Time-frequency segmentation : statistical and local phase analysis

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Sommaire

Introduction I

Context

- Segmentation of time-frequency plane
- Instantaneous frequency law estimation

Application to Passive Acoustics Monitoring (PAM) of marine mammals

- Impact of anthropic pressure (shipping noise, sonar, seismic exploration, etc.) on marine mammal's health
- Detection, classification, density estimation and localization of marine mammals
- Passive tomography

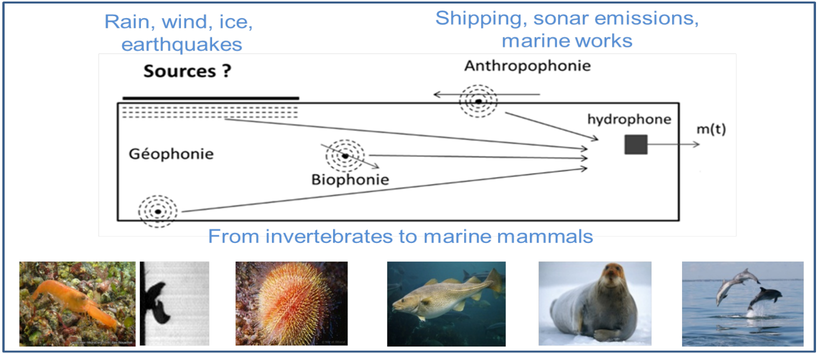
Introduction II

Signal processing constraints

- Colored and/or non-stationary noise
- Non linear frequency modulations
- Multi-component (unknown number), time-frequency overlapping, channel fading
- Large databases
- Single sensor (hydrophone)

Ocean Polyphony - Acoustic landscapes

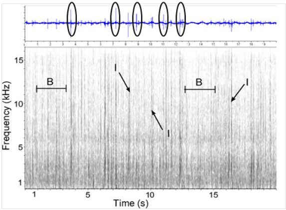
Ocean is not a world of silence ("The silent world" [Cousteau & Malles 1956])



[Pijanowski2011], 'Soundscape ecology: the science of sound in the landscape', BioScience 61(3), 203--216.

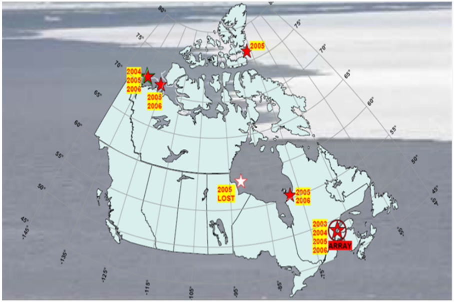
Study of populations & Anthropic activities : Meso-acoustic scale ($10{,}000 m^2$)

Coral life
Maerl.



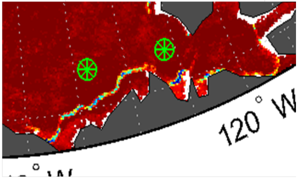
First recording session : 10/10/2012 – 10/20/2012

Arctic & Global warming : Macro-acoustic scale (10,000km^2)



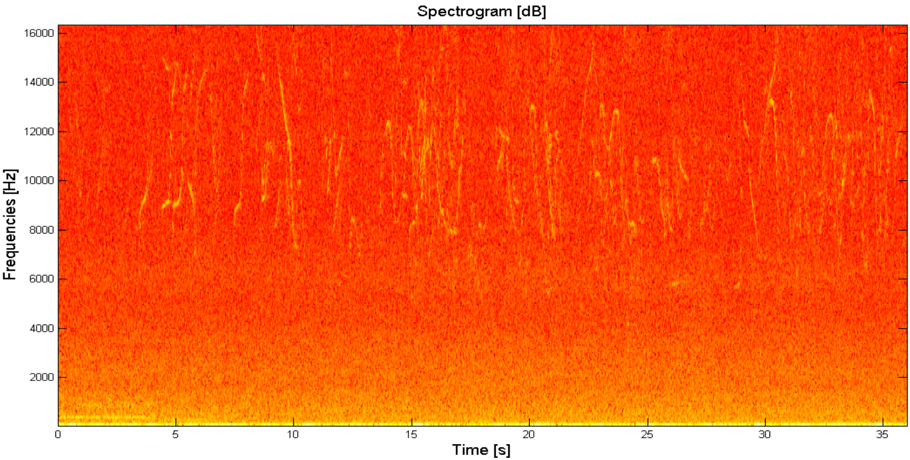
UQAR ISMER

Pêches et Océans Canada

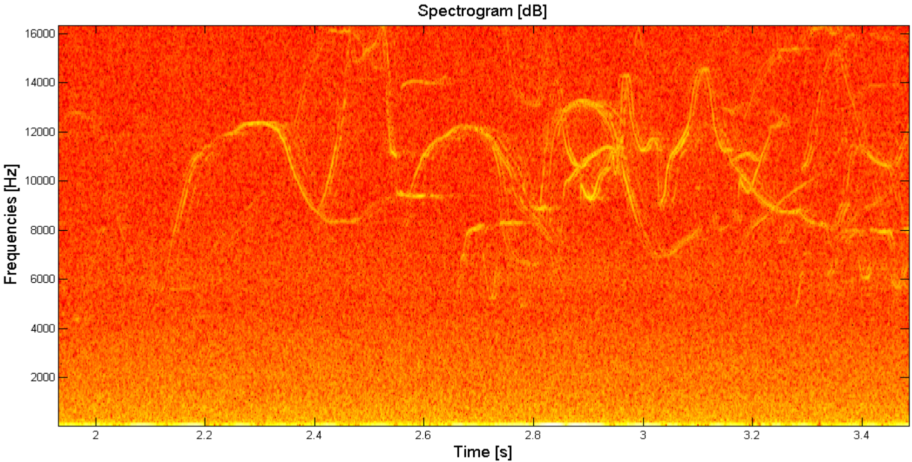


- Kinda, Simard, Gervaise, Mars & Fortier (2012), 'Under-ice ambient noise in Eastern Beaufort Sea, Canadian Arctic, and relations with ice drift', JASA, submitted
- Simard, Gervaise, Kinda, Fortier & Mars (2012), 'Tenfold increase of arctic ocean noise from global warming alone', JASA, submitted

