

3D multiple whale tracking by passive acoustics, & classification by sparse coding for *'etho-acoustics'*



Int. Workshop Erice 2013

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SABIOD MASTODONS CNRS Big Data project

<http://sabiody.univ-tln.fr>

Port-Cros with Razik J., Paris S., Giraudet P.,

Parc National

Prevot J.M., Doh Y., Abeille R., Bénard F., Monnin A.



SABIOD



I. Introduction

II. Single hydrophone 'etho-acoustics'

III.3D RT Single whale tracking by Passive Acoustics

IV.3D RT Multiple whale tracking by PA

V. Classification by sparse coding

VI. Fast Tracking by sparse coding

VII. Conclusion: Scaled Acoustic Methods SABIOD

20 minutes from univ. Toulon :
Physeter, Minke whale, dolphin, fin whale,...



ONCET : Online Cetacean Tracking Bombyx (2012-2017) [<http://sabiod.org>]



**Tested on NEMO (see IV)
Wait for ANTARES data**

Project (with ADAM)

location

technical properties

data
Go/month

tasks



Ste Marie

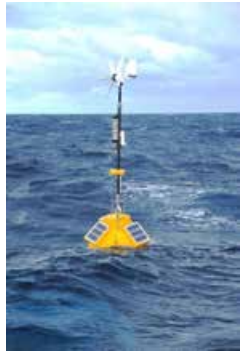


Array of 6 hydrophones
sampling frequency : 44 kHz or
192 kHz, coded by 16 or 24 bits

200 to 9000

Inventory of Humpback whales in the
Indian Ocean
Estimation of the trend of the size of the
population
Impact of the human activities
Impact of the global change

Guadeloupe



Single hydrophone

sampling frequency : 44 kHz or
192 kHz, coded by 16 or 24 bits

200 to 2000

Inventory of the different species of
resident/non resident cetaceans
Presence in the new sanctuary AGOA of
marine mammals
Impact of the human activities (touristic,
fishermen, harbour)

