Wavelet-Based Extraction of Transient Noise in Gravitational-Wave Interferometers using a Learning Architecture Guided by Manifold Clustering

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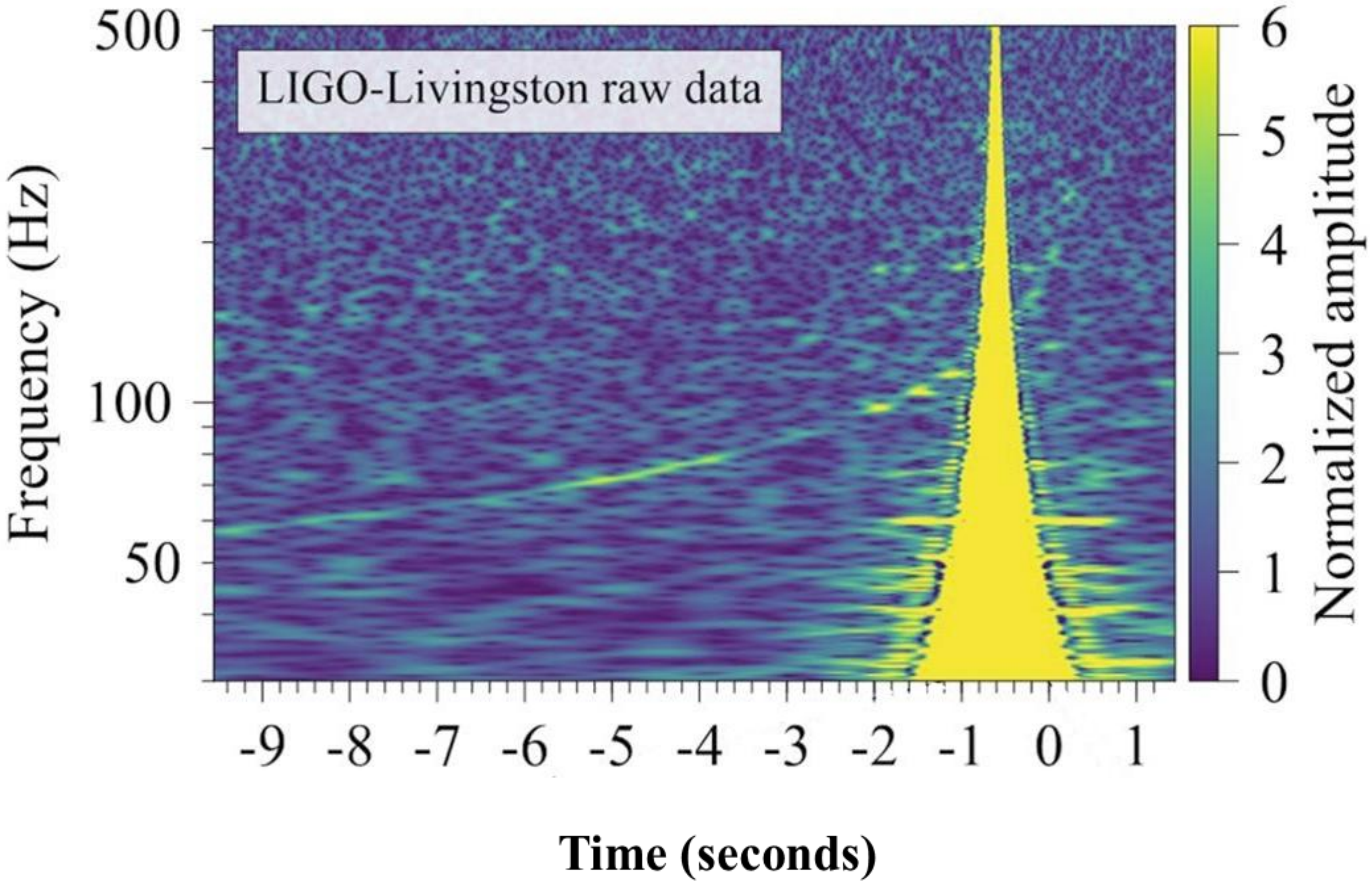
JSPS

Glitch



Glitch:

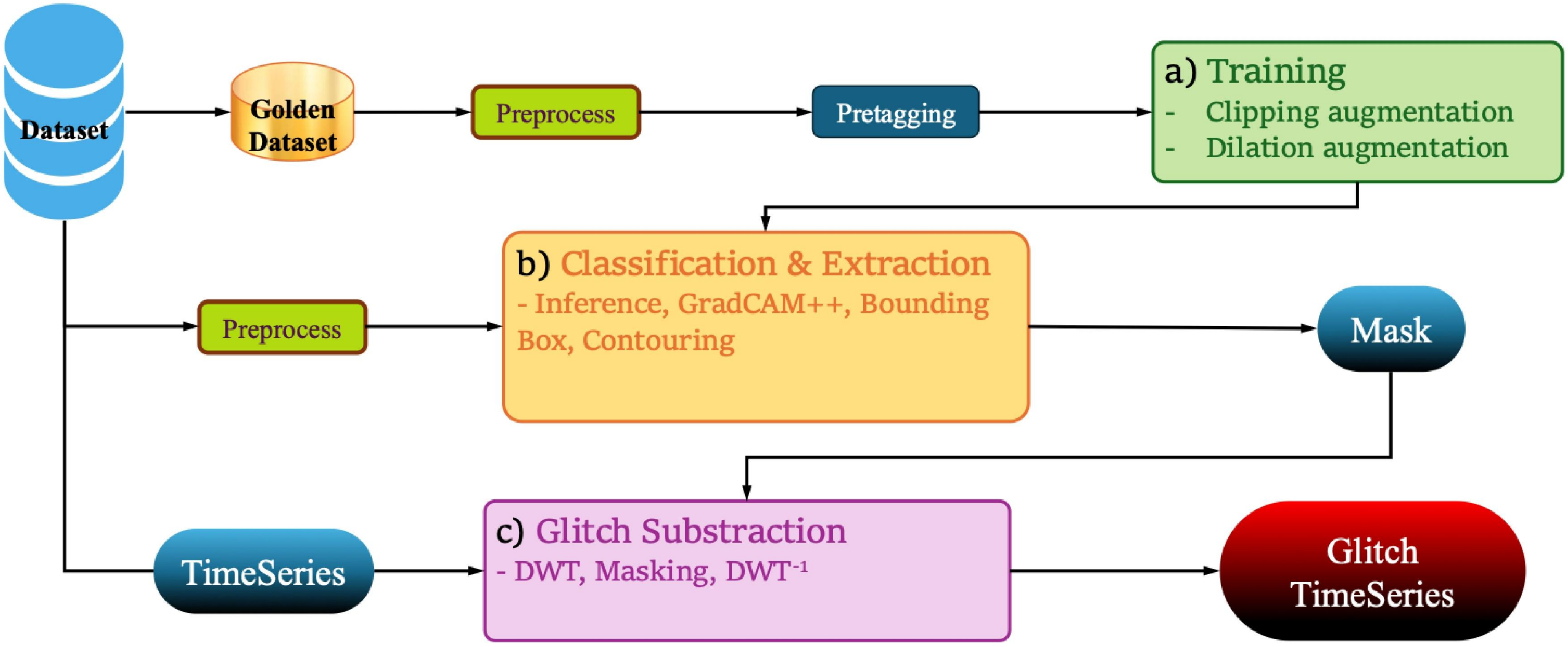
- Short-duration transient noise;
- Can be superimposed on astrophysical signal;
- Can be very loud;
- Can last until ~4 s;

Motivation

- To isolate glitches;
- Better understanding of the noise (non-gaussian one especially);
- Be able to produce bank of glitch to simulate noise with non-gaussianities;

⇒ We need then to be able to **segment** and to **subtract** glitches

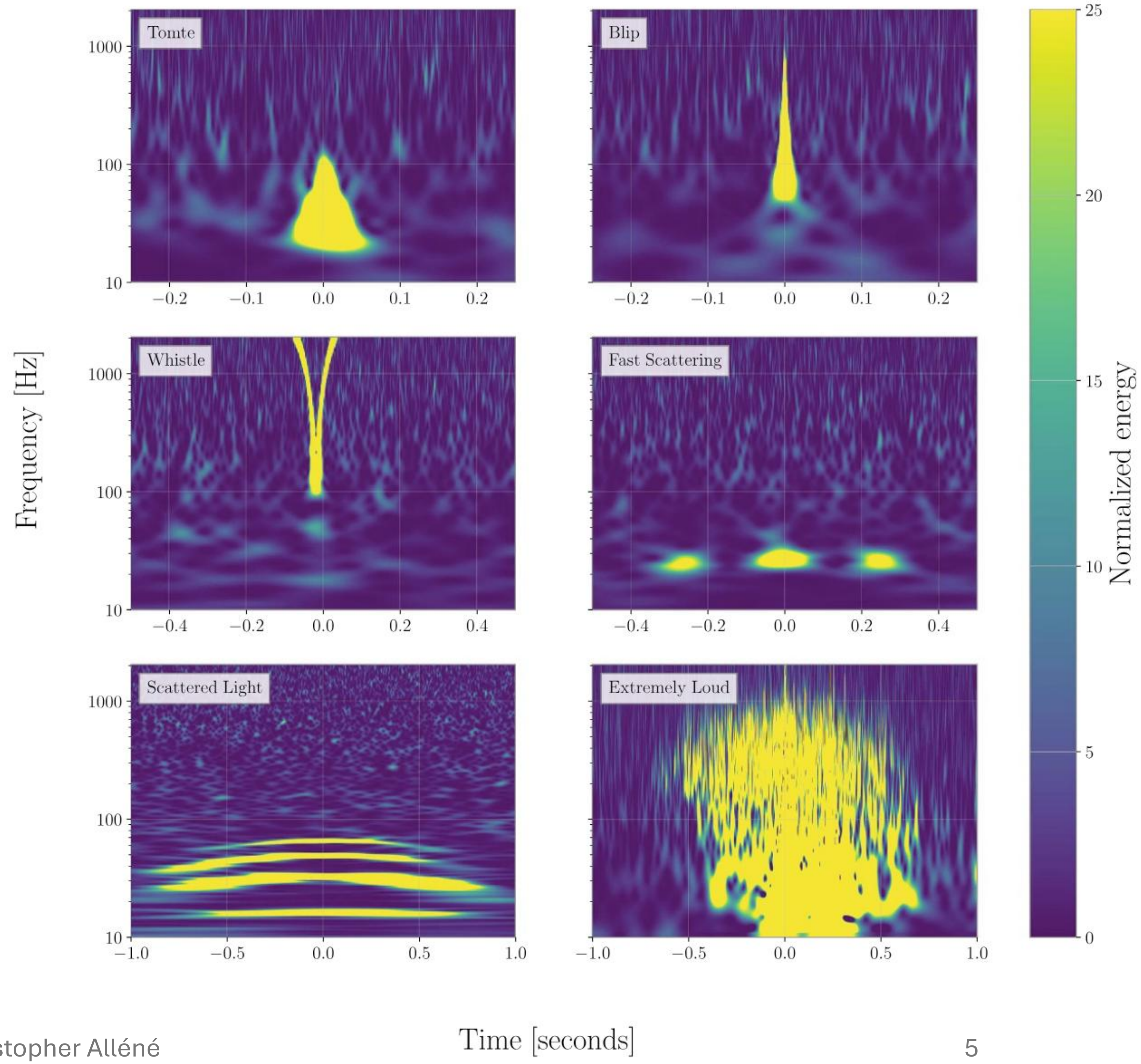
Workflow


Dataset
Golden Dataset
Preprocess
Pretagging
a) Training
- Clipping augmentation
- Dilation augmentation
Preprocess
b) Classification & Extraction
- Inference, GradCAM++, Bounding Box, Contouring
Mask
TimeSeries
c) Glitch Substraction
- DWT, Masking, DWT-1
Glitch TimeSeries

Golden Dataset Sele

- Among 26 classes* focus on Blip, Whistle or Scattered Light;
- Equipartition of event type
- GravitySpy CL> 95%
- No siblings or neighbour events
  - No events in a ±2 s window

*according the GravitySpy classification (Zevin et al. 2017)



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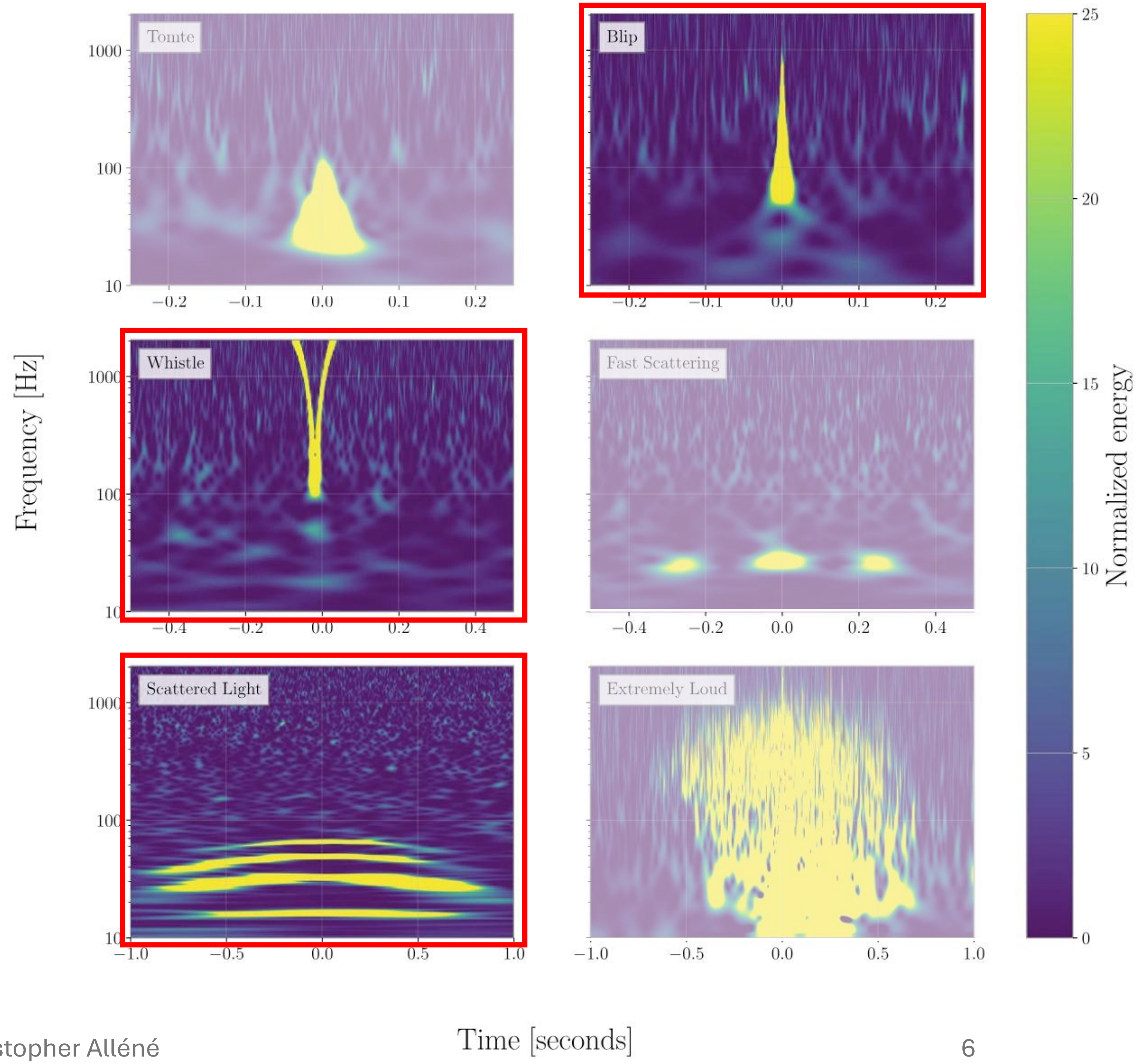