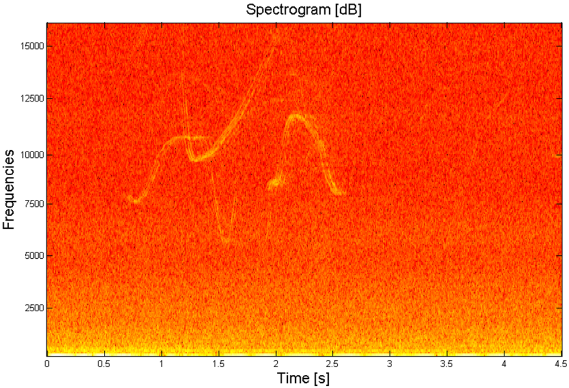
Example of dolphin signals



Example of dolphin signals



Example of dolphin signals



State of the Art : Segmentation / Instantaneous frequency law estimation I

Instantaneous Frequency Law Estimation (I)

- Kalman filtering / Extended Kalman filtering [Mallawaarachchi2008]
  $\rightarrow$ Optimal for Gaussian distributions
  $\rightarrow$ Only Gaussian/Locally Gaussian distributions
- Particle filtering [Roch2011]
  $\rightarrow$ Non-Gaussian distributions, nearly optimal
  $\rightarrow$ Initialization of the seeds, mono-component
- Bayesian models : Maximum likelihood [Urazghildiiev & Clark 2004], Approximate maximum likelihood [Michel & Clergeot 1991]
  $\rightarrow$ Sensitive to low SNR

State of the Art : Segmentation / Instantaneous frequency law estimation II

Instantaneous Frequency Law Estimation (II)

- Empirical Mode Decomposition (EMD) [Huang1996], Hilbert Spectrum Analysis, Teager-Kaiser
  → Data-driven (no a priori model)
  → Low SNR, close components
- Wigner-Ville distribution
  → Interferences between components
- Higher-Order Ambiguity function (HAF) / Time-frequency-phase tracker [Ioana2010, Josso2009]
  → Phase coherence / Time series
  → Computational complexity

State of the Art : Segmentation / Instantaneous frequency law estimation III

Time-frequency plane Segmentation

- Morphological mathematics (closing) [Simard2010]
  $\rightarrow$ Removal of spurious peaks, efficient segmentation
  $\rightarrow$ Shape of the structuring element
- Edge detection [Gillespie2004]
  $\rightarrow$ Simple method
  $\rightarrow$ Impulsive noise, borders widening
- Hough transform [Pearson & Amblard 1996]
  $\rightarrow$ Model
  $\rightarrow$ Number of components, model

State of the Art : Segmentation / Instantaneous frequency law estimation II

Problems

- Methods operating on spectrogram and/or time series : sensitive to low local SNR
- Methods operating on binary spectrogram : sensitive to spurious peaks
- Computational complexity of the methods

Solutions

- Use of efficient binary spectrogram
- Denoising of time series
- Identification of the regions of interest

Sommaire

Global methodology

Time-frequency tracking methodology

- Time series
- Statistical segmentation of the time-frequency regions of interest (ROI)
  1. Detection of time-frequency bins exhibiting higher power than their neighbors
  2. Detection of the time-frequency regions of interest
- Time-frequency tracking of the structures in signals

Detection of the time-frequency regions of interest I

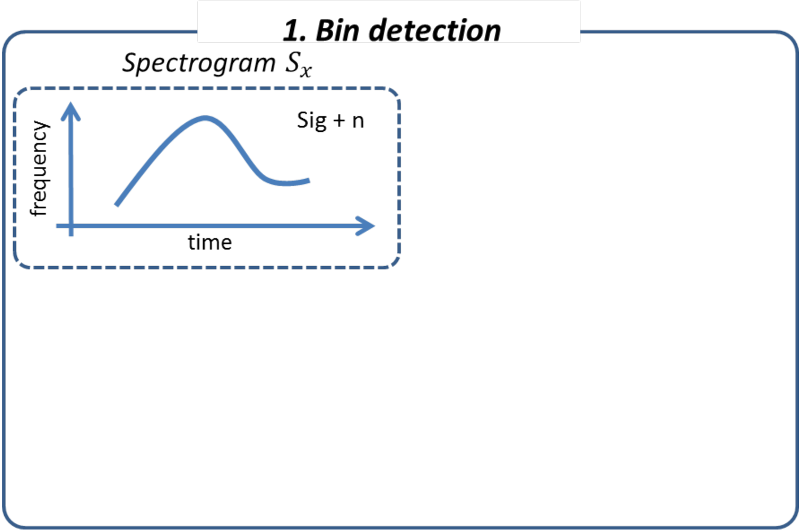
Step 1 : Detection of time-frequency bins

1. Binary hypothesis test on spectrogram $S_x[t,k]$:

$$\begin{cases} H_0^{bin} : S_x[t,k] = S_n[t,k] \ ; \\ H_1^{bin} : S_x[t,k] = S_{sig+n}[t,k] \end{cases} \tag{1}$$

2. Noise model $p(S_x|H_0^{bin})$: χ^2 distribution with 2 degrees of freedom
3. Estimation : Minimal statistics (small coefficients = noise)
4. Decision criterion : Neyman-Pearson (choice of the p_{FA})
5. Output : set of detected bins

Scheme of the methodology : time-frequency bin detection



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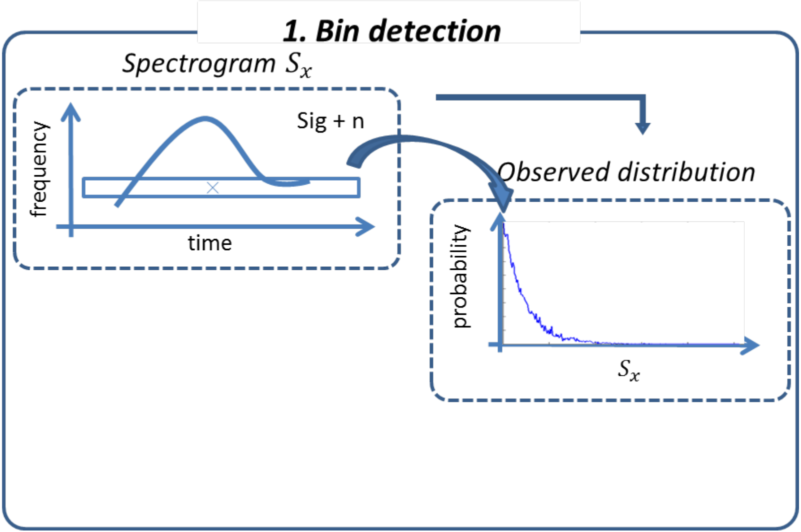