St Pierre et Miquelon



2 single hydrophones
sampling frequency: 32 kHz,
coded by 16 bits

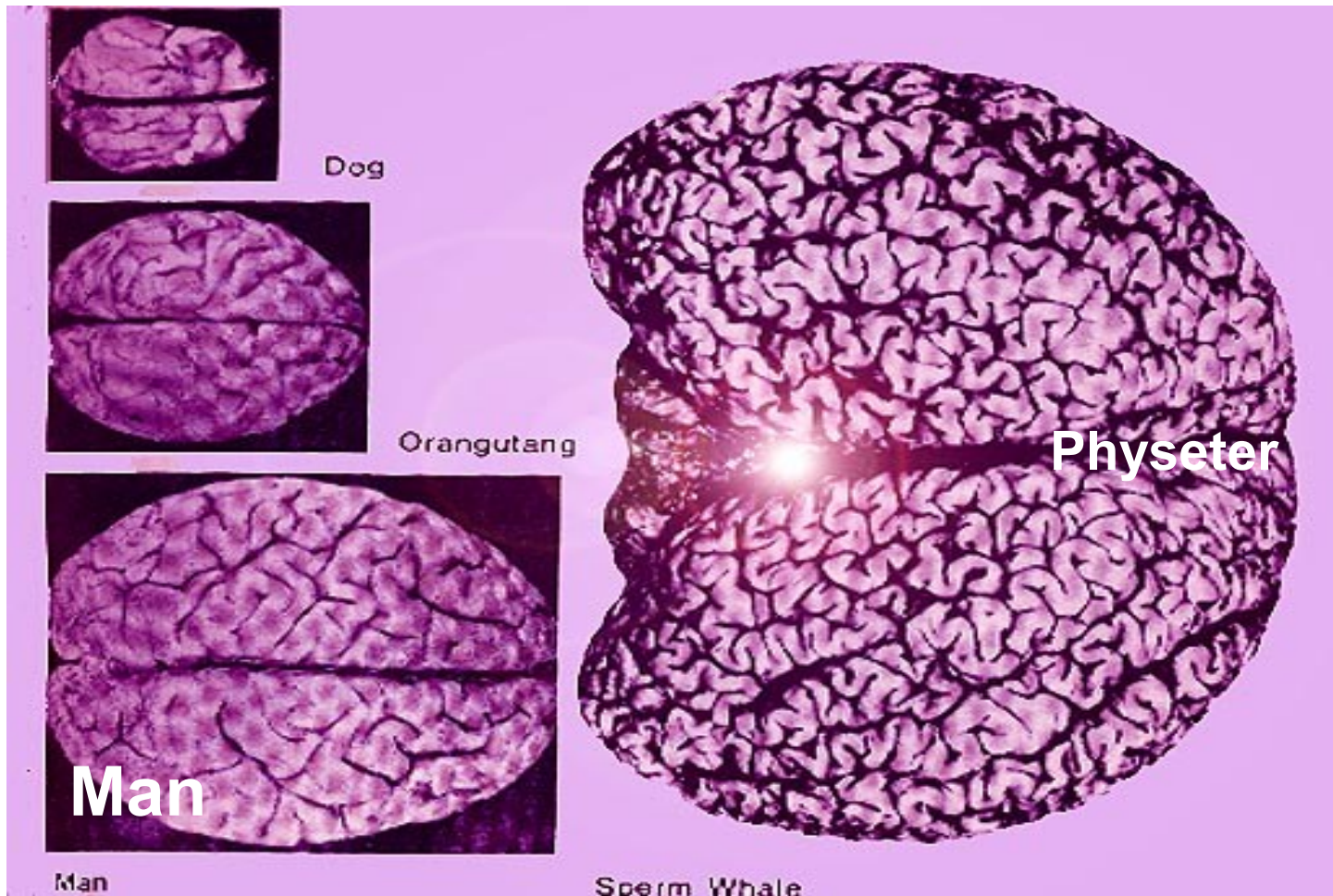
350

-Inventory of the different species of
resident/non resident cetaceans
-Migration routes / feeding areas

total

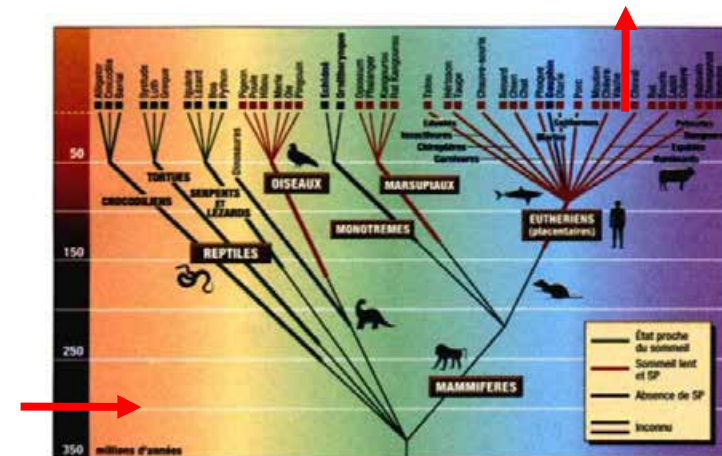
**800 Go to 11
To/month**

Marine Mammals process highly complex sounds,
with which representation ?



A challenge : Classification on large number of classes, with high class variability

- Usually organized (Hierarchical or Graph) through ontology
 - Examples : DMOZ (> 600 000) classes, Wikipedia, etc
 - Often multilabel
- **Quantitative change implies a qualitative change in methods**
- Problems
 - Which criterion to use for training ?
 - What to do to perform fast inference ?
 - Connexion to on-line learning, learning with imbalanced data, large scale learning, ...



- New trend in **machine learning** and data mining

Thousands of classes

Large Scale Classification : which model ?

• **Approaches**

- Flat (none relational information between classes e.g. one vs all classifiers)
Accurate but slow at test time $O(\# \text{ classes})$
- Hierarchical (modeled on the taxonomy)
Less accurate than flat methods but **fast inference** $O(\log(\# \text{ classes}))$
- In between methods
Compromise wrt accuracy and inference time between the two extremes

[L Cai, T Hofmann, Hierarchical document categorization with support vector machines, CIKM 2004

K. Weinberger, O. Chapelle, Large Margin Taxonomy Embedding with an Application to Document Categorization, Neural Information Proc. Sys. NIPS 2008

J. Weston, S. Bengio and D. Grangier, Label Embedding Trees for Large Multi-Class Tasks, NIPS 2010

M. Cissé, T. Artières, P. Gallinari, Learning compact class codes for fast inference in large multi class classification, ECML 2012]

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Predation and Moon effect ?

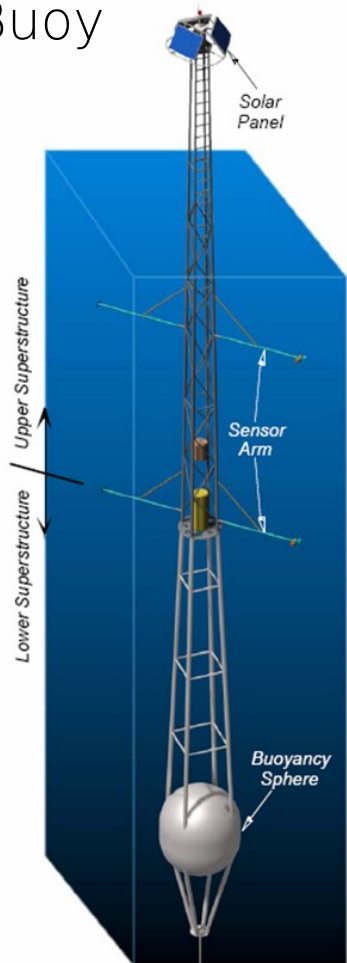
BOUSSOLE project

- Definition of the click detector and noise filtering
- Detection results
- Conclusion on ICI at new-moon versus full-moon