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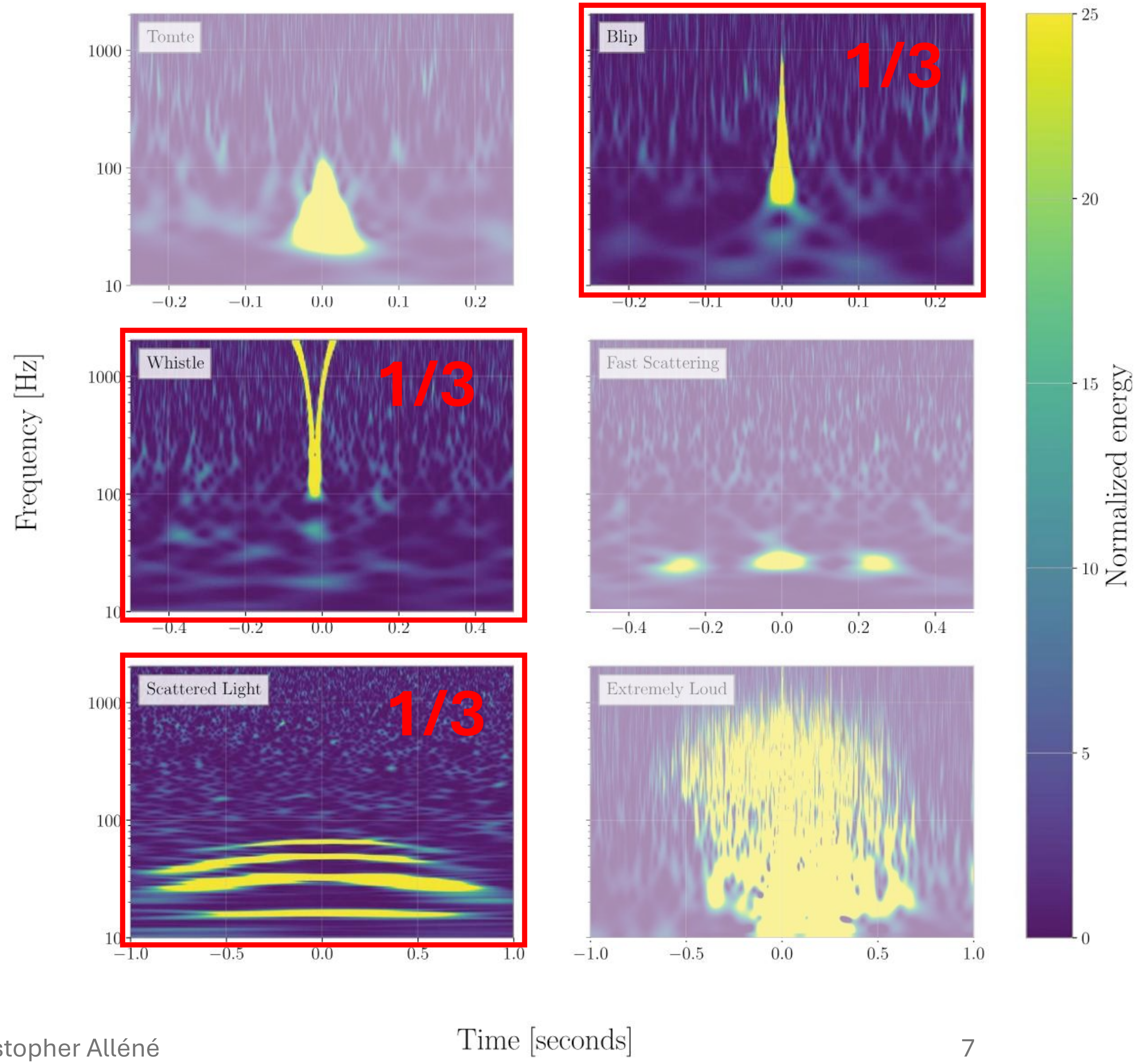

Golden Dataset Selection

- Among 26 classes* focus on Blip, Whistle or Scattered Light;
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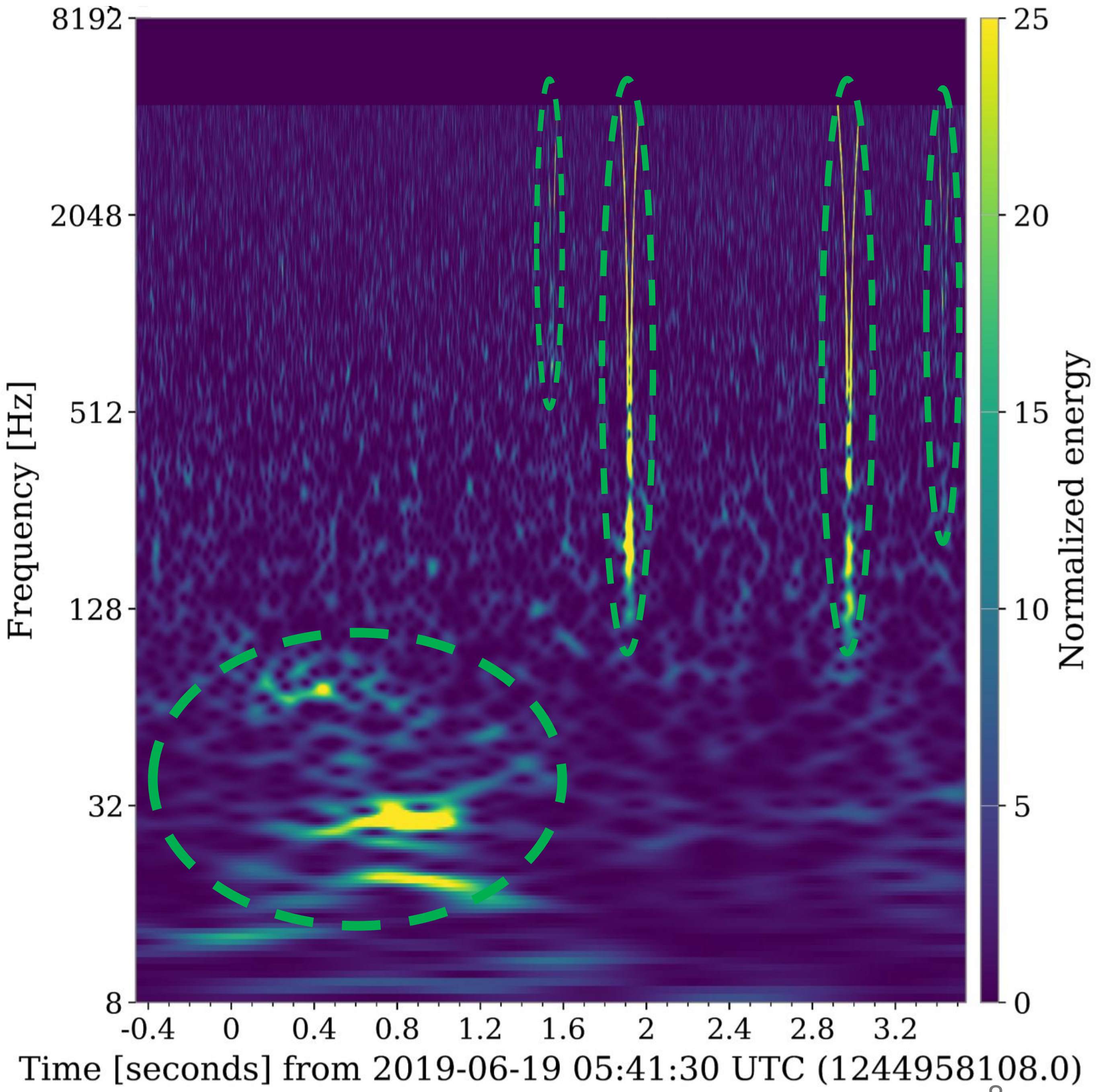
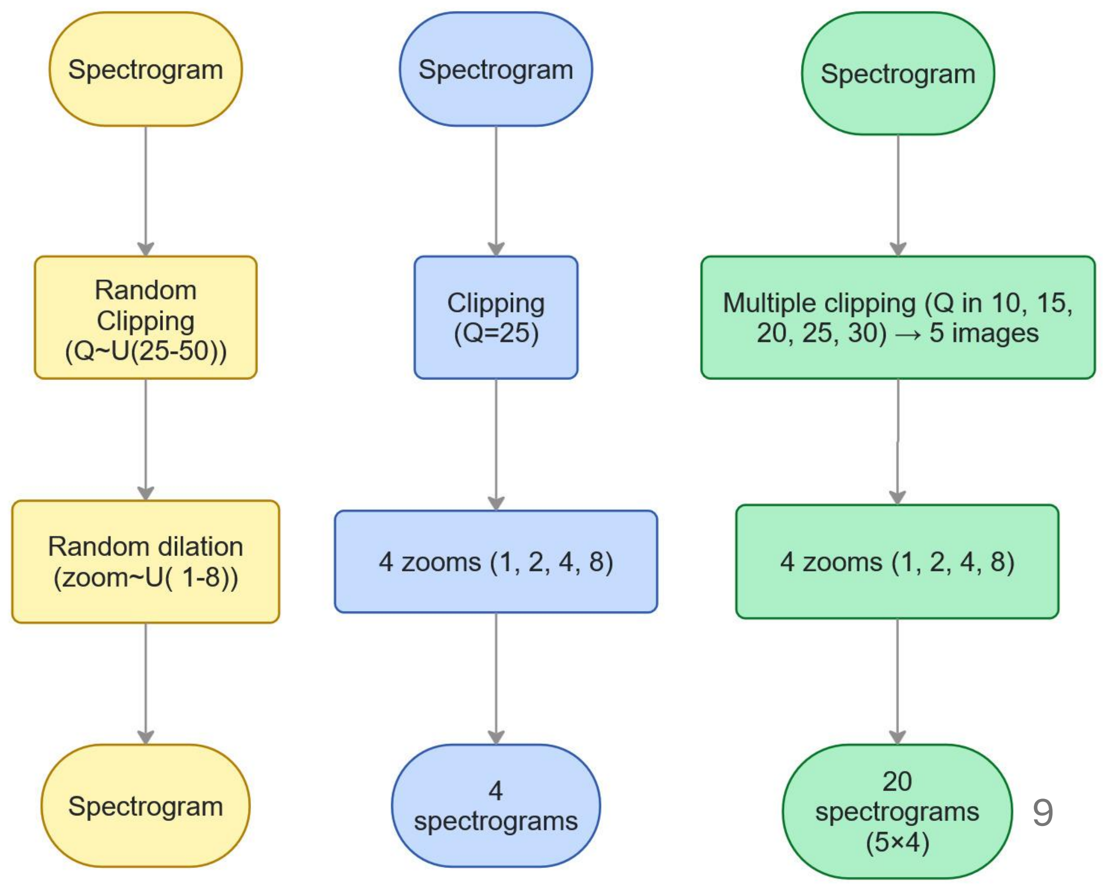


Preprocessing and data augmentation

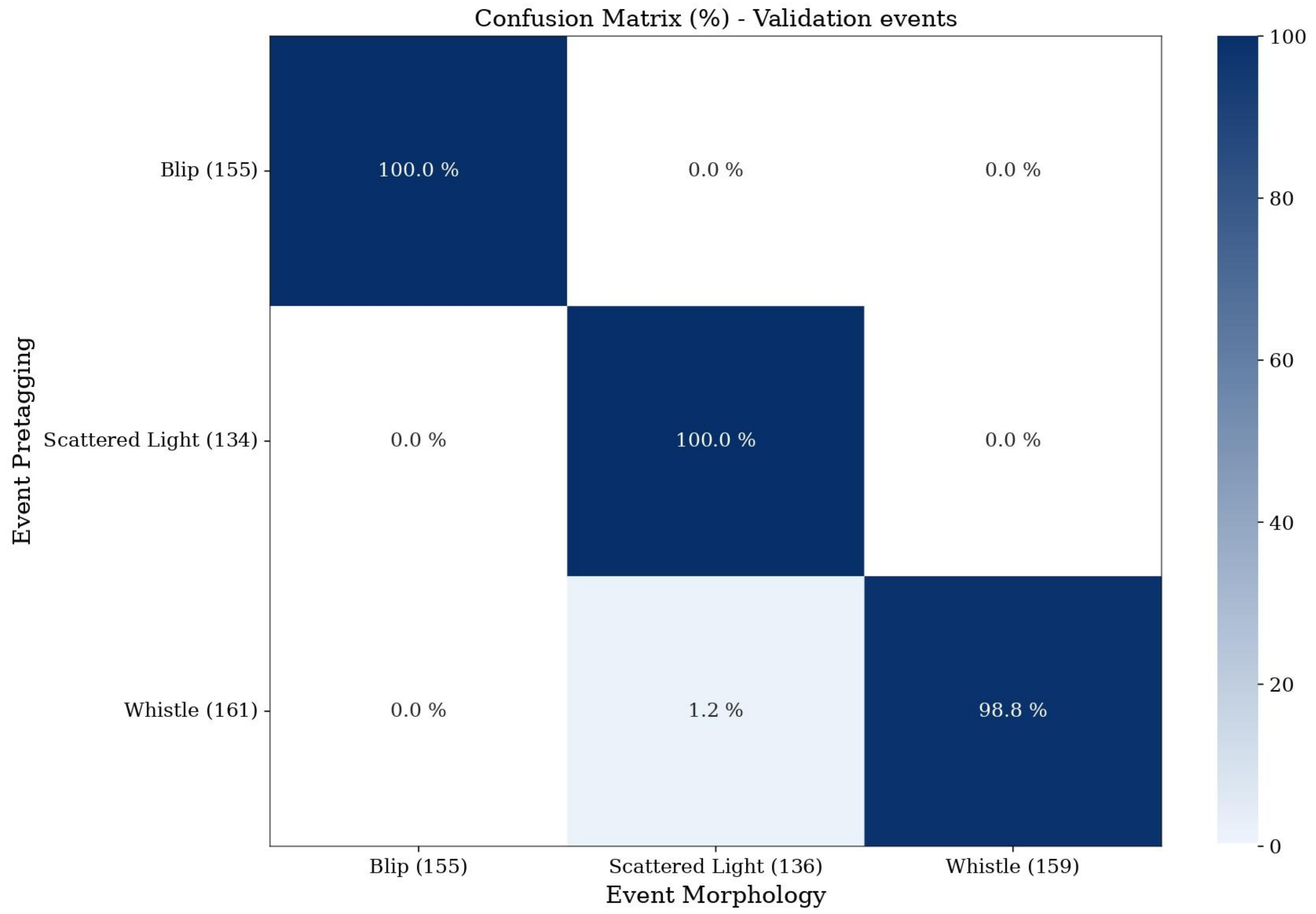
- Q-transform the Timeseries signal;
- Keep frequencies between 8 Hz and 8192 Hz;
- Keep only a 4 second window centered on the trigger;
- Put the frequency axis in log-scale;
- Apply the data augmentation;
- Add padding on the 4 borders;
- Resize to have a 224×224 image;