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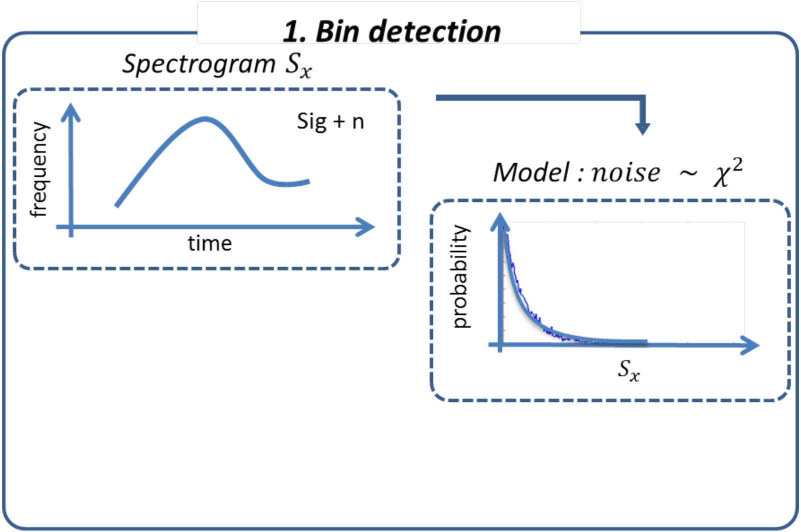
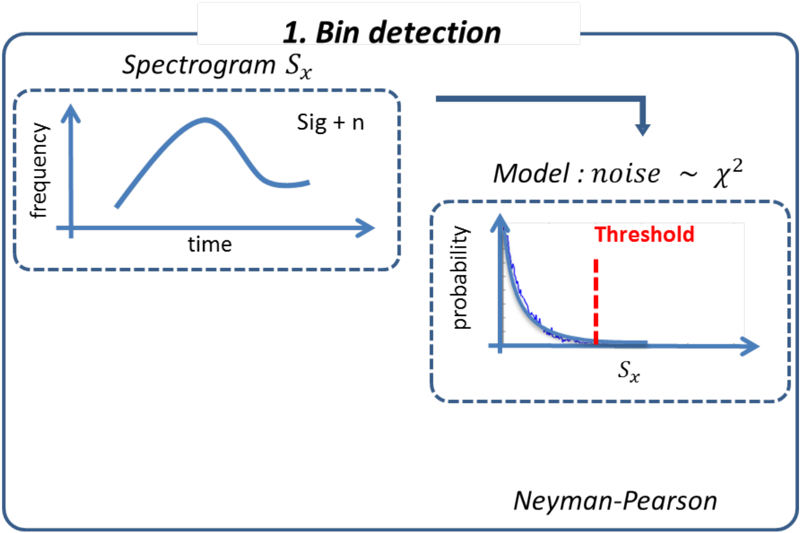


Scheme of the methodology : time-frequency bin detection



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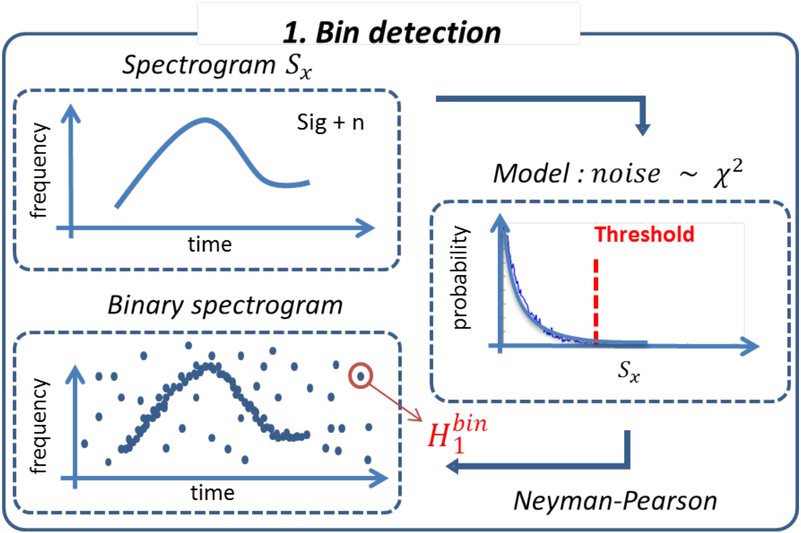
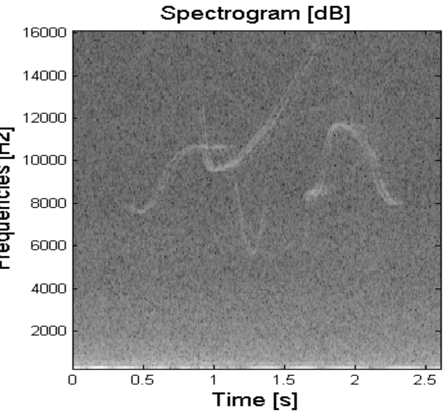




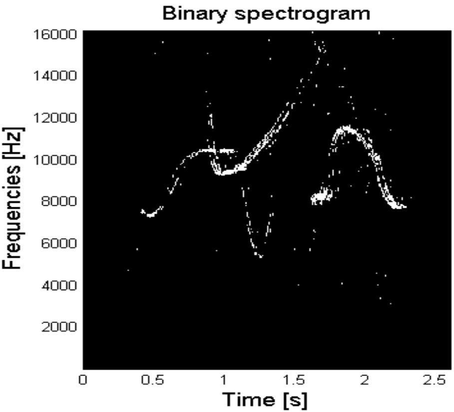
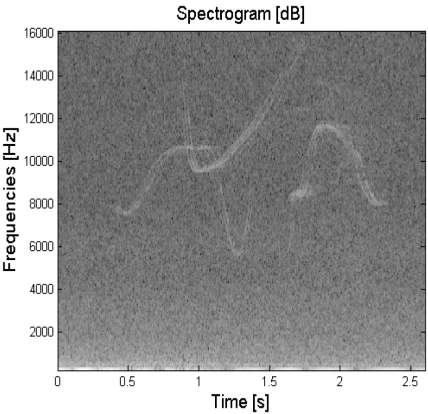