BOUSSOLE project

BOUSSOLE

Buoy



periods of recording:

- 15 october to 9 december 2008
- 5 january au 2 march 2009
- 15 april au 15 juin 2009
- 16 july au 1 september 2009

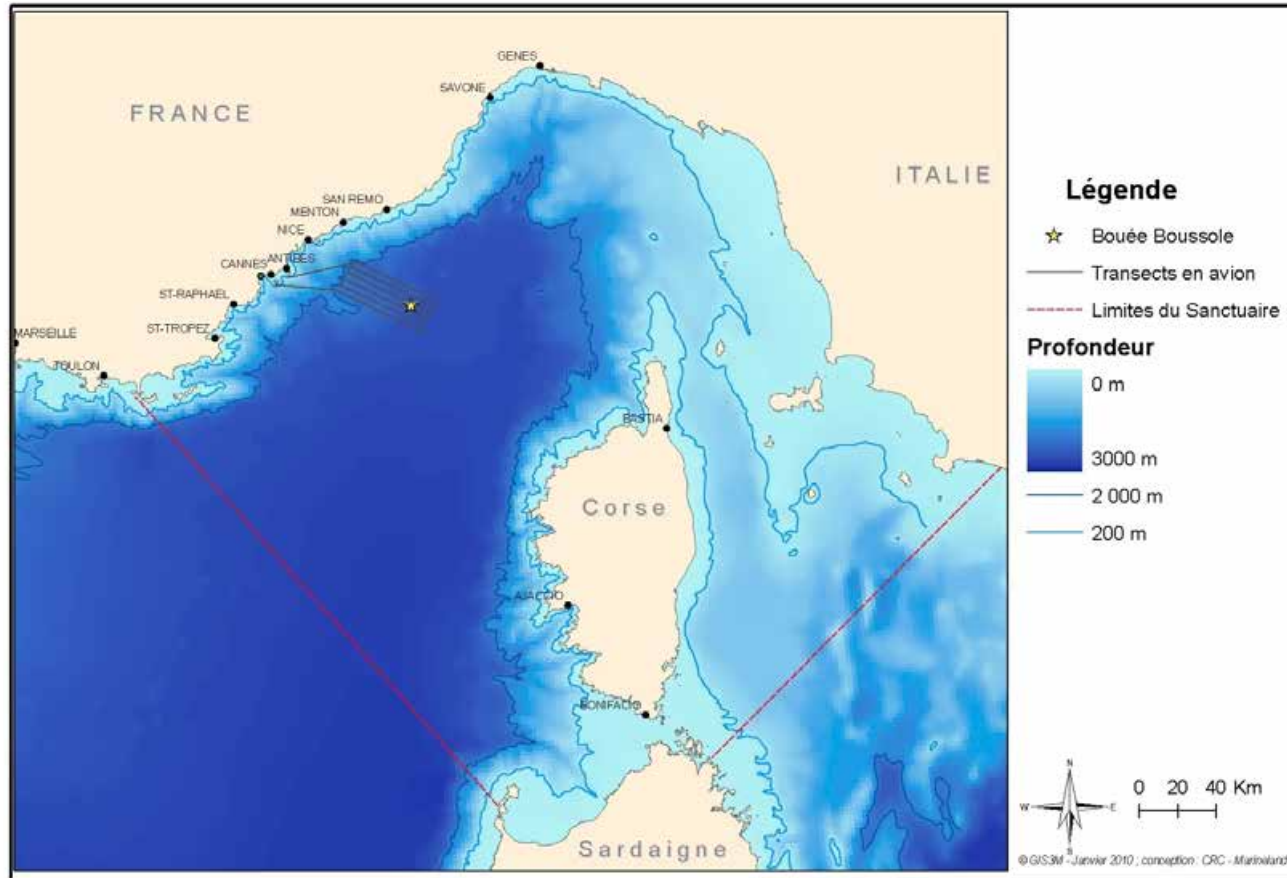
5 minutes audio files recorded every quarter of an hour by the Ecological Acoustic Recorder (EAR, cf LAMMERS)