Data augmentation



Training

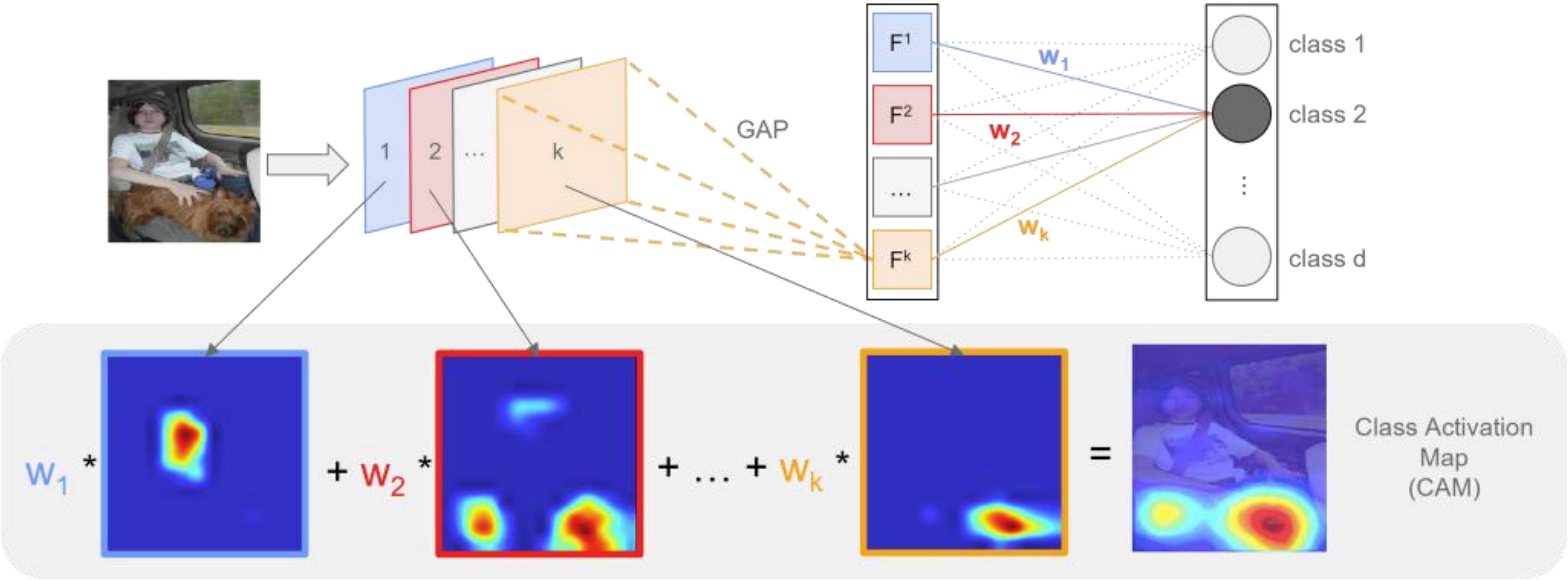
- ResNet50 Model basis;
- Trained on Golden Dataset;
- Pre-processed events;
- Curiculum Learning (based on triggers SNR level;
- 4500 events dataset (1500 of each class);
  - 70% training set
  - 20% validation set
  - 10% test set
- 50 epochs;



⇒ (a) Glitch events can be classified

Class Activation Map

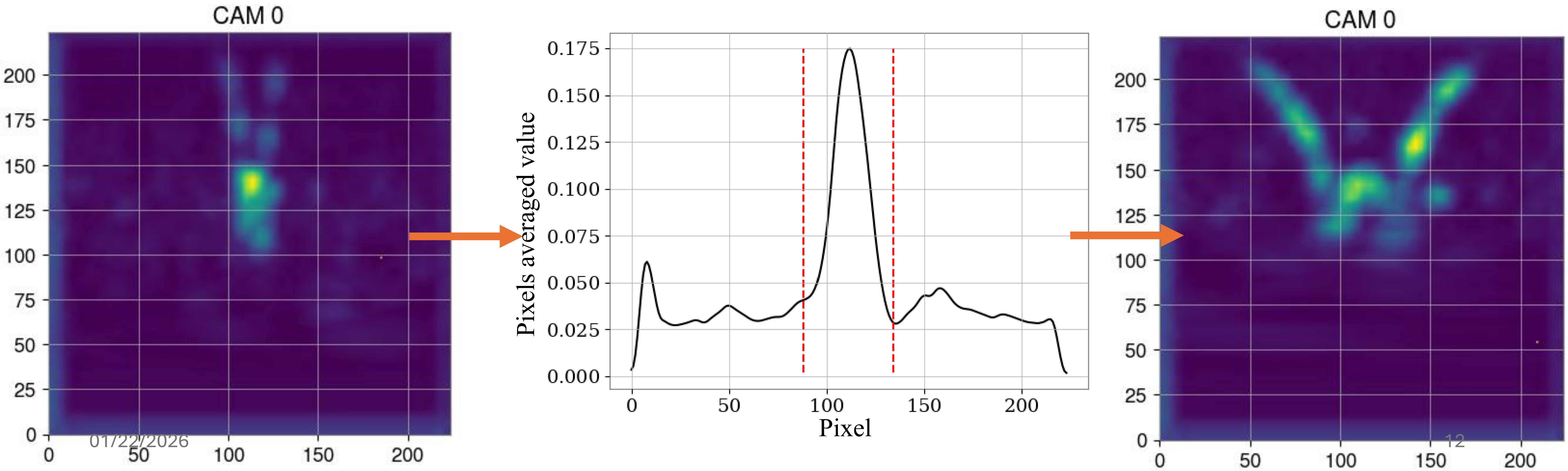
Having a heatmap of the activate neurons on a given layer:
➢Tells where is the relevant information on the input image.



*Zhou, Bolei, et al. "Learning deep features for discriminative localization." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016

From CAM to zoom selection

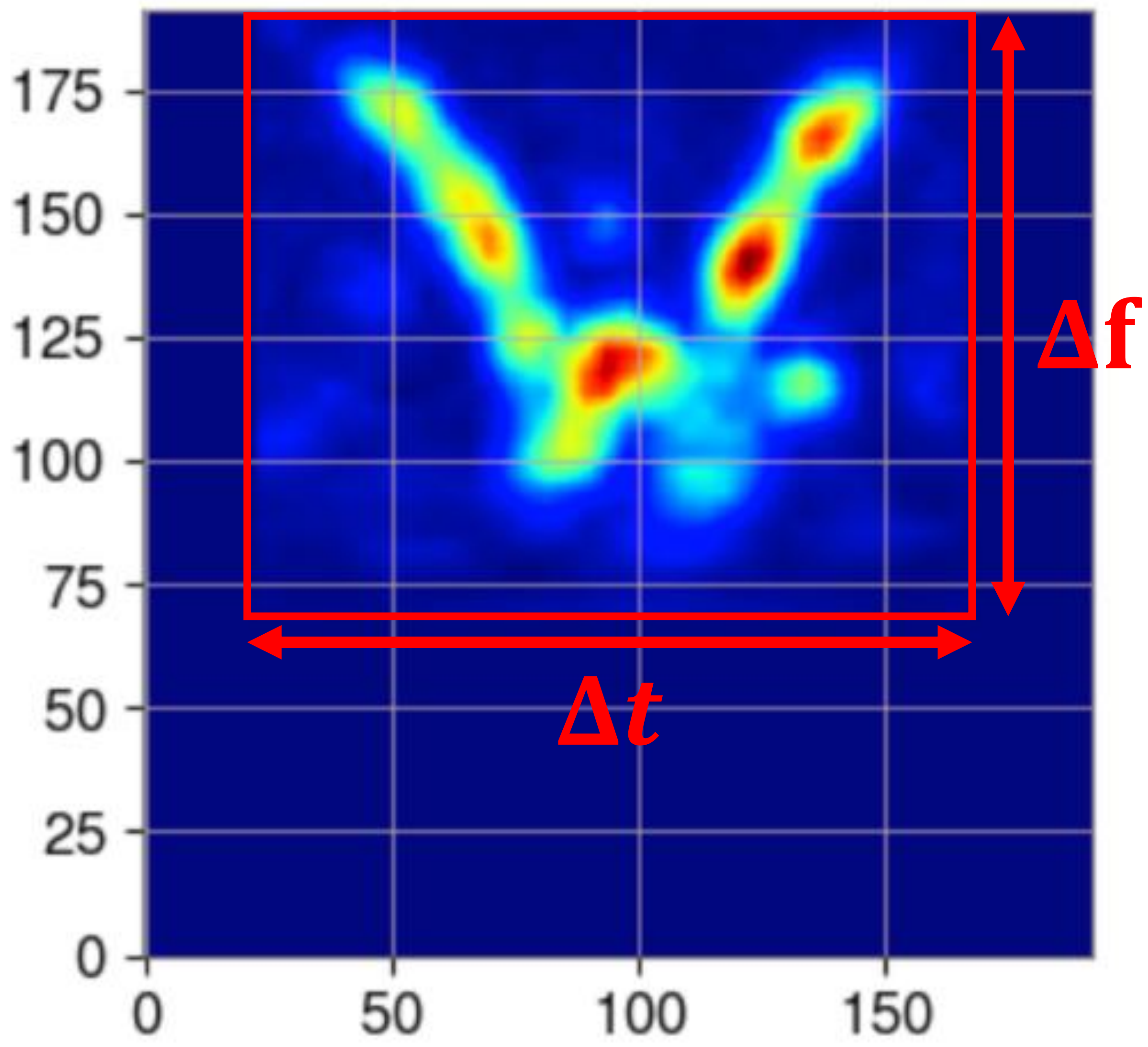
- Layer of the first bottleneck;
- Integrate over the frequency axis;
- Refine the zoom level by estimating the event duration;



Glitch Emboxing

Do once more the integrations of the CAM;

- First on frequencies;
  - Gives time duration Δt;
- Second over time;
  - Gives frequency bandwidth Δf;



⇒ (b) First glitch extraction

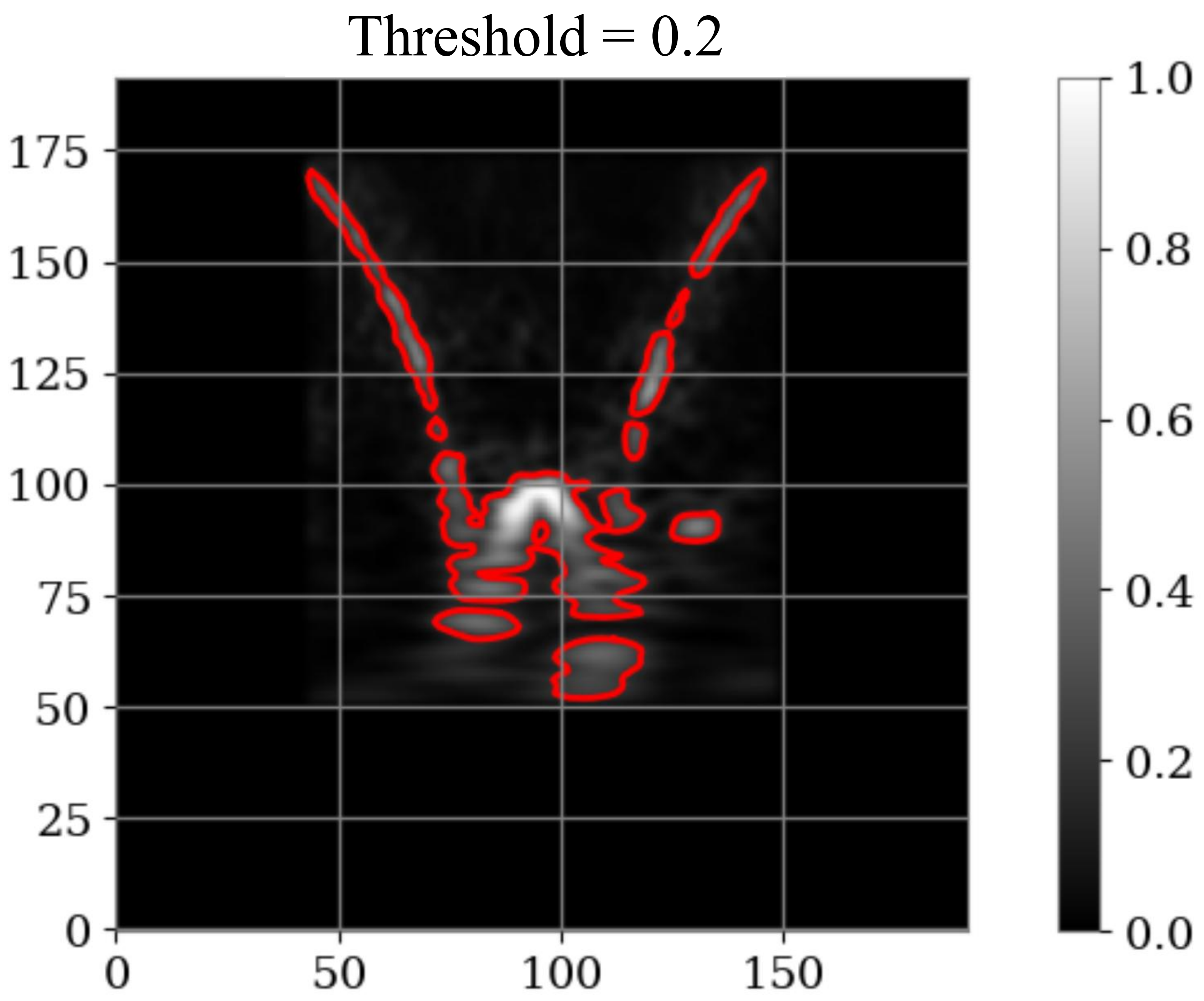
Contouring & Mask

Preprocessing the contouring:

- Make Rectangular window (of size $\Delta t \times \Delta f$);
- Apply the rectangular window to input and CAM;
- Contouring for {5, 10, … , 50}% thresholds on:

$$\mathrm{w_{ij}} = \sqrt{input_{ij} \times CAM_{ij}}$$

- Fill the contour with ones to make binary mask base.