Figure : Spectrogram thresholding, $p_{FA} = 10^{-}5$



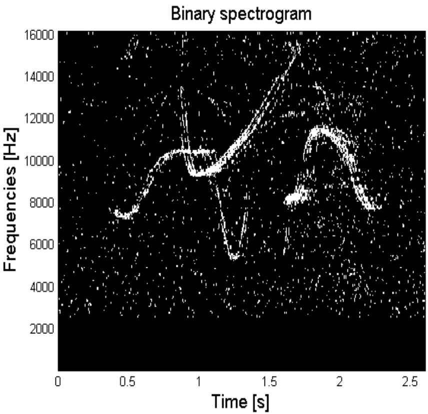


Figure : Spectrogram thresholding, $p_{FA} = 0.005$

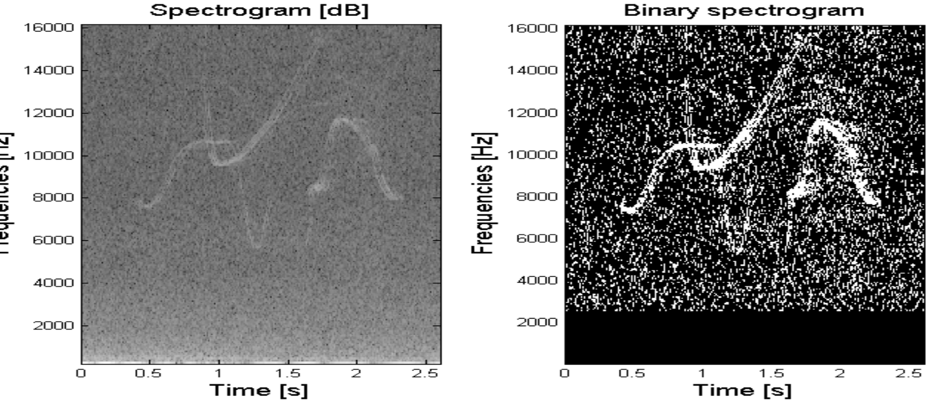
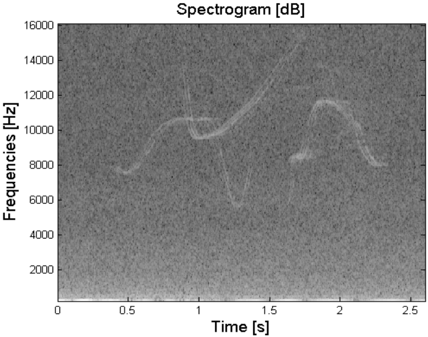
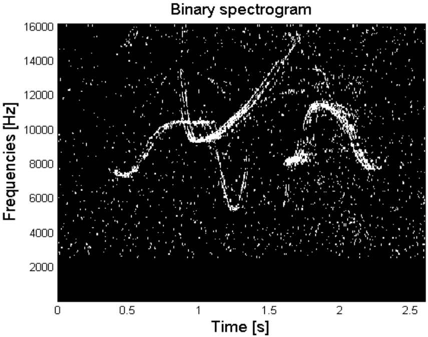


Figure : Spectrogram thresholding, $p_{FA} = 0.1$





Issues

- Lack of connectedness of detected components : missed detections, channel fading, sources directivity, etc.
- False detections (noise)

Detection of the time-frequency regions of interest II

Step 2 : Detection of cells hosting signal

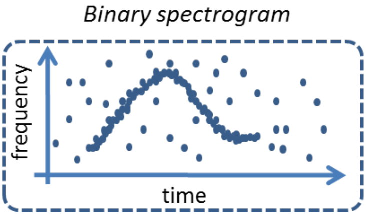
1. Starting from step 1 (binary spectrogram)
2. Partitioning of the binary spectrogram in cells (of fixed size A)
3. Counting of the number Σ_x of detections in cells
4. Hypothesis : large $\Sigma_x \rightarrow$ cell hosting signal
5. Binary hypothesis test on regions :

$$\begin{cases} H_0^{cell} : \Sigma_x = \Sigma_{FA} \;; \\ H_1^{cell} : \Sigma_x = \Sigma_{sig+FA} \end{cases} \tag{2}$$

6. False alarm model : $p(\Sigma_x | H_0^{cell}) \rightarrow$ Binomial law $B(A, p_0)$
7. Estimation : $\hat{p}_0$ that minimizes the Kullback-Leibler divergence between the histogram of the data $p(\Sigma_x)$ and the model $B(A, \hat{p}_0)$
8. Decision criterion : Neyman-Pearson

Scheme of the methodology : Cell detection

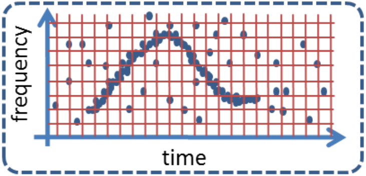
2. Segmentation of the time-frequency plane



Scheme of the methodology : Cell detection

2. Segmentation of the time-frequency plane

Partitioned binary spectrogram



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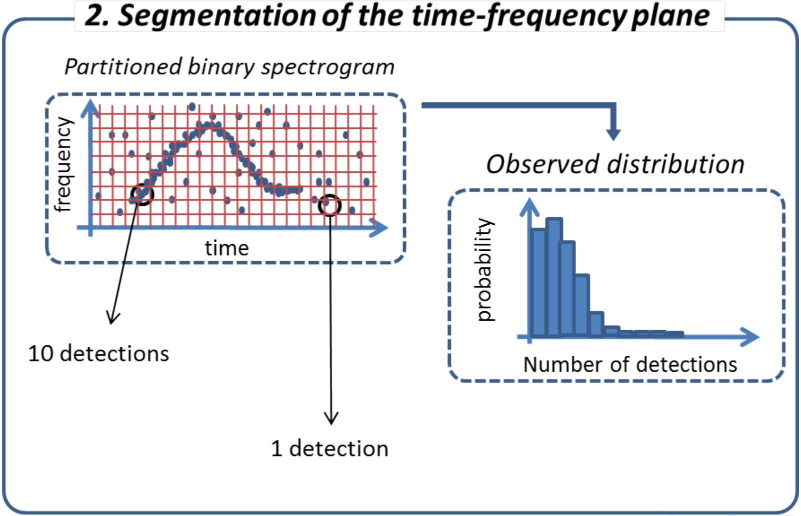