→ 6000 files of 19Mo

Fe = 32000Hz

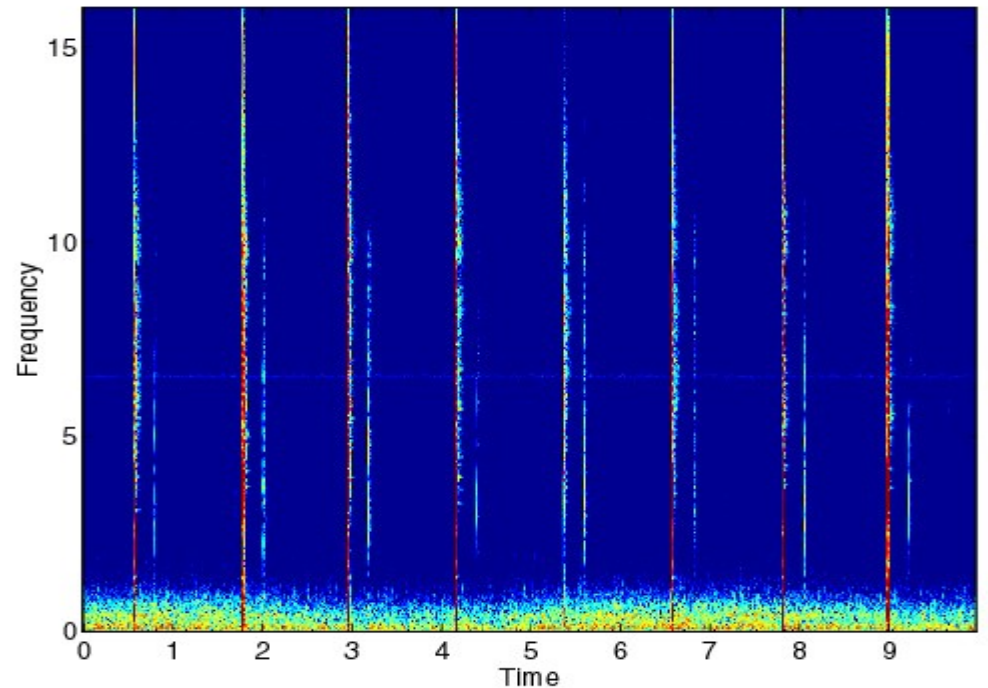
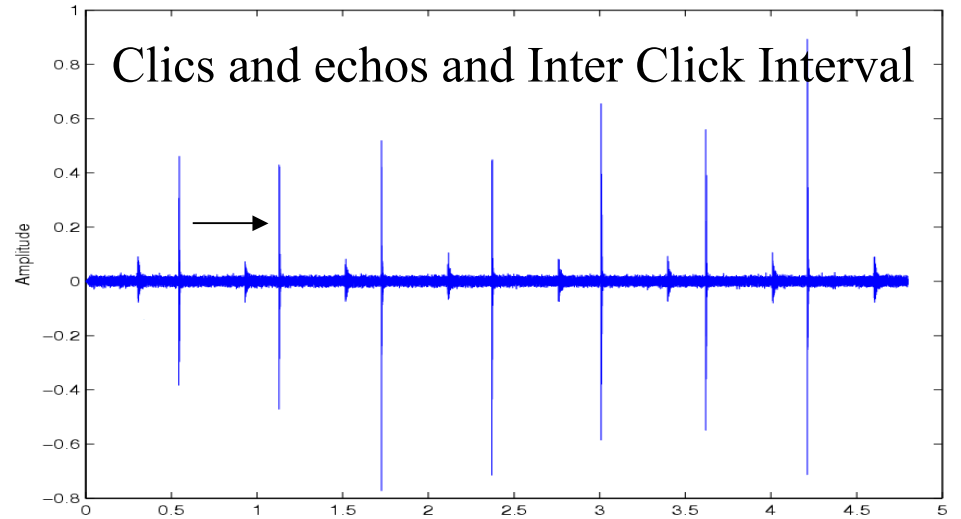


18 months of recording south Antibes



The Pelagos Sanctuary for Mediterranean Marine Mammals is a special marine protected area extending about 90.000 km² in the north-western Mediterranean Sea between Italy, France and the Island of Sardinia, encompassing Corsica and the Archipelago Toscano.