Finding optimal contour threshold

Protocol to statistically test the threshold:

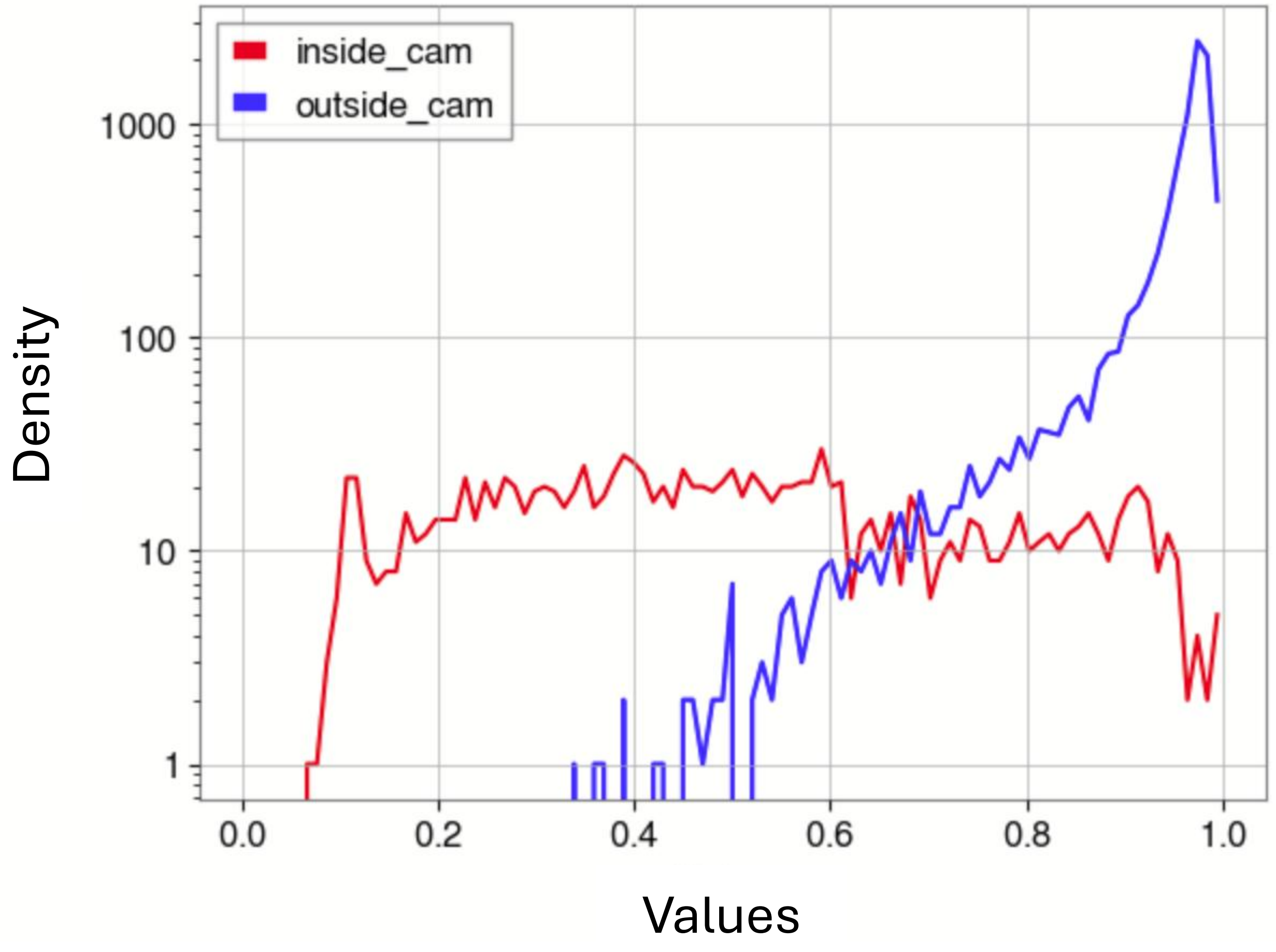
- Normalize the CAM
- Apply the binary mask (contouring result) on CAM :

$$inside_{cam,ij} = mask_{\mathrm{ij}} \times CAM_{ij}$$

- Apply the inverse mask on CAM, then invert it again :

$$outside_{cam,ij} = 1 - \left(1 - mask_{ij}\right) \times CAM_{\mathrm{ij}}$$

- Make the associated distributions : (p_{in}, p_{out})
- Get a statistic of it



Statistic to optimize

Maximize the common surface under both of the histograms :

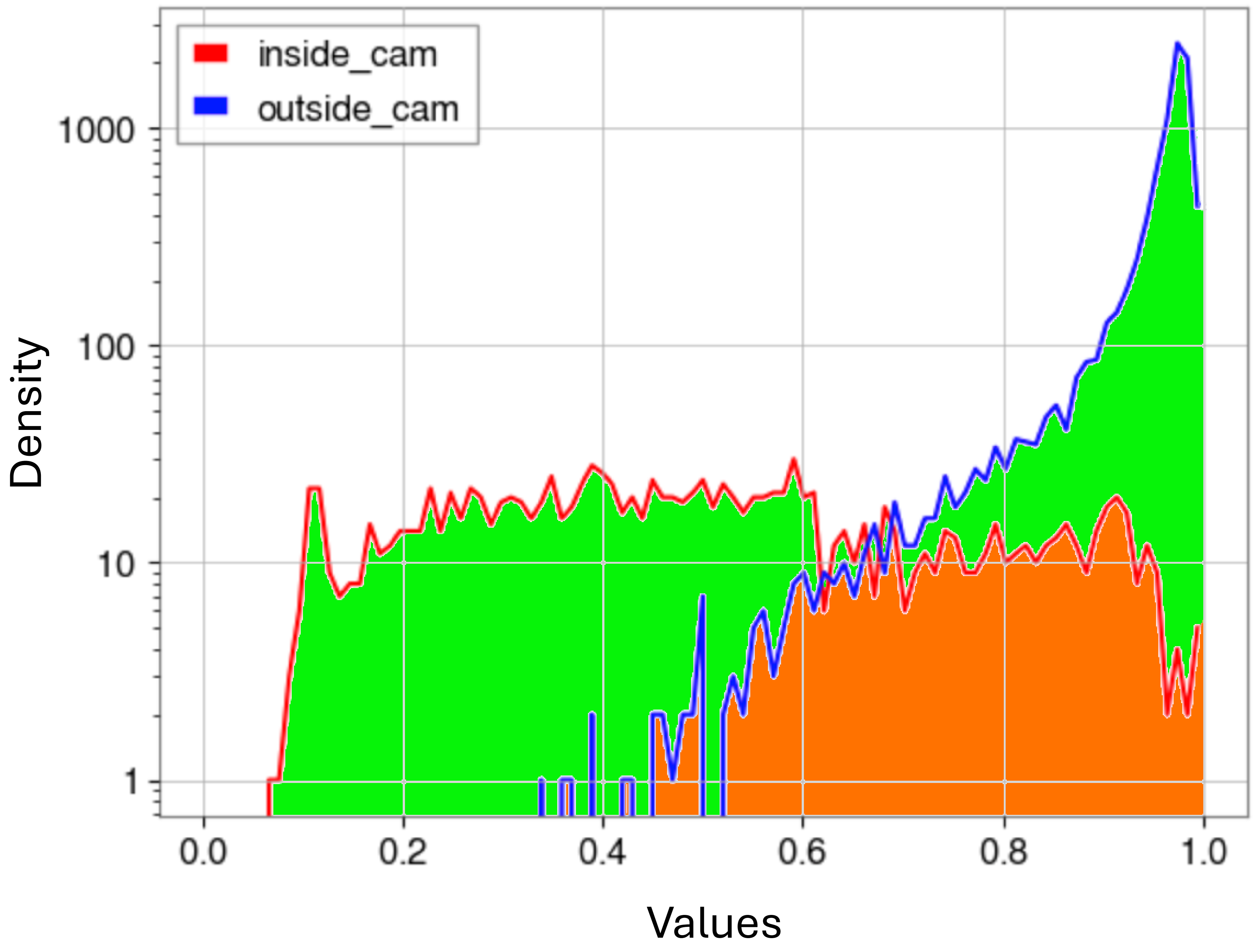
$$\eta_{min} = \sum_{i}^{N} \min(p_{in,i}, p_{out,i})$$

Minimize the difference between the 2 histograms :

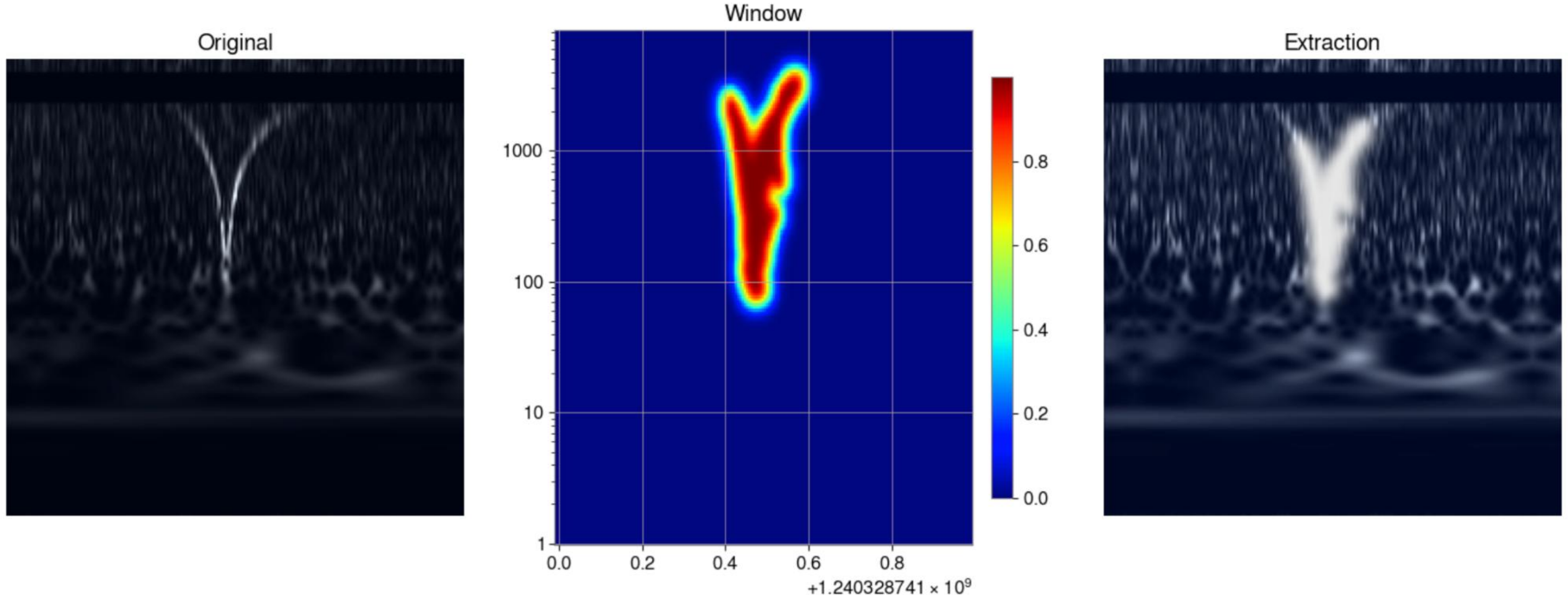
$$\eta_{diff} = \sum_{i}^{N} |p_{in,i} - p_{out,i}|$$

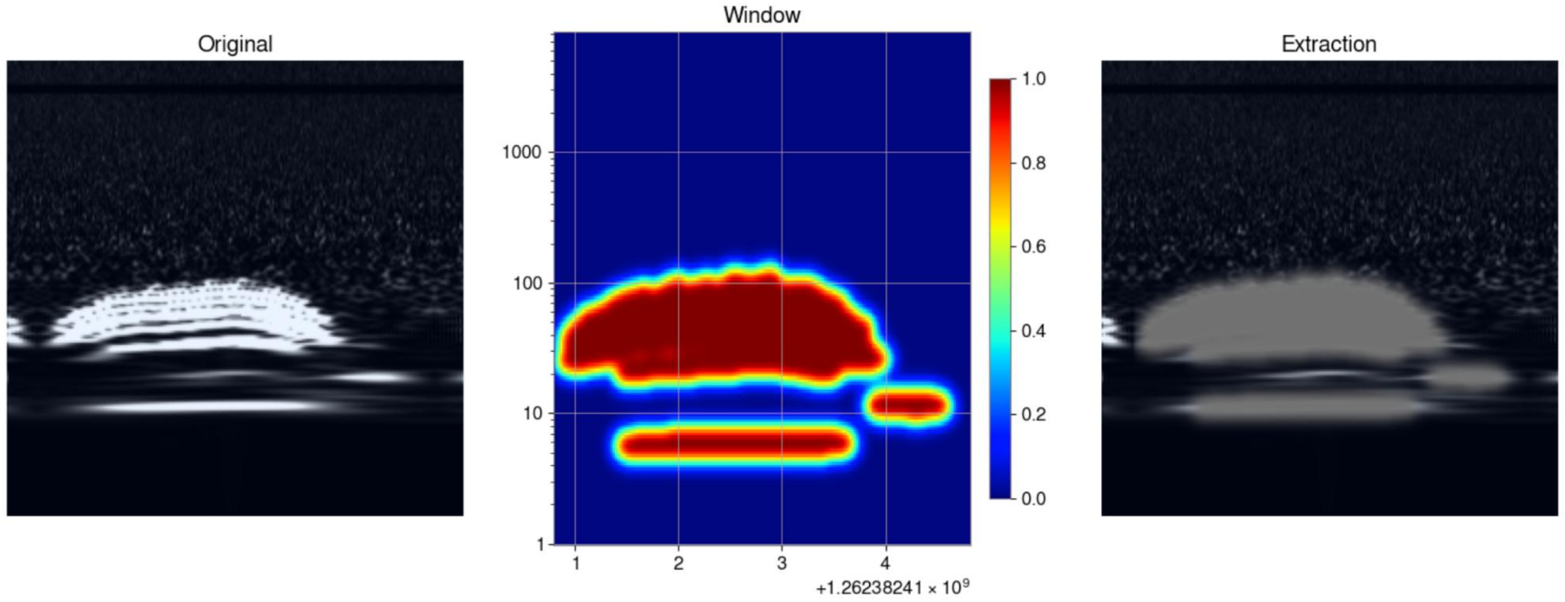
Find the threshold maximizing :

