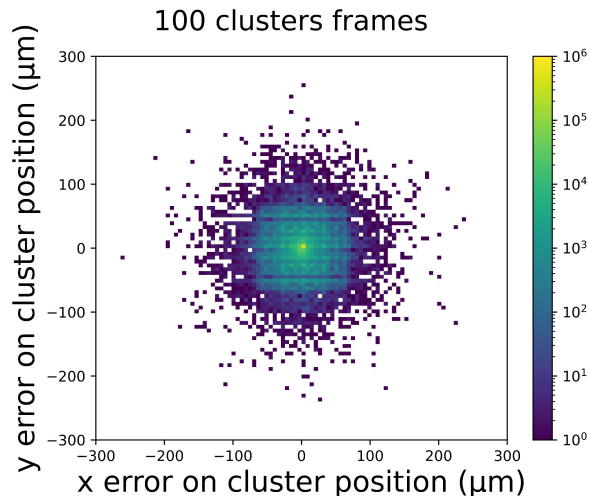
Affinity propagation algorithm - Spatial performances

Spatial study : Error on cluster barycenter

- **Errors** on x and y axis: mean σ of **16.5 μm** and **26.2 μm**
→ 95% error equal or smaller than pixels size (2σ)
- Error ($\approx \mu\text{m}$) < explored structures (ie: rat striatum $\approx \text{mm}$)



$\sigma_x = 23.9 \mu\text{m}$ $\sigma_y = 88.9 \mu\text{m}$



$\sigma_x = 15.5 \mu\text{m}$ $\sigma_y = 17.5 \mu\text{m}$



The use of **Affinity propagation** algorithm:

- Offers a **fast and reliable** clustering of counts in frames
- Improves the counting of events
- Allows for an **accurate spatial localization** of events



Perspectives:

- Calibrate the algorithm with Data from the **new sensor prototype**
- Impact of other parameters → improve **computing time**
- Apply AP for ***in vivo* measurements** (e.g. for non homogeneous frames)

New Sensor prototype and electronics developed and being tested

MAPSSIC collaboration



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Franck Agnese
Jérôme Baudot
Maciek Kachel



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Christian Morel
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THANKS FOR YOUR ATTENTION