An Inter-Click Interval study on Physeter catodon

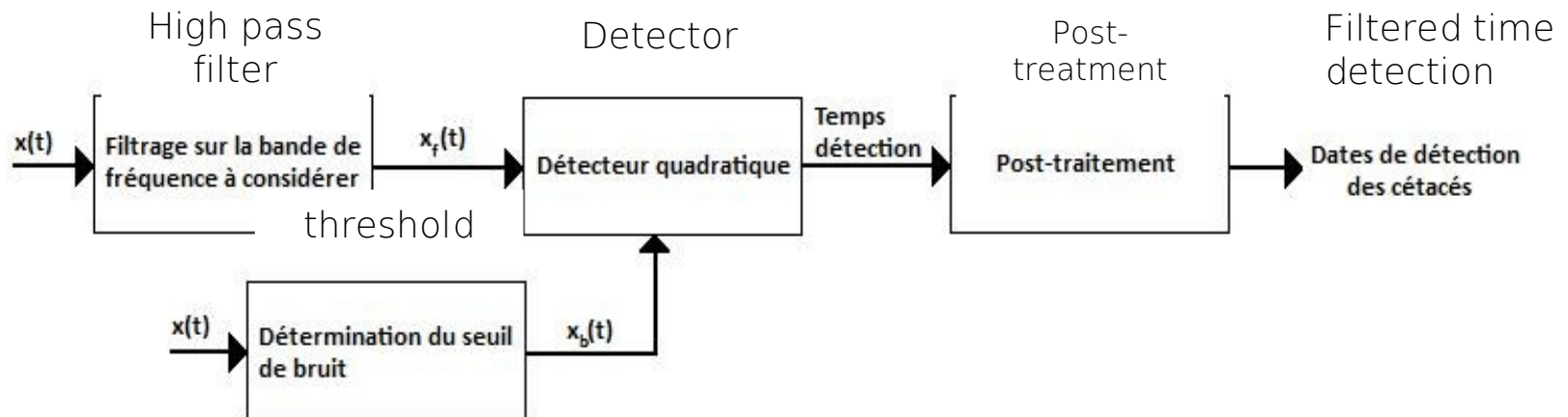


Click detector and noise filter

For scaled processes, we designed a quadratic detector.

=> 2h30 to process one month of data.

followed by a filter in order to remove chain noises.



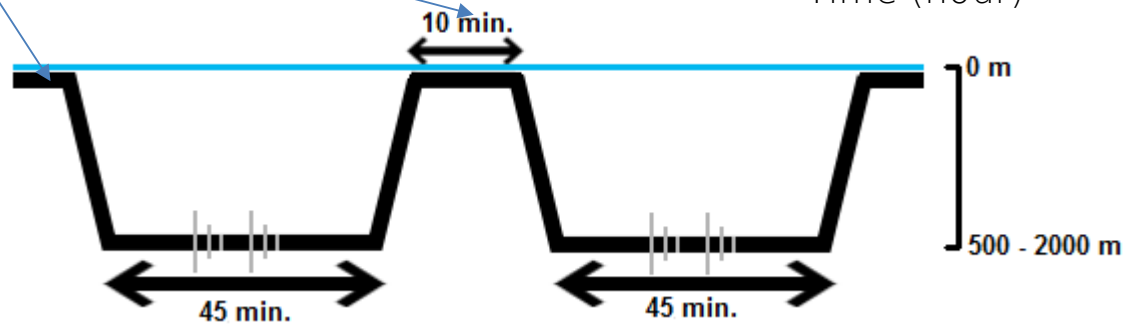
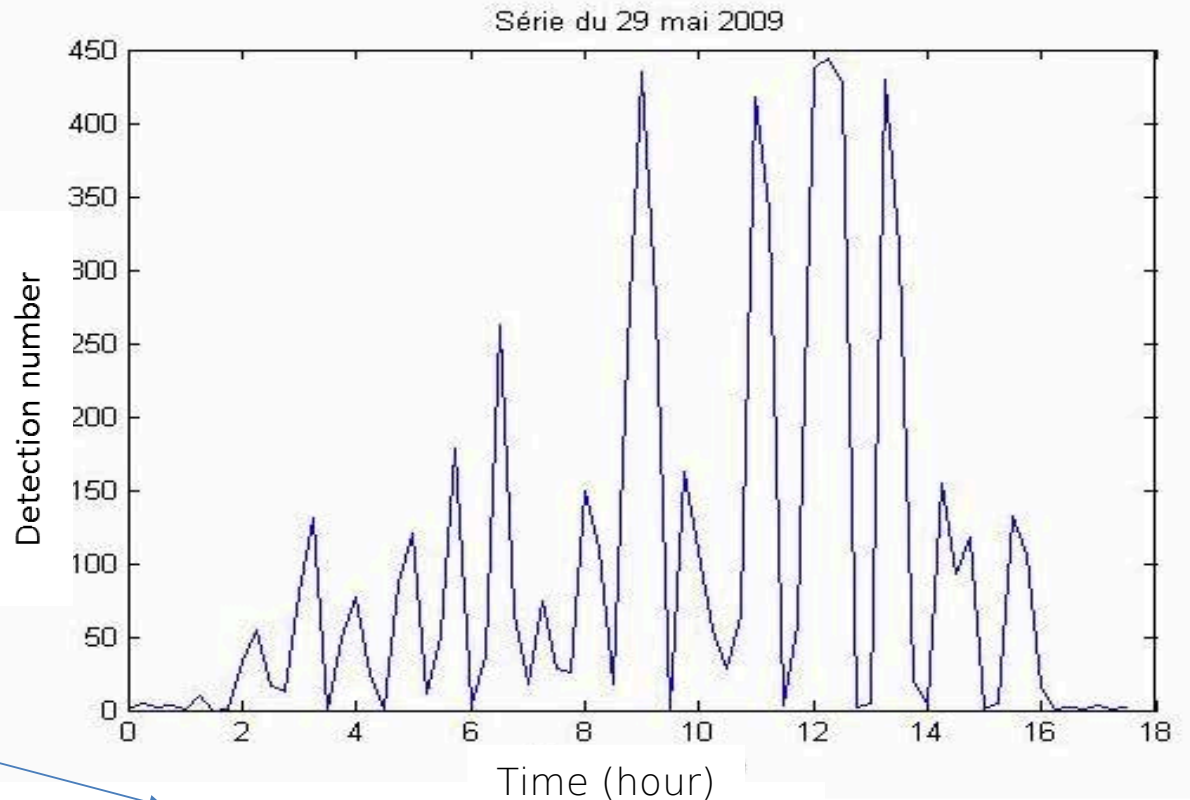
(high pass filter 5000Hz ; window length: 40 ms)

Detection results

Continuous detection on 15 hours of one Physeter !