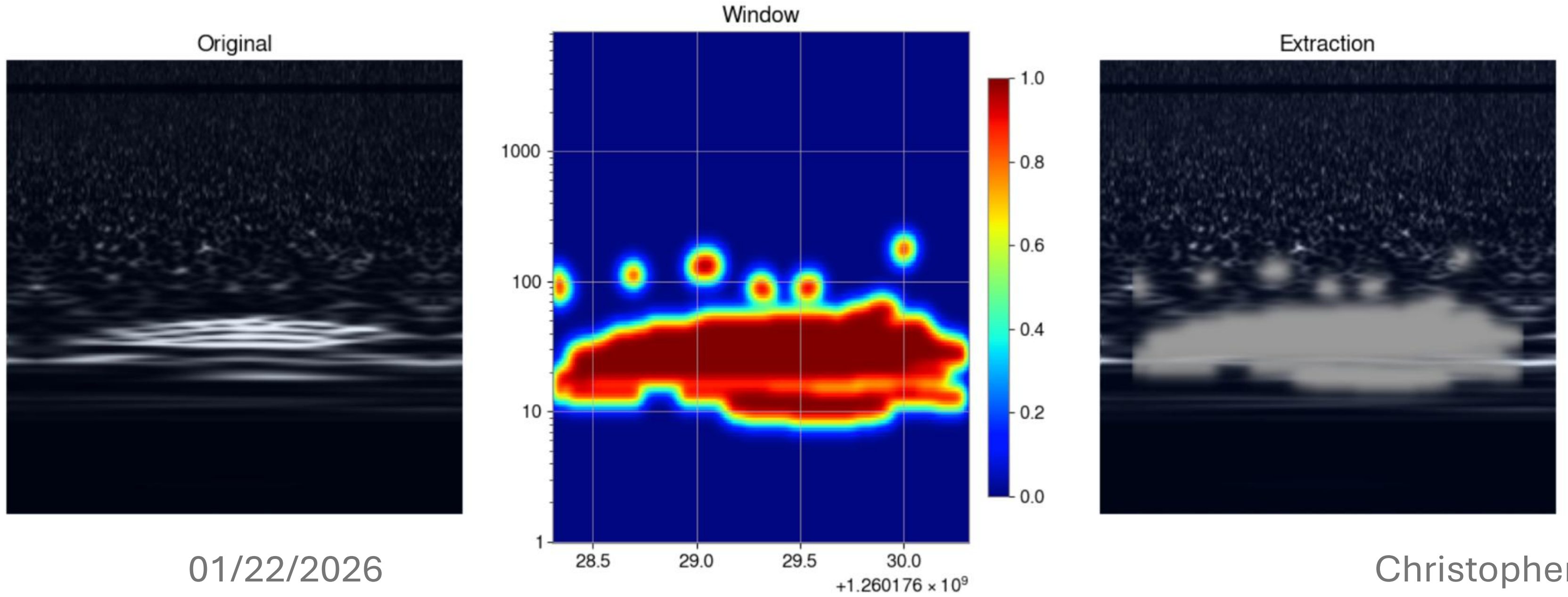
$$\eta_{tot} = \eta_{min} - \eta_{diff}$$

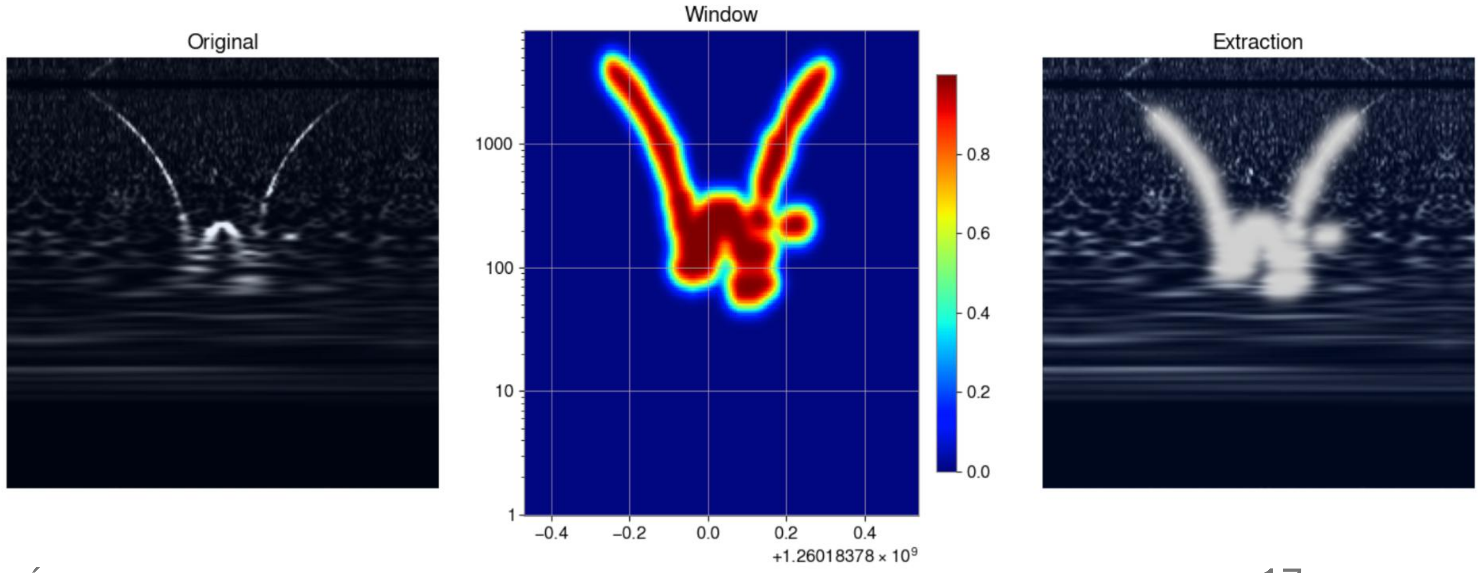


Example of masking









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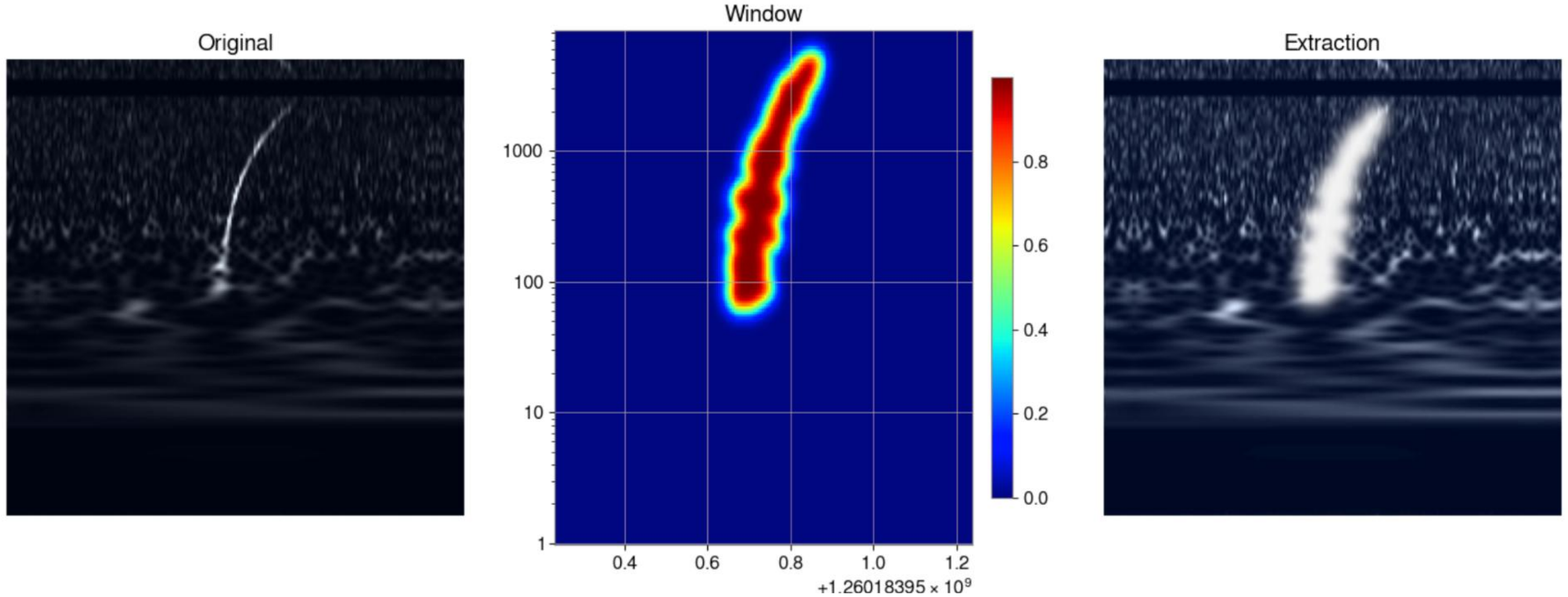
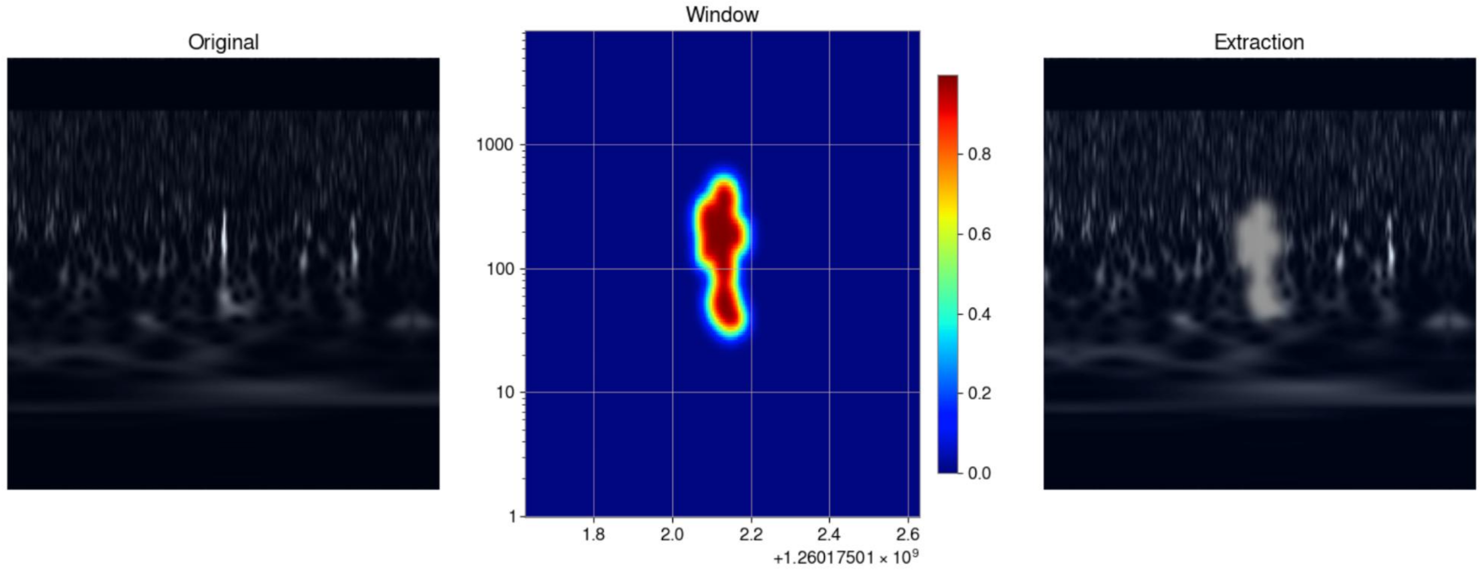
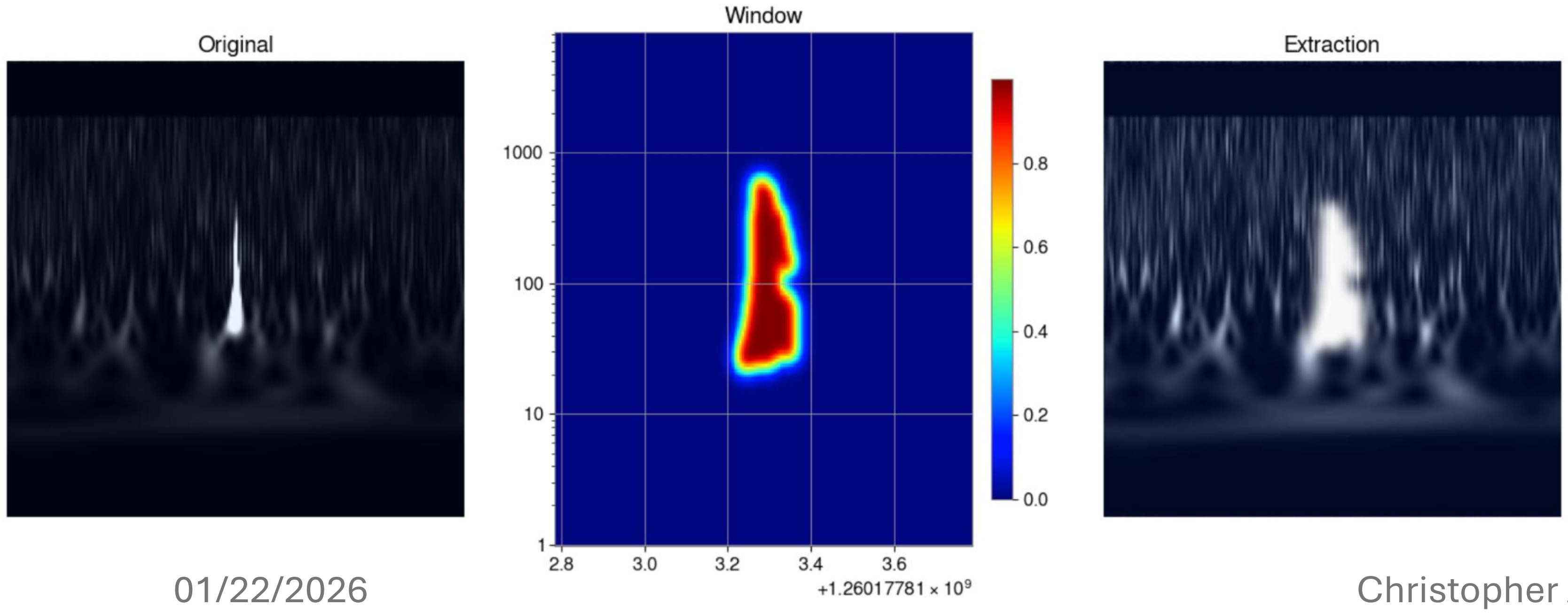
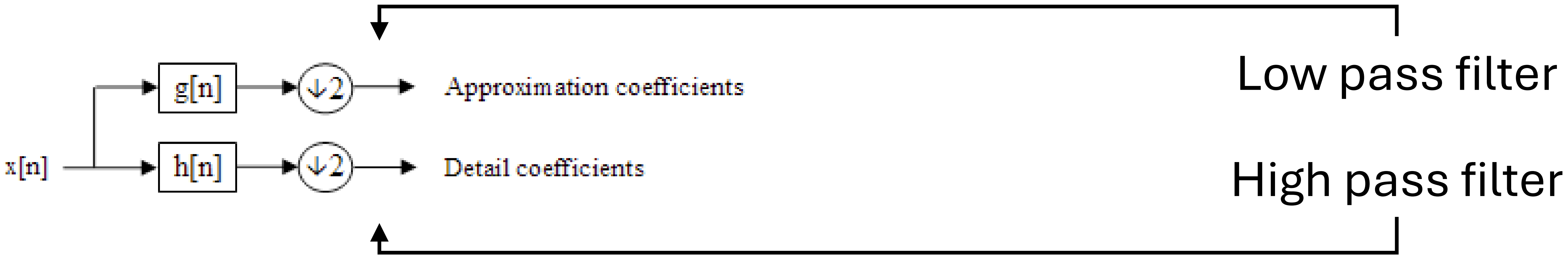