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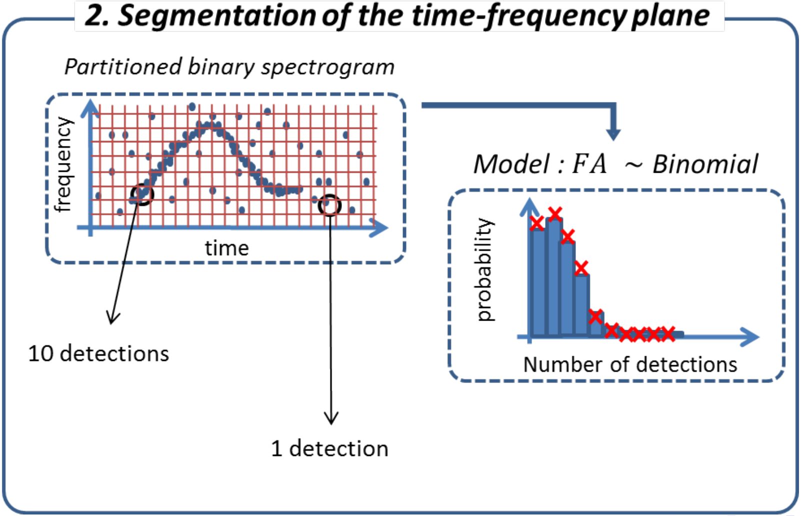

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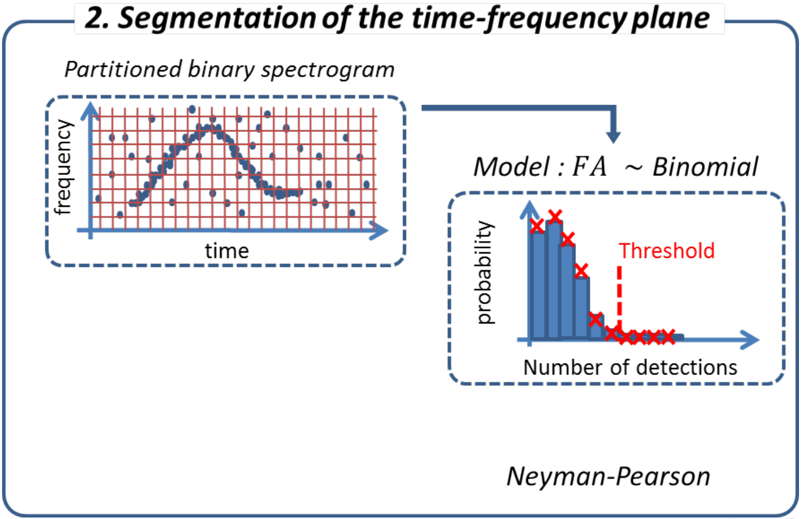
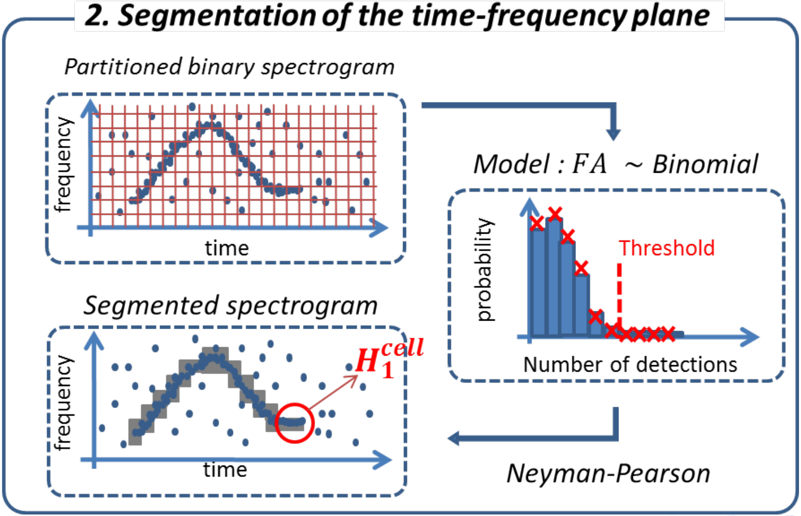


Scheme of the methodology : Cell detection



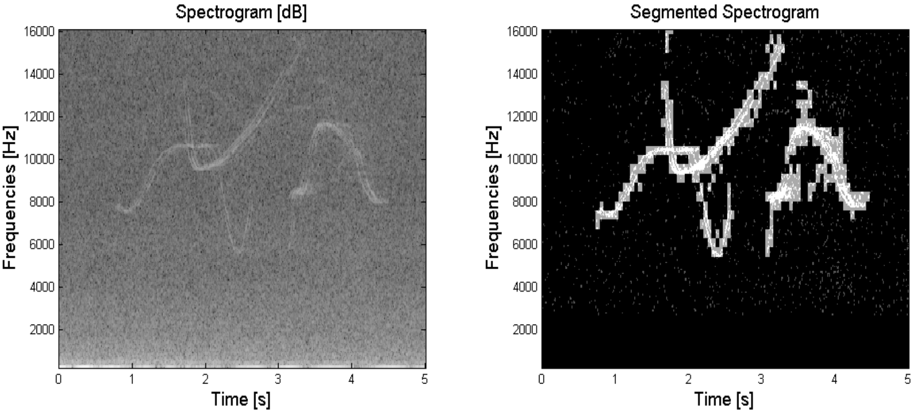


Figure : Spectrogram thresholding, $p_{FA}^{cell} = 0.001$, minimum duration of connected cells = 20 ms

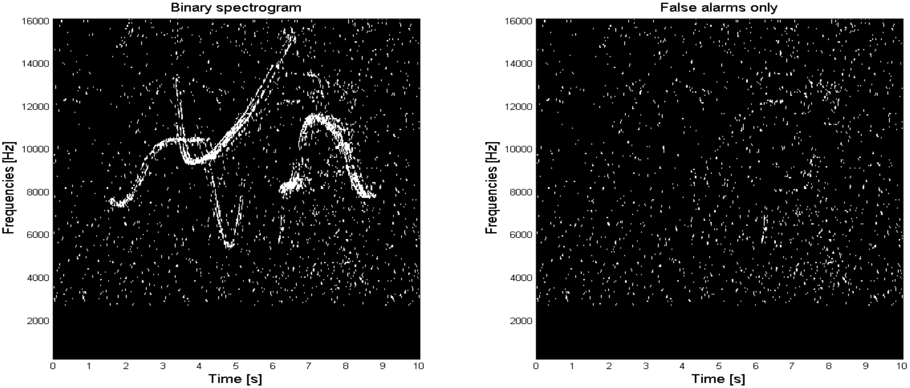
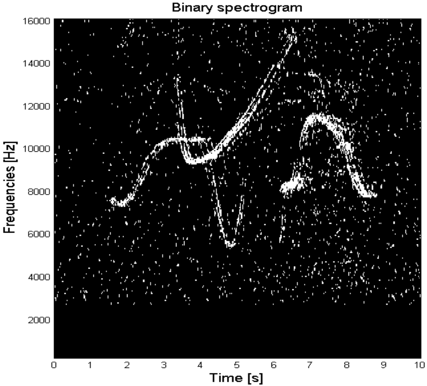