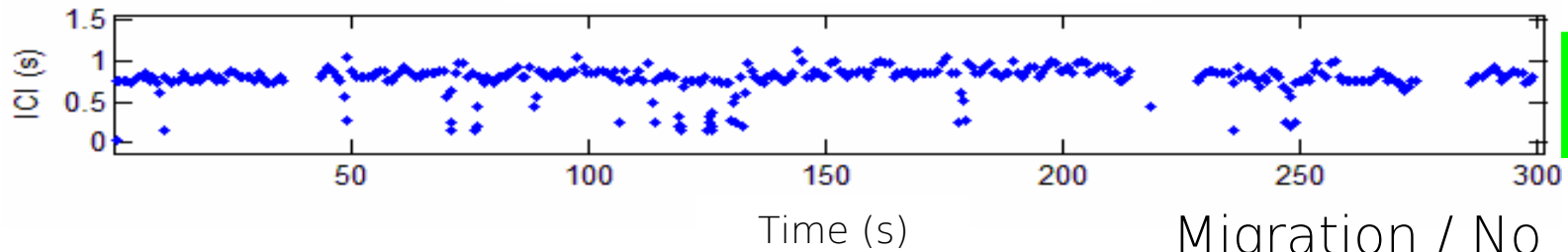
Coherent detections profile according to the resting time at surface and diving periods :

No acoustic activity



Inter-Clic Interval (ICI)

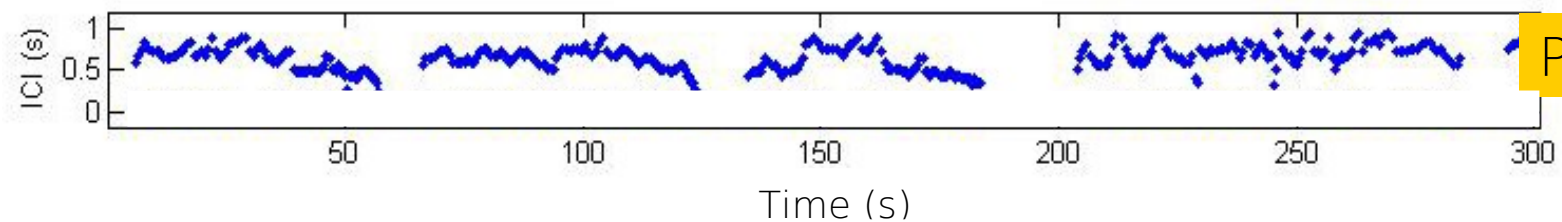
January 2009



Explo
CODA

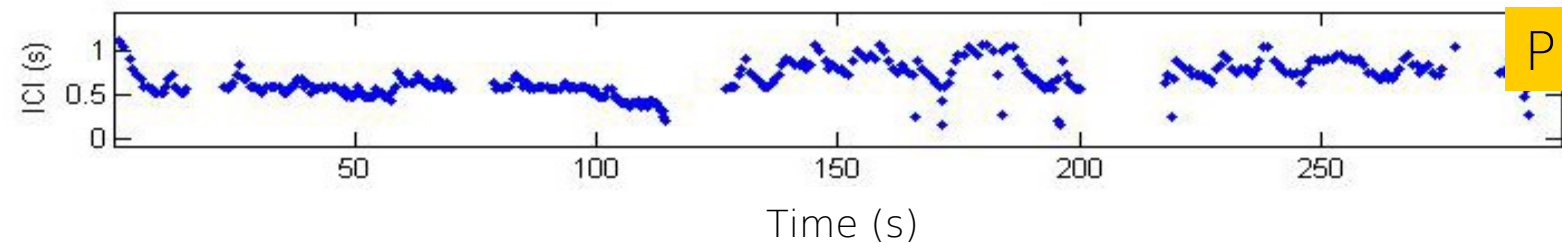
Migration / No
predation

July 2009



Predation

March 2009



Predation

Predation behavior

(B nard, Giraudet, Glotin 2007 - AUTECH Bahamas)