⇒ (b) Second glitch extraction

Discrete Wavelet Transform



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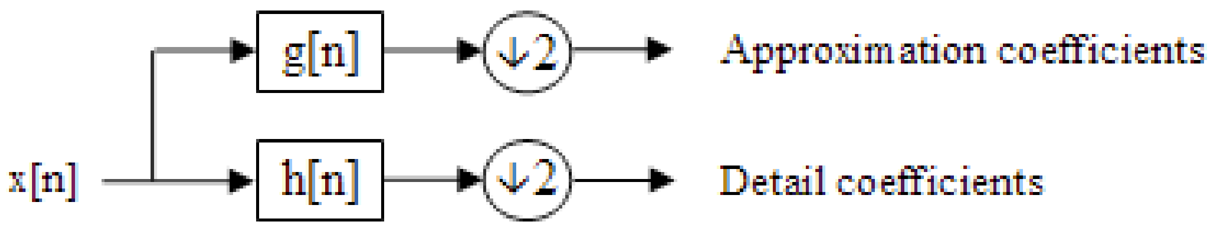
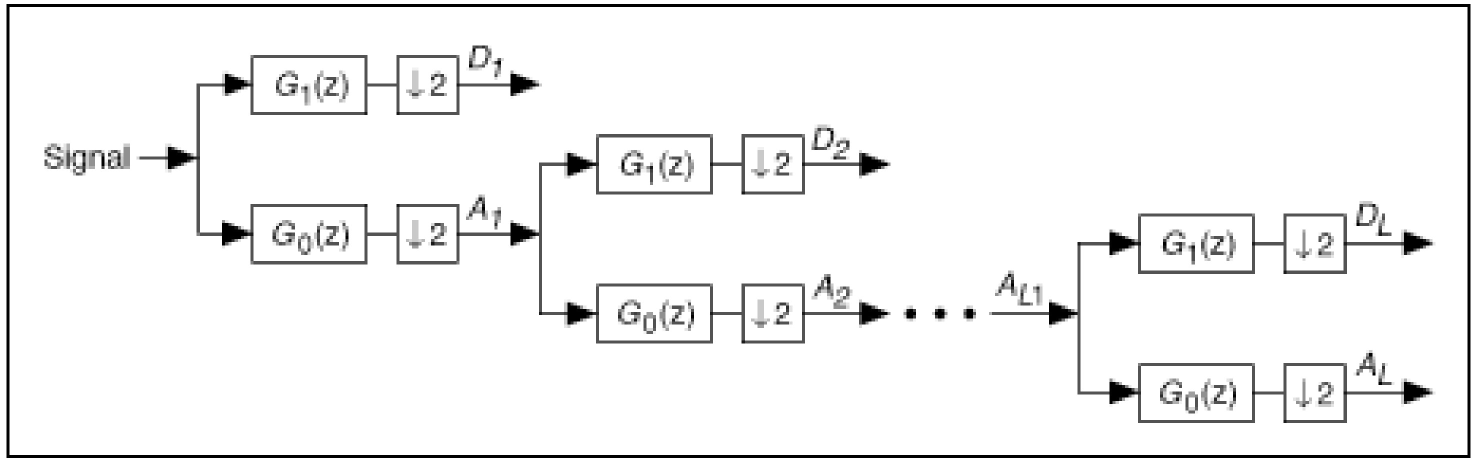


Low pass filter

High pass filter

Transformation



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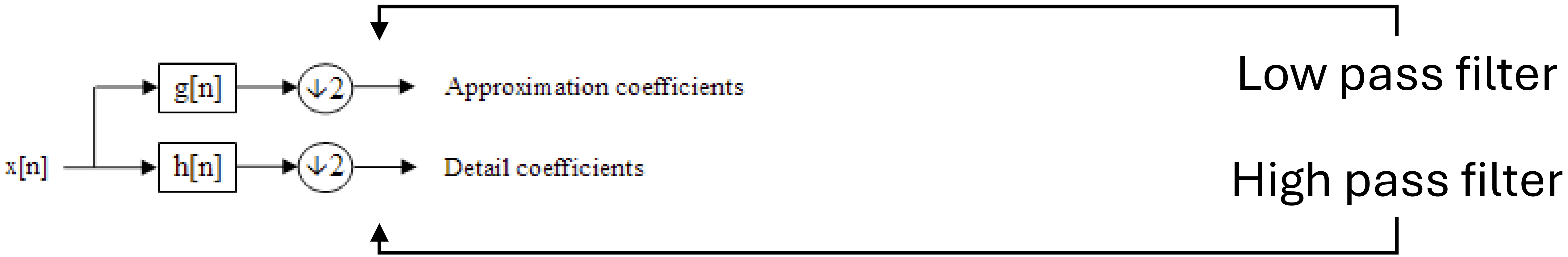

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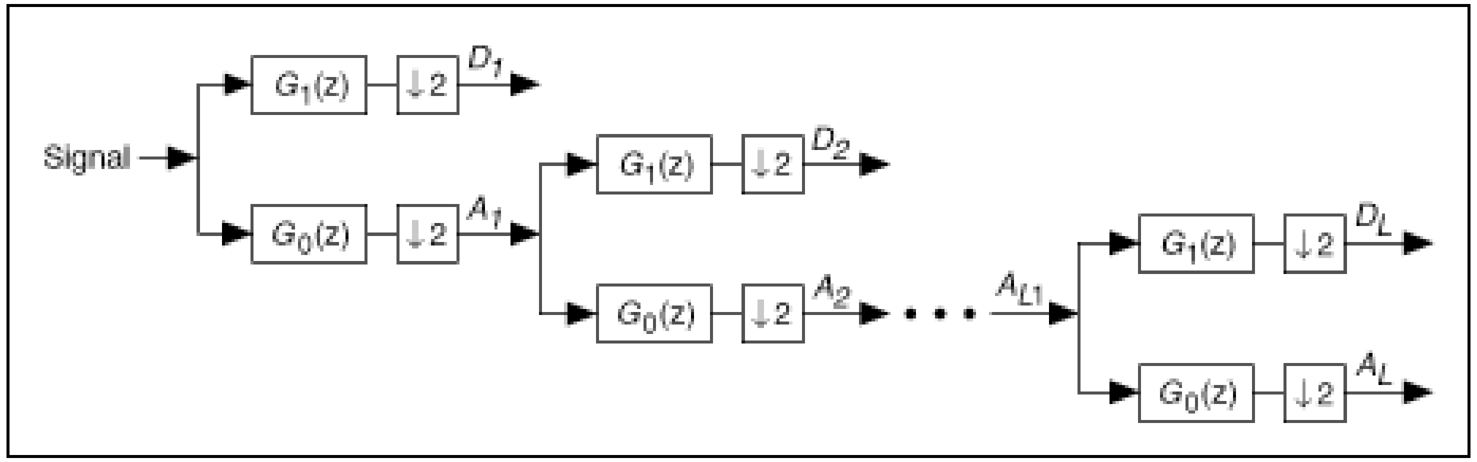
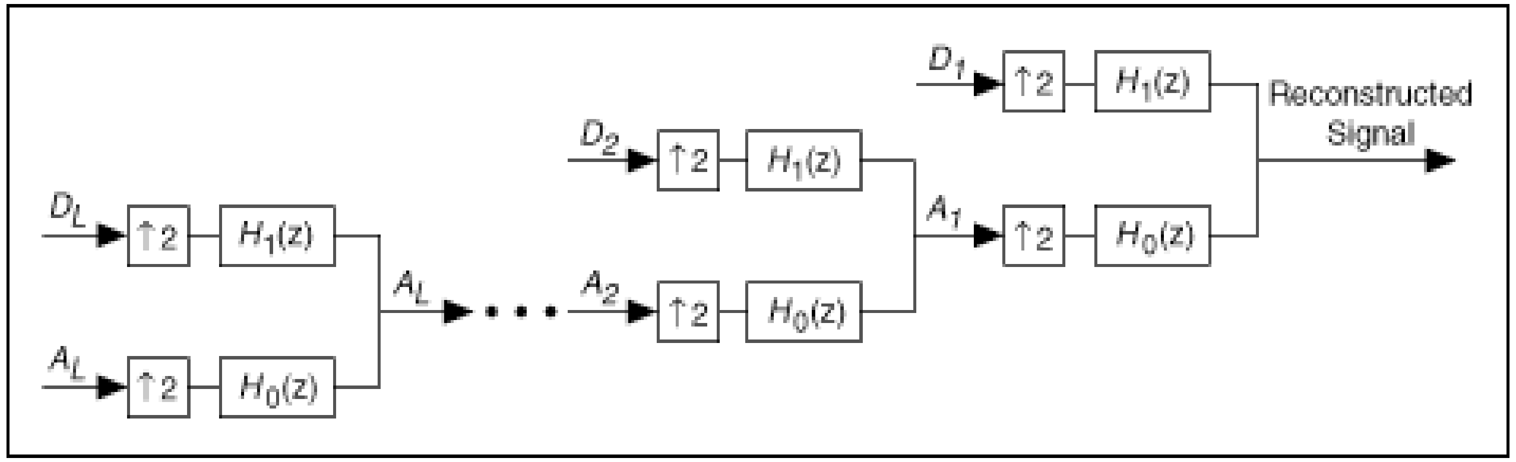


Reconstruction



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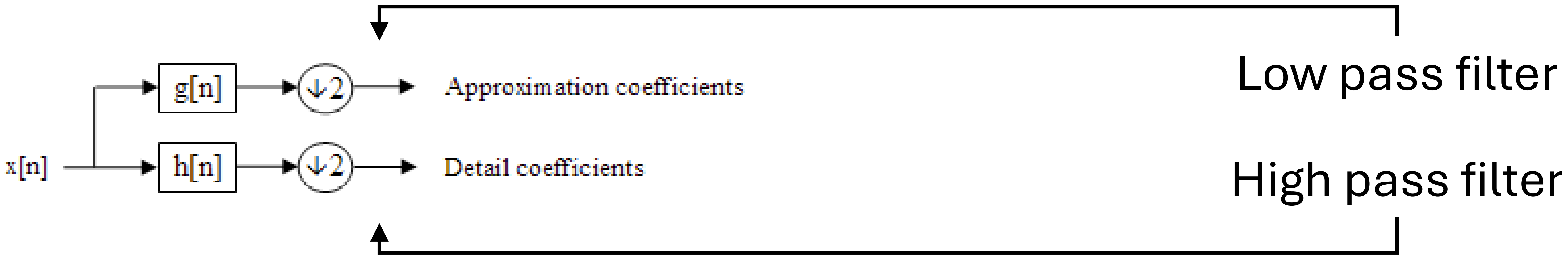

Transformation

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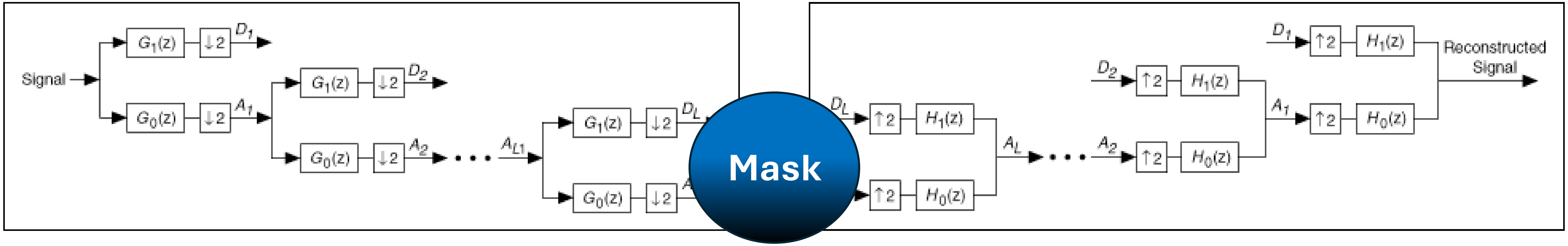
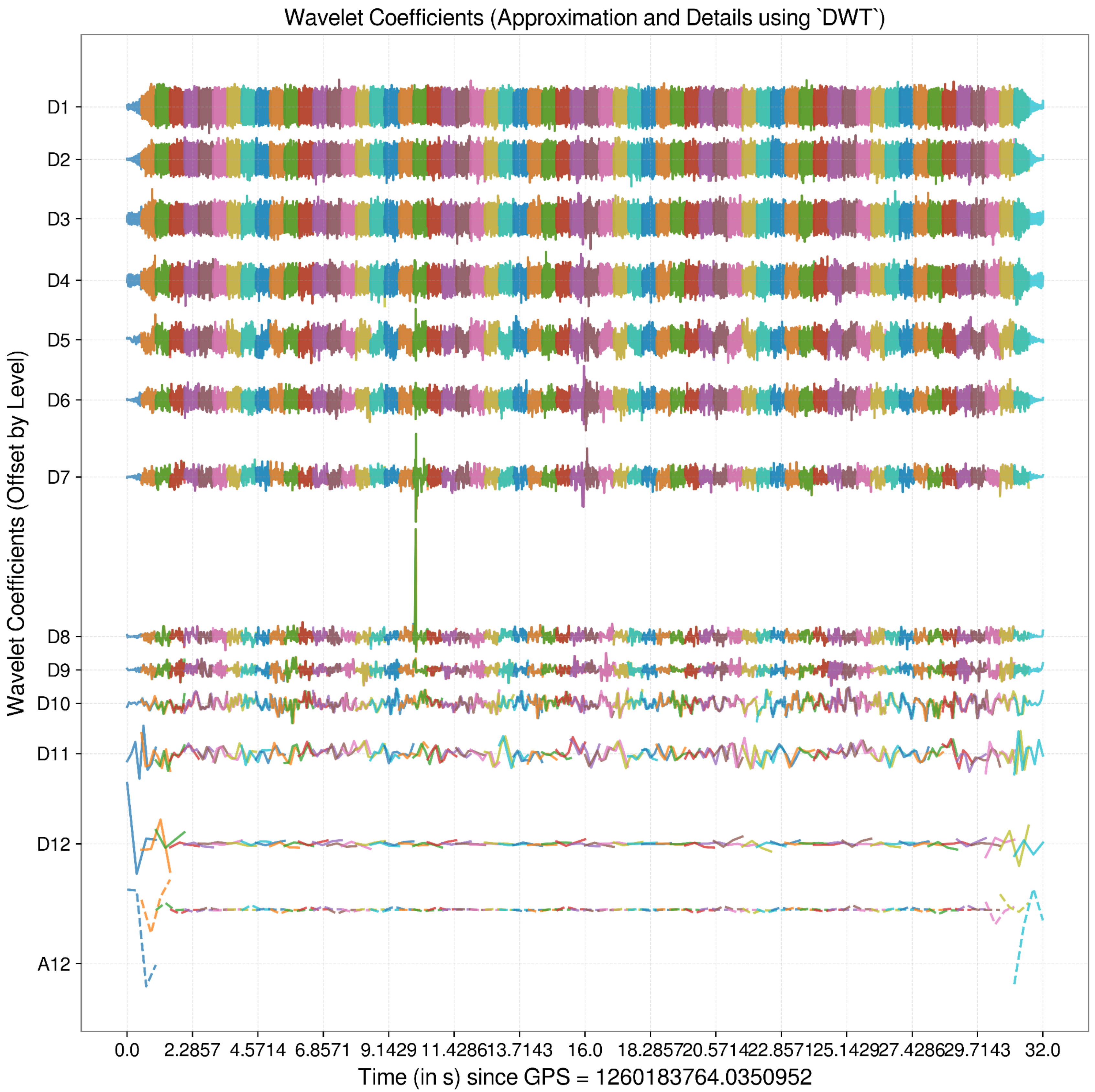