Figure : Spectrogram thresholding, $p_{FA}^{cell} = 0.001$, minimum duration of connected cells $= 20$ ms



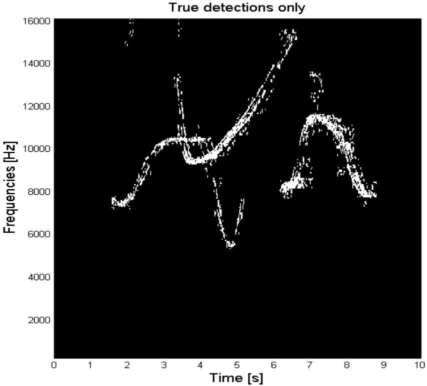


Figure : Spectrogram thresholding, $p_{FA}^{cell} = 0.001$, minimum duration of connected cells = 20 ms

Input parameters of the method

1. Neighborhood for noise estimation
2. Probability of false alarm for bin detection p_{FA}^{bin}
3. Partitioning of the binary spectrogram (size of cells A)
4. False alarm probability for cell detection p_{FA}^{cell}
5. Minimum duration of components (physical considerations)

Issue

- Final segmentation heavily influenced by the choice of p_{FA}^{bin} for bin detection
- Optimal p_{FA}^{bin} ?

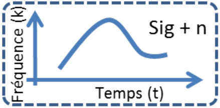
Adopted solution

- Try multiple p_{FA}^{bin}
- Keep the one maximizing the detection probability of (connected) regions

Multi-threshold methodology

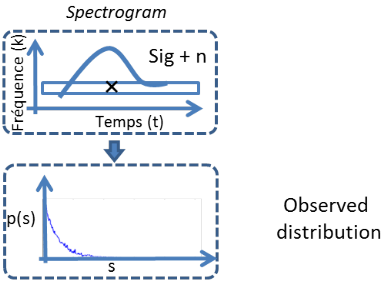
1. Bin detection

Spectrogram



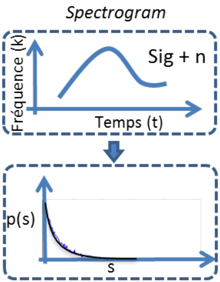
Multi-threshold methodology

1. Bin detection



Multi-threshold methodology

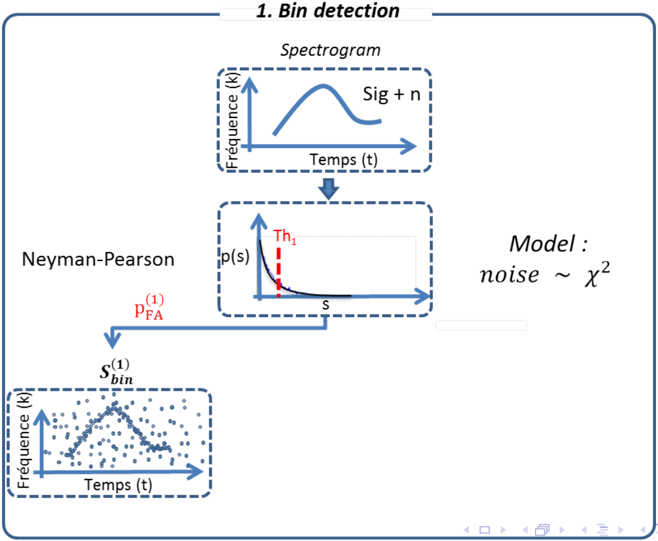
1. Bin detection



Model :

$noise \sim \chi^2$

Multi-threshold methodology



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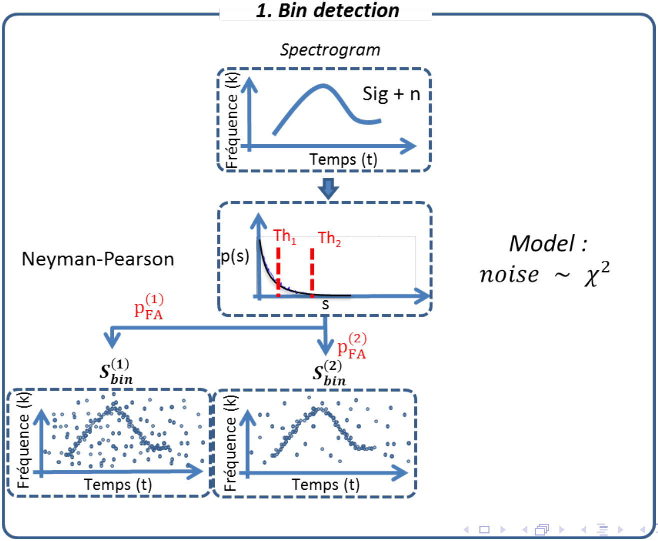

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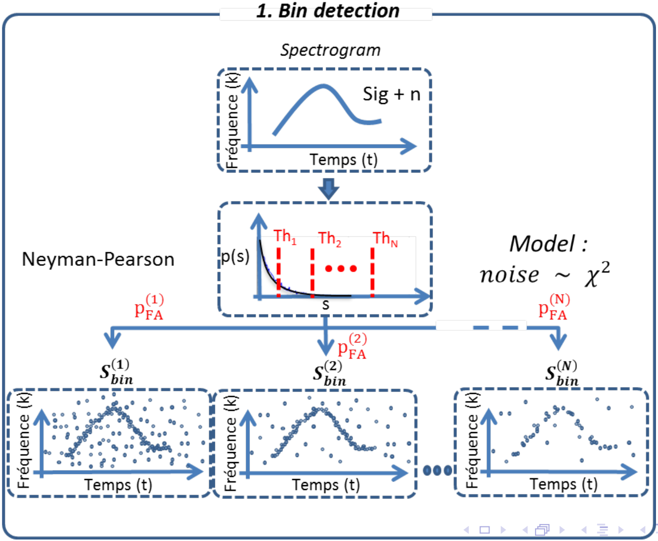