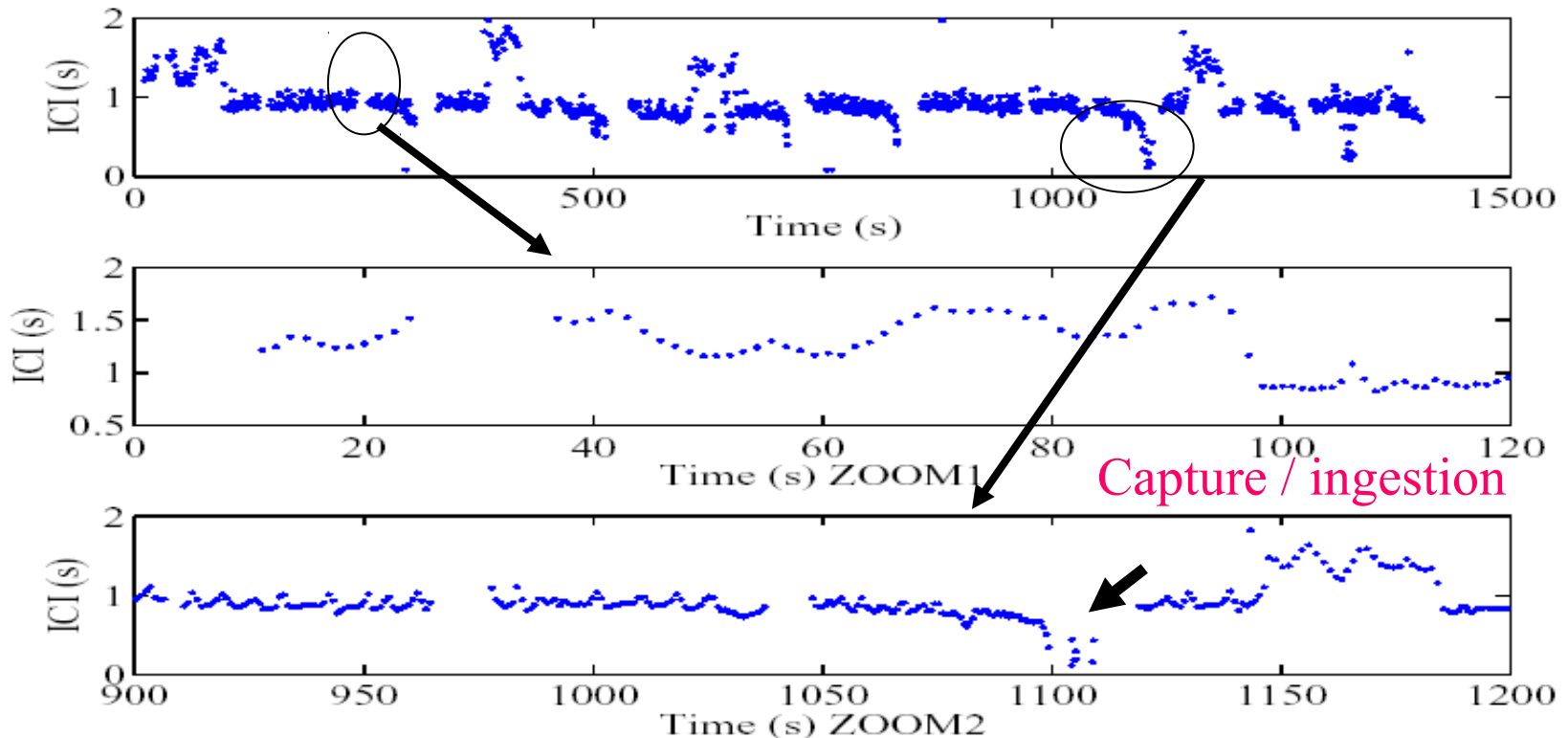
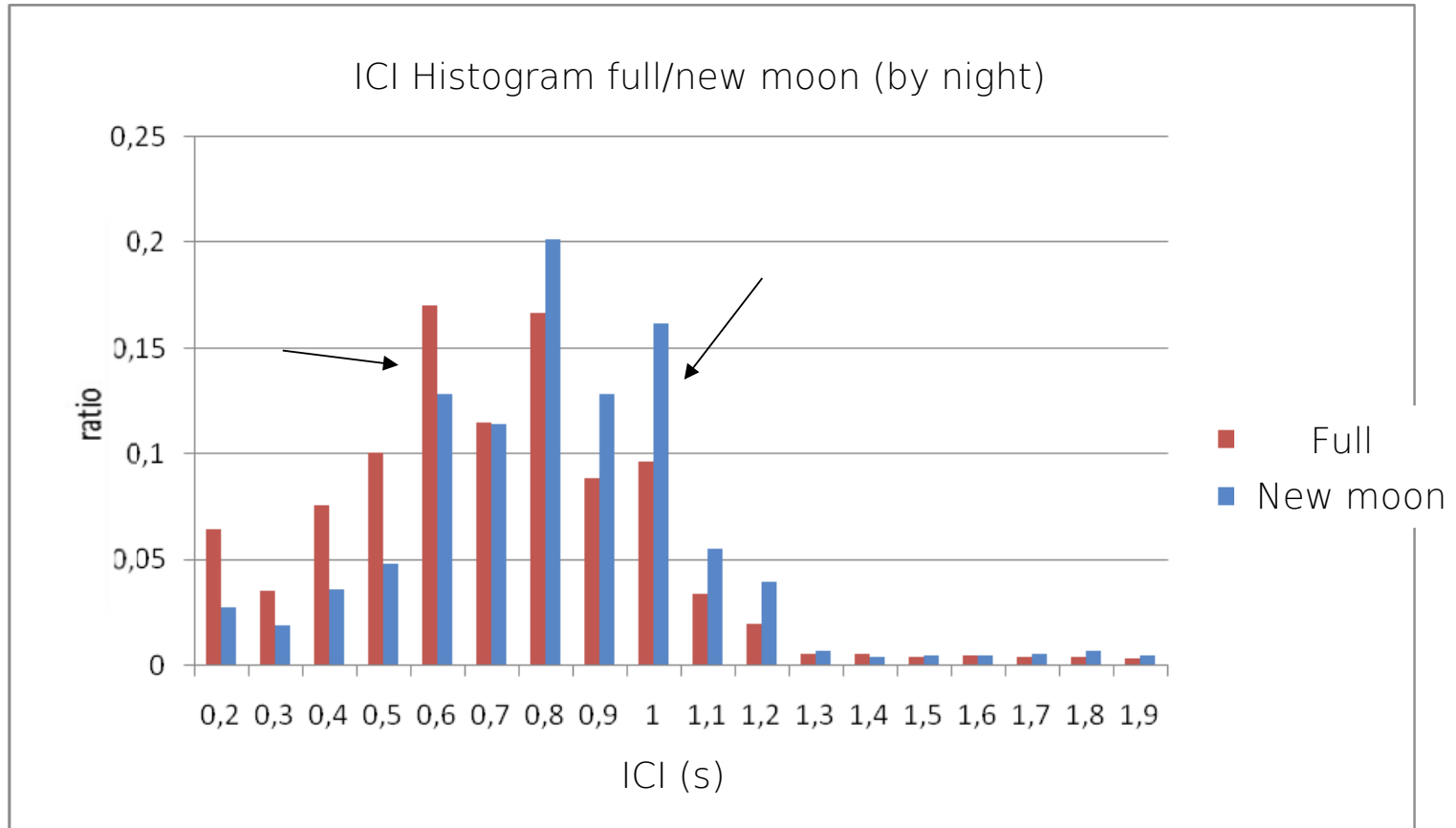