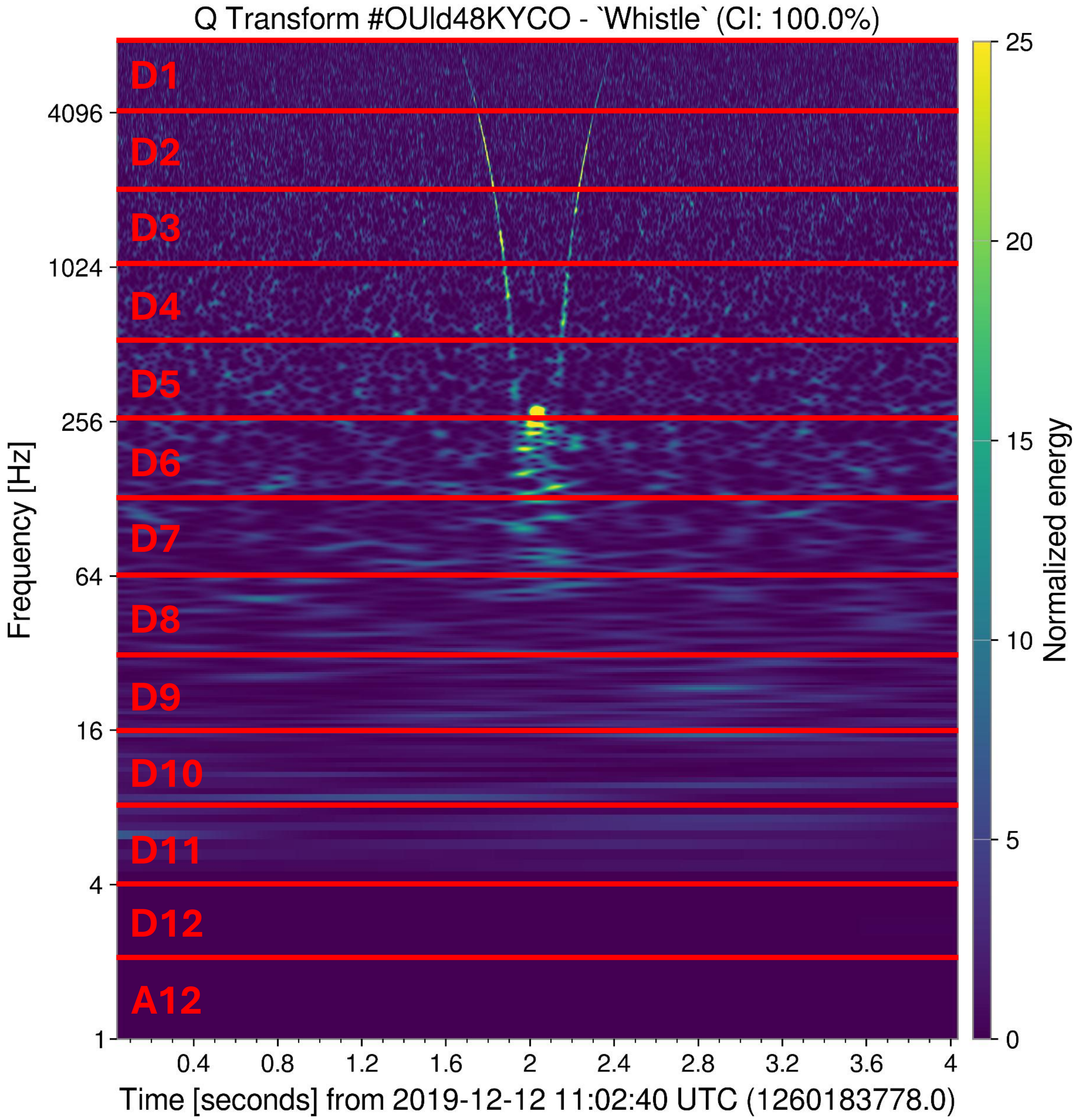
Masking the DWT of the signal

- Each details coefficients follows:
  - $D_n \in \left[\frac{f_s}{2^{n+1}}; \frac{f_s}{2^n}\right]$;
  - D_1 from 8192 to 4096;
  - D_2 from 4096 to 2048;
  - D_3 from 2048 to 1024;
  - …
- And the approximant :
  - $A_n \in \left[0; \frac{f_s}{2^{n+1}}\right]$;



Masking the DWT of the signal

1. Split the Q-Transform space according DWT splitting;
2. Integrate the mask along frequencies;
3. Resample to fit the DWT sampling;
4. Multiply the DWT by the translate mask;
5. Transform back to a time series;



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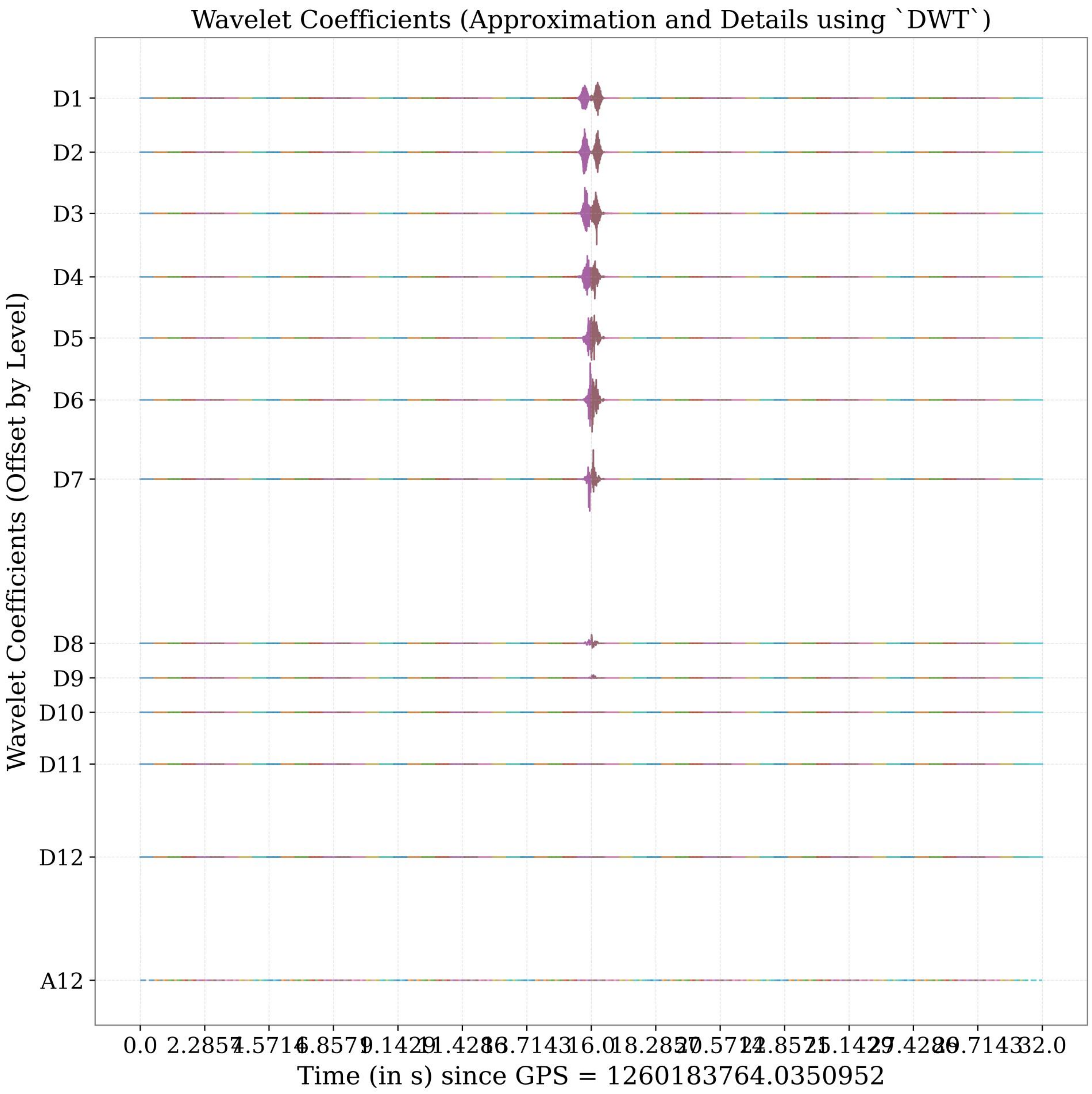

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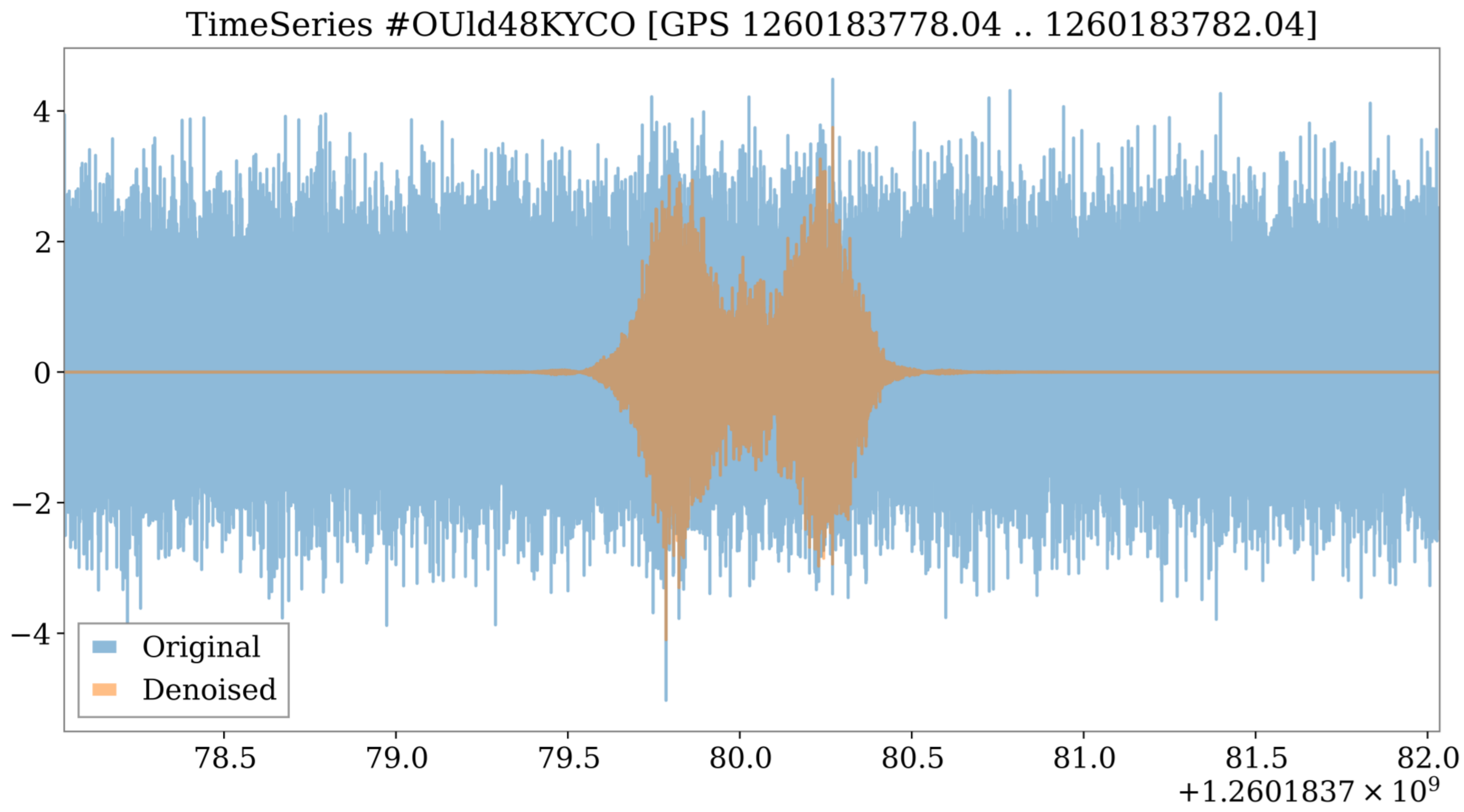
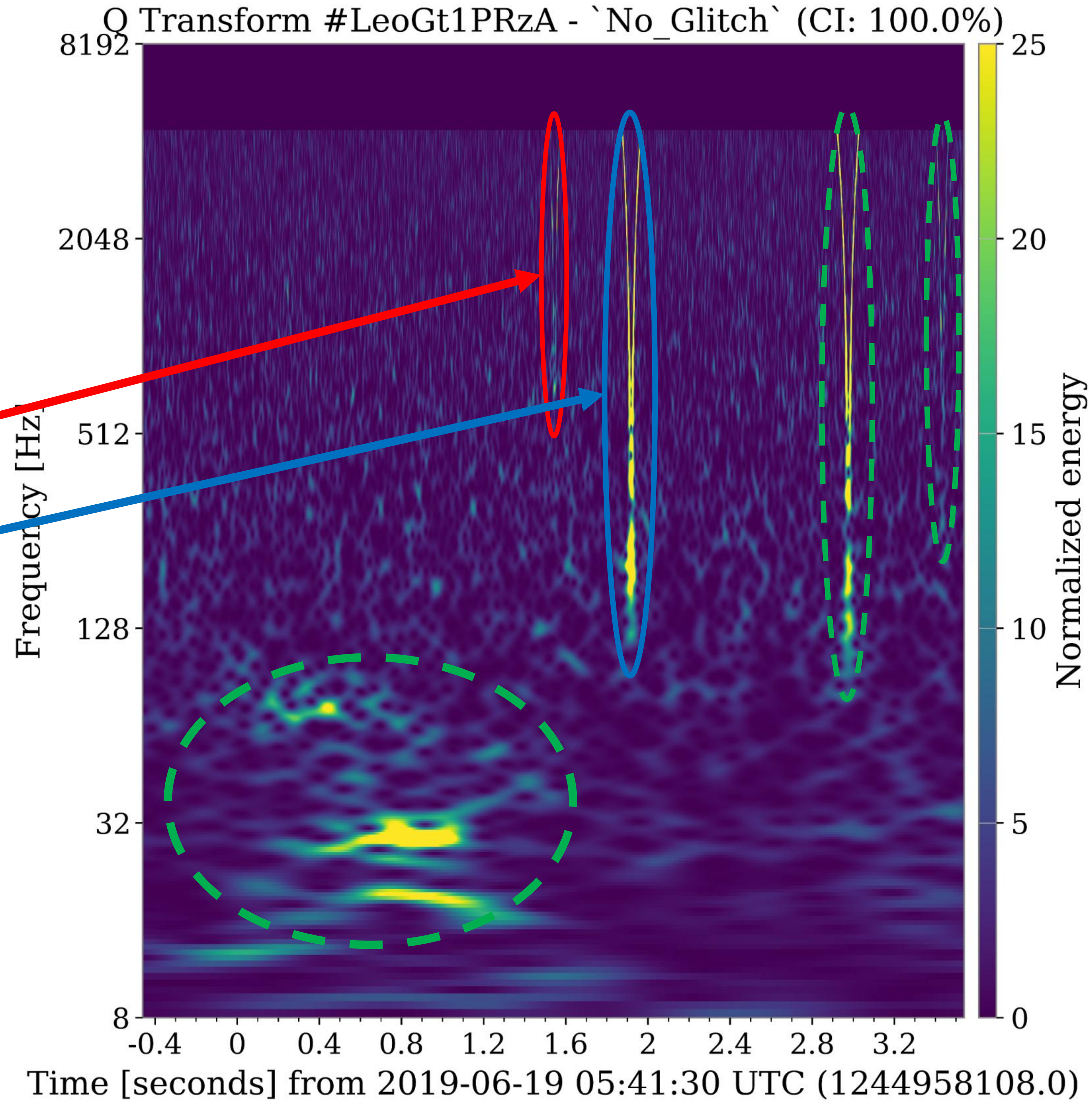