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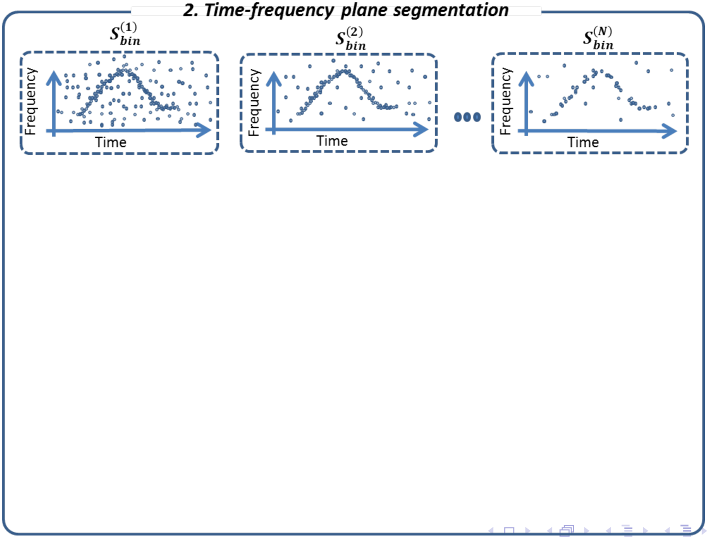

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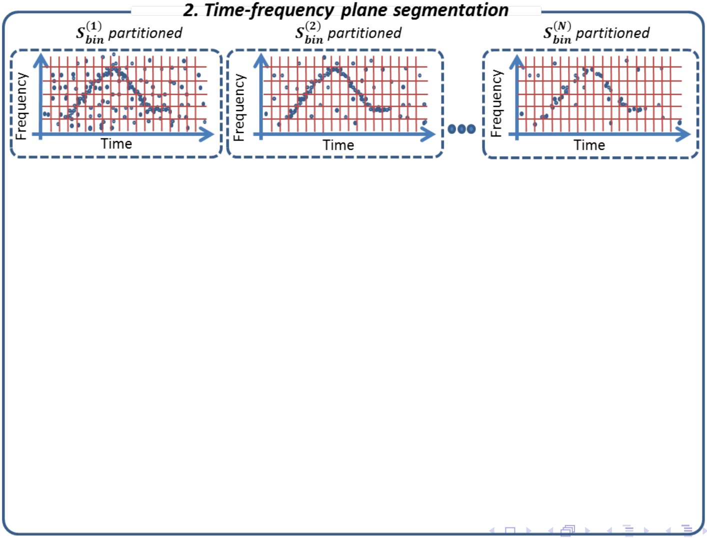

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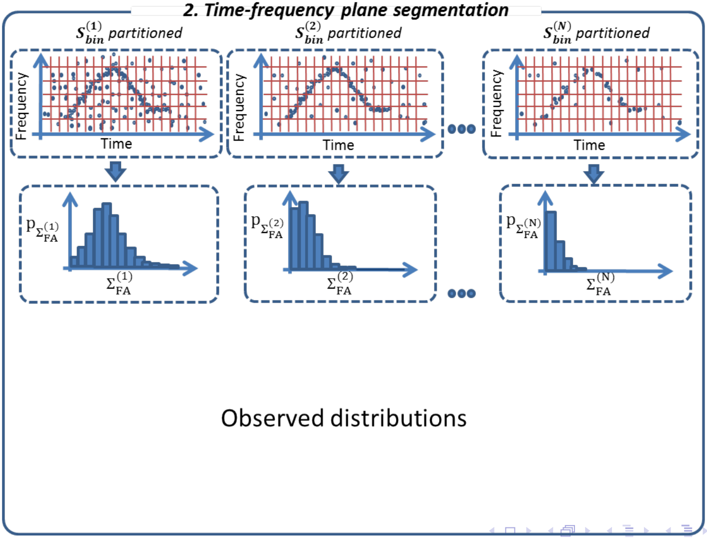
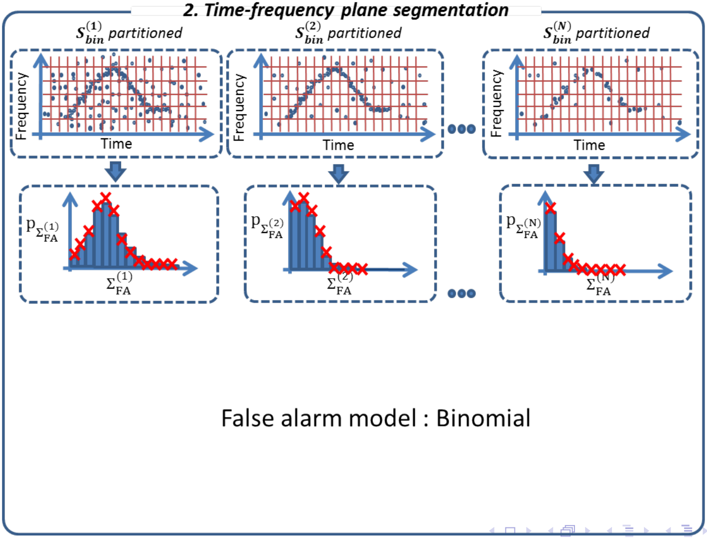