Complex Conditions Glitch

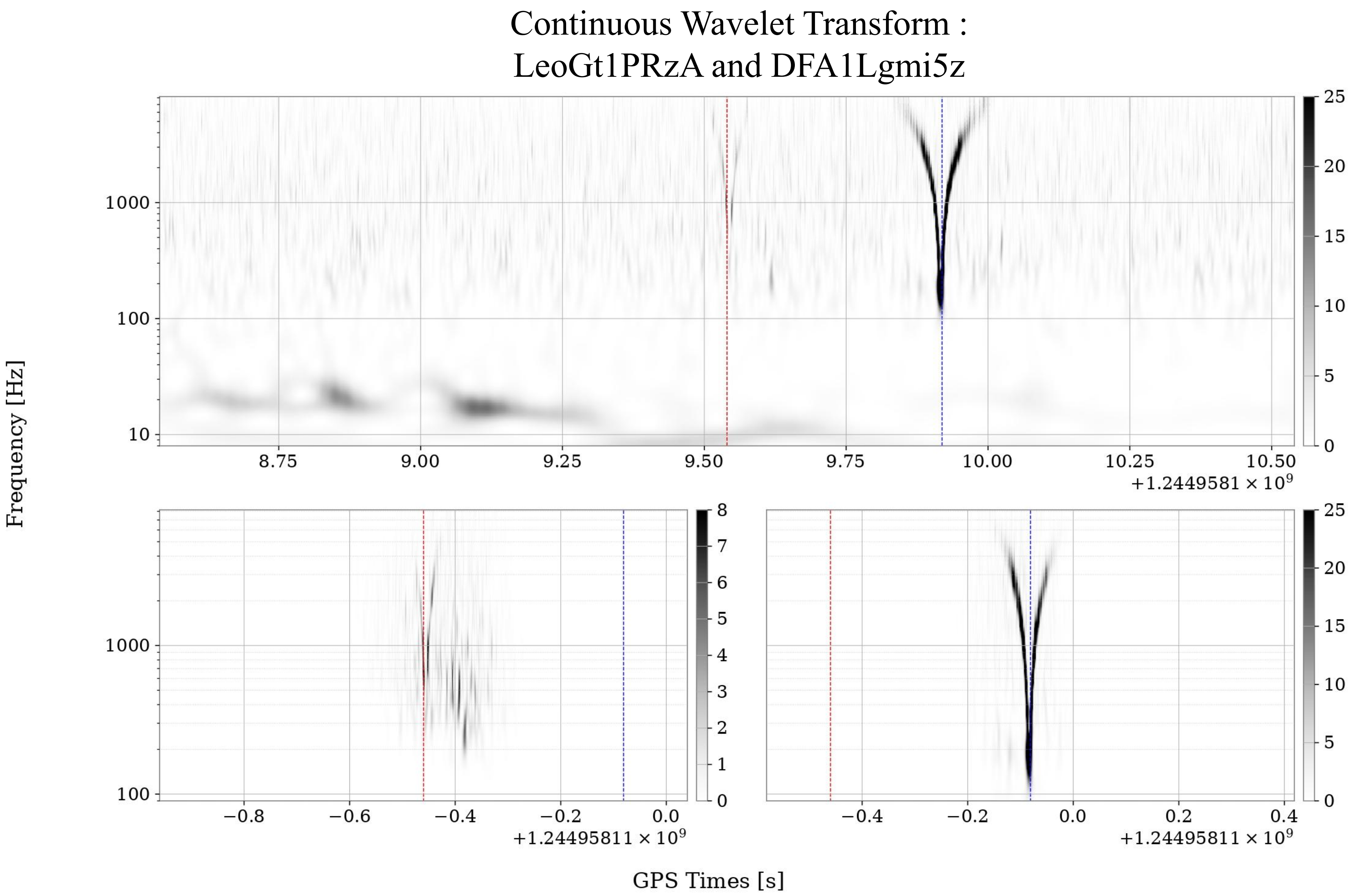
1. Multiples glitches:
   - LeoGt1PRzA
   - DFA1Lgmi5z
   - ...
2. Very fainted glitch



Complex Conditions
Glitch

1. Multiples glitches:
   - LeoGt1PRzA (red line)
   - DFA1Lgmi5z (blue line)
   - ...
2. Very Fainted glitch

⇒ (c) Glitch subtracted



Conclusion

- We have a complete framework to (a) classify, (b) segment and (c) subtract glitches from noise.

- The segmentation and subtractions apply on fainted glitch

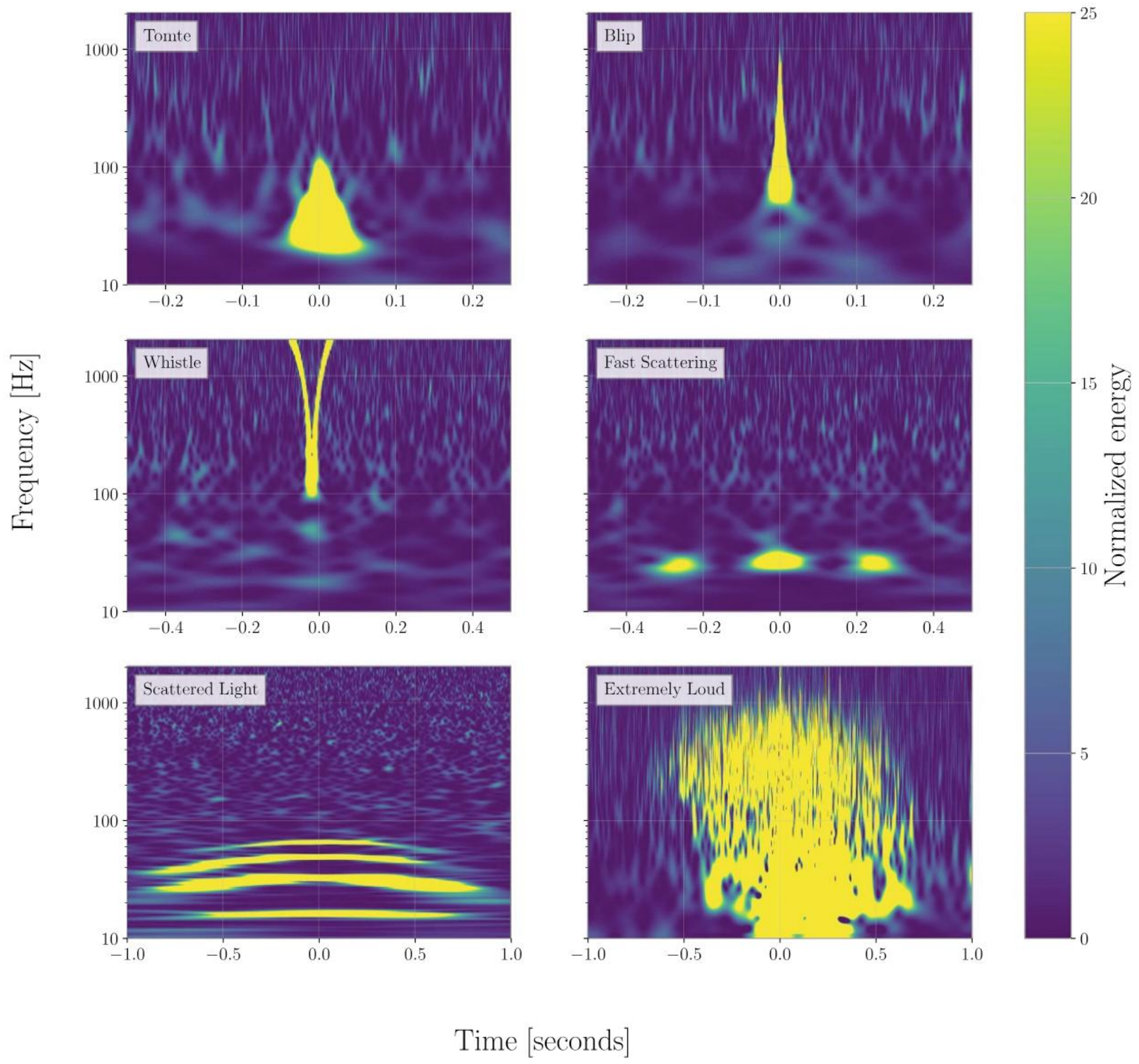
- A whole procedure to deal with multiple glitch in a narrow neighbouring allows to subtract them separately

Thanks for your attention

Glitch

GravitySpy classifies Glitches on events (Omicron triggers) among 26 classes.
Focus on :

- Whistle
- Scattered Light
- Blip



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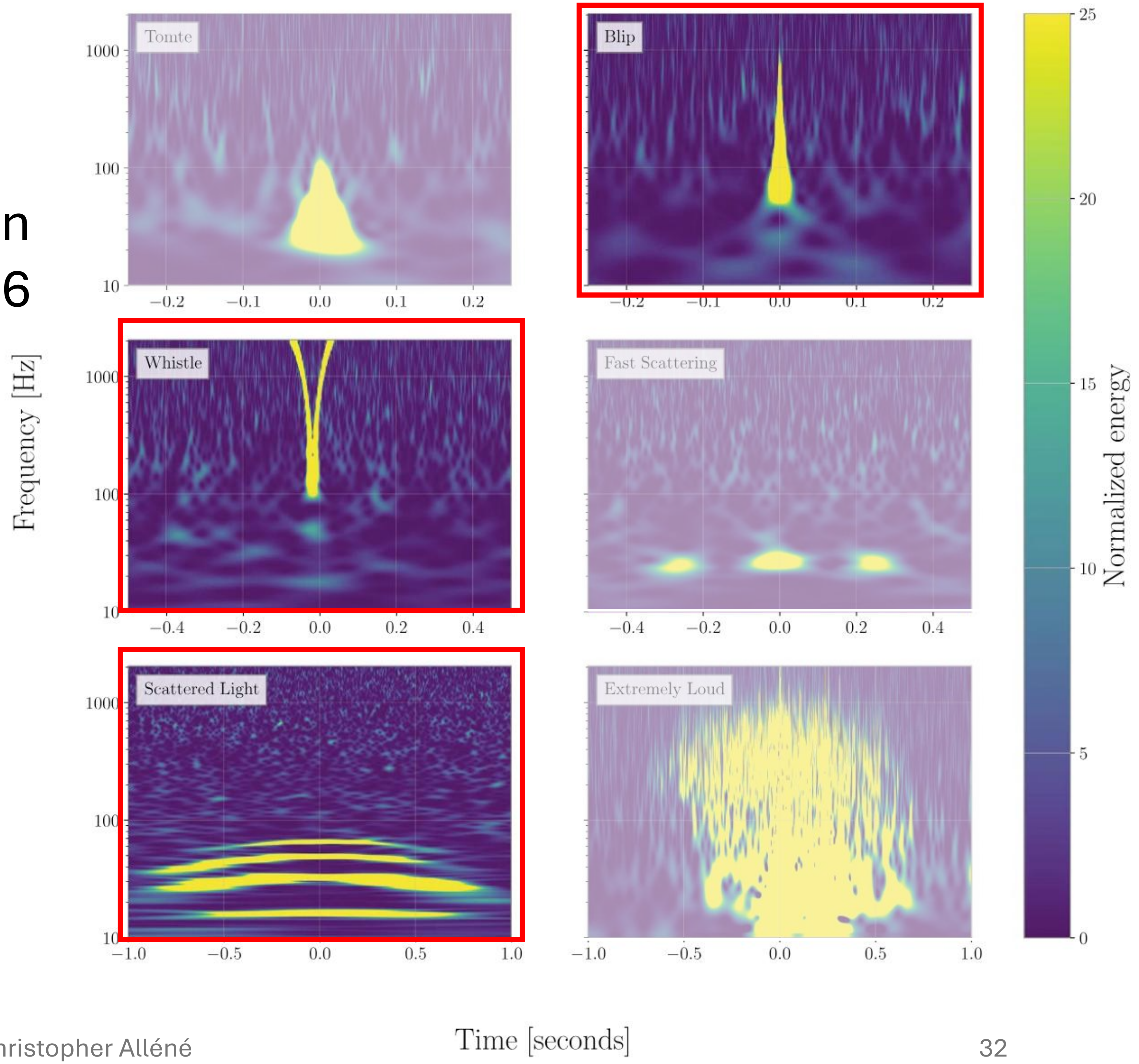

Data augmentation