Multi-threshold methodology



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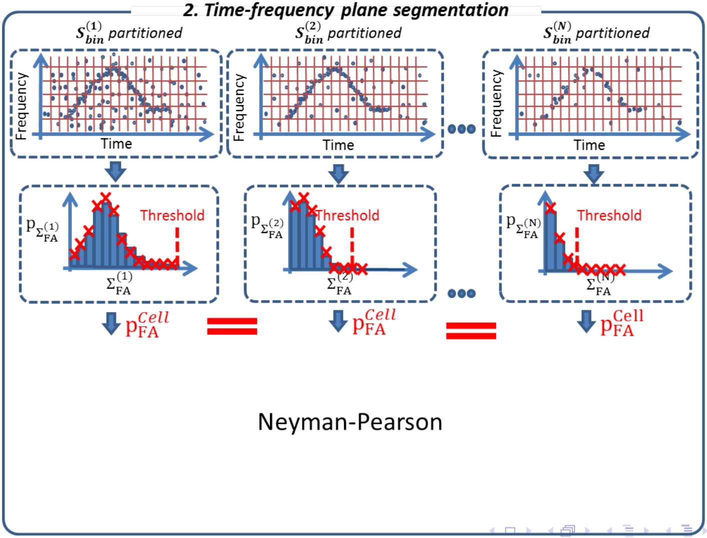
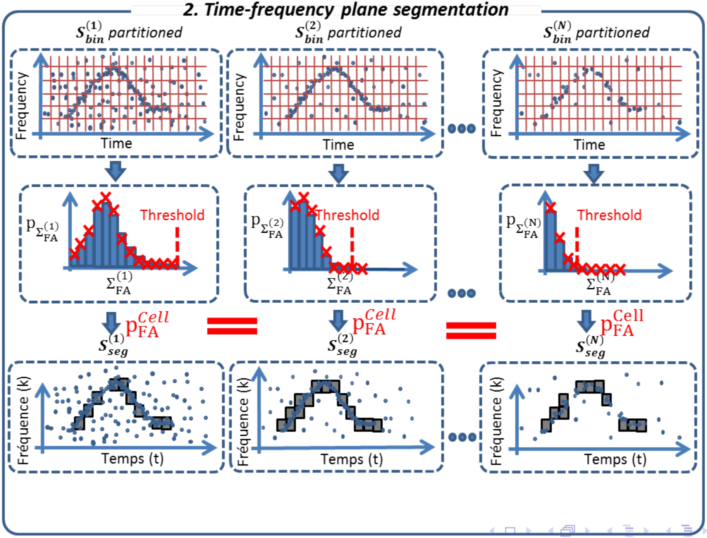
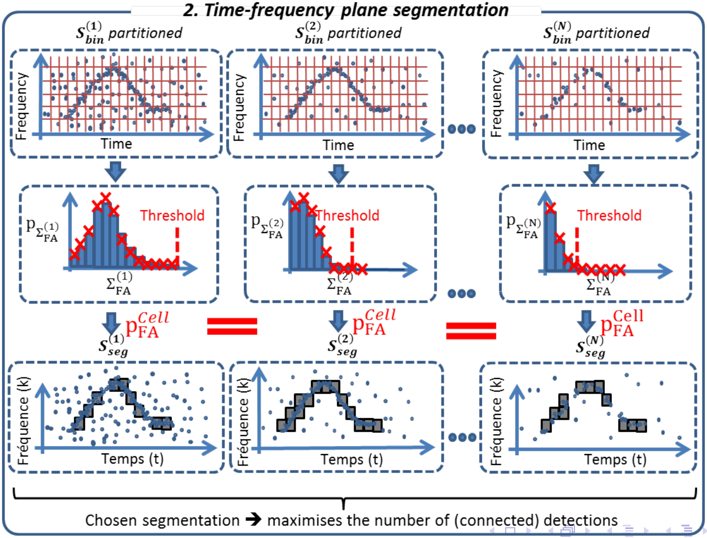


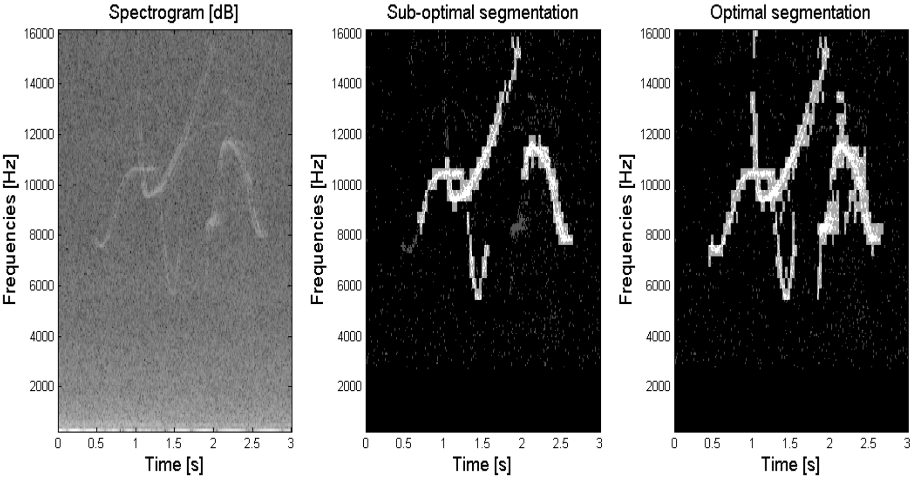
Multi-threshold methodology



Multi-threshold methodology



Example on real signals



- Output of last step :

  $\rightarrow$ Set of time-frequency regions of interest

- Possible uses :

  $\rightarrow$ Tracking on efficient binary spectrogram
  $\rightarrow$ Denoising of time series : design of time-varying filters
  $\rightarrow$ Sparse communication : sensor transmits 'useful' information only

- Example in this presentation :

  $\rightarrow$ Denoising to guide a time-frequency-phase tracker operating on time series

Sommaire

Time-frequency-phase tracking methodology

Principle of the Local Phase Analysis

- Local polynomial modeling of the phase
- Extraction of the waveform

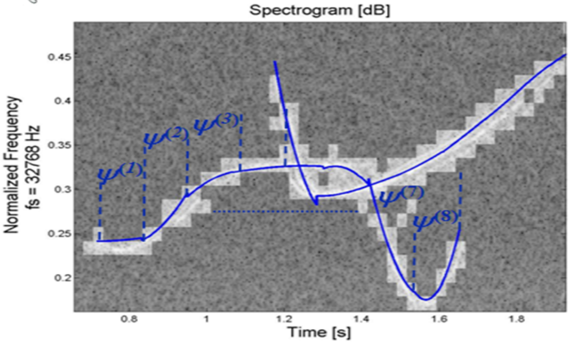
Methodology [Ioana2010, Josso2009]

- 3rd Order polynomial modeling of the phase

$$s(t) = A\ exp(\,j \sum_{k=0}^{k=3} a_k t^k)$$

- Multiple Estimation of the phase *via* Product High Order Ambiguity Function (PHAF)
- Design of time-frequency filters around the phase estimates and filtering
- Fusion of the local waveforms *via* maximization of the correlation

Results of the methodology applied to real signals



Sommaire

Results

- Efficient Statistical segmentation
- Few input parameters
- Handles large databases (fast)

Perspectives

- Choice of A ?
- Shape of the partitioning grid ?

Thank you, any questions ?