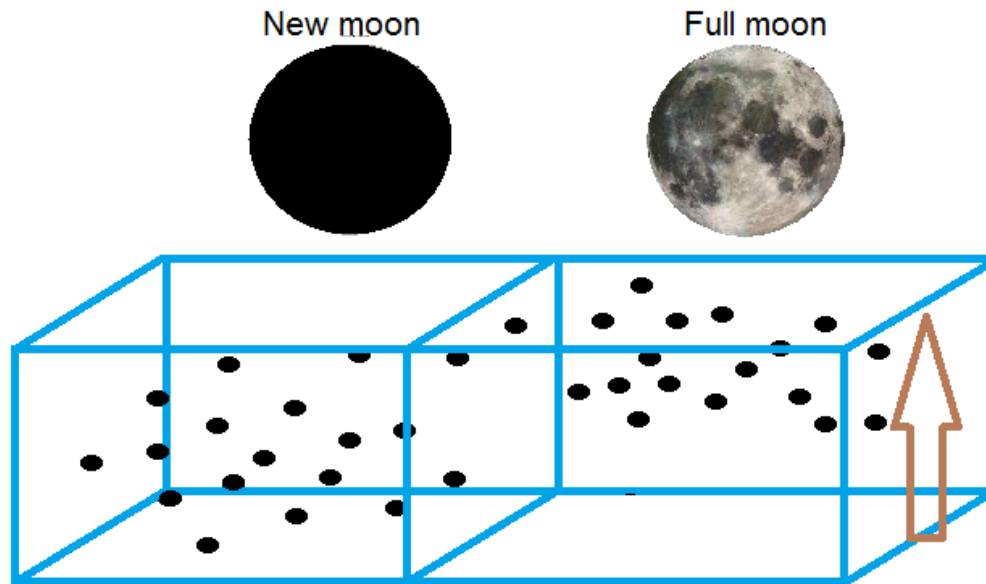
FIG. 3.11 – Intervalles inter-clics $ICI(t)$ estim s sur le set 2. En haut sur 1400s, en bas deux zoom. On observe des modulations qui correspondent au comportement de pr dation. Dans le zoom de 900   1200s, on observe un creak   1100s, suivi de l'ingestion d'une proie (silence).

Statistics on ICI distribution new moon versus full moon



Again, Kolmogorov Smirnov test positive for $p < 0,01$.
nb : Recordings with more than 1 sperm whale are processed.

? : $ICI(\text{new-moon}) \gg ICI(\text{full moon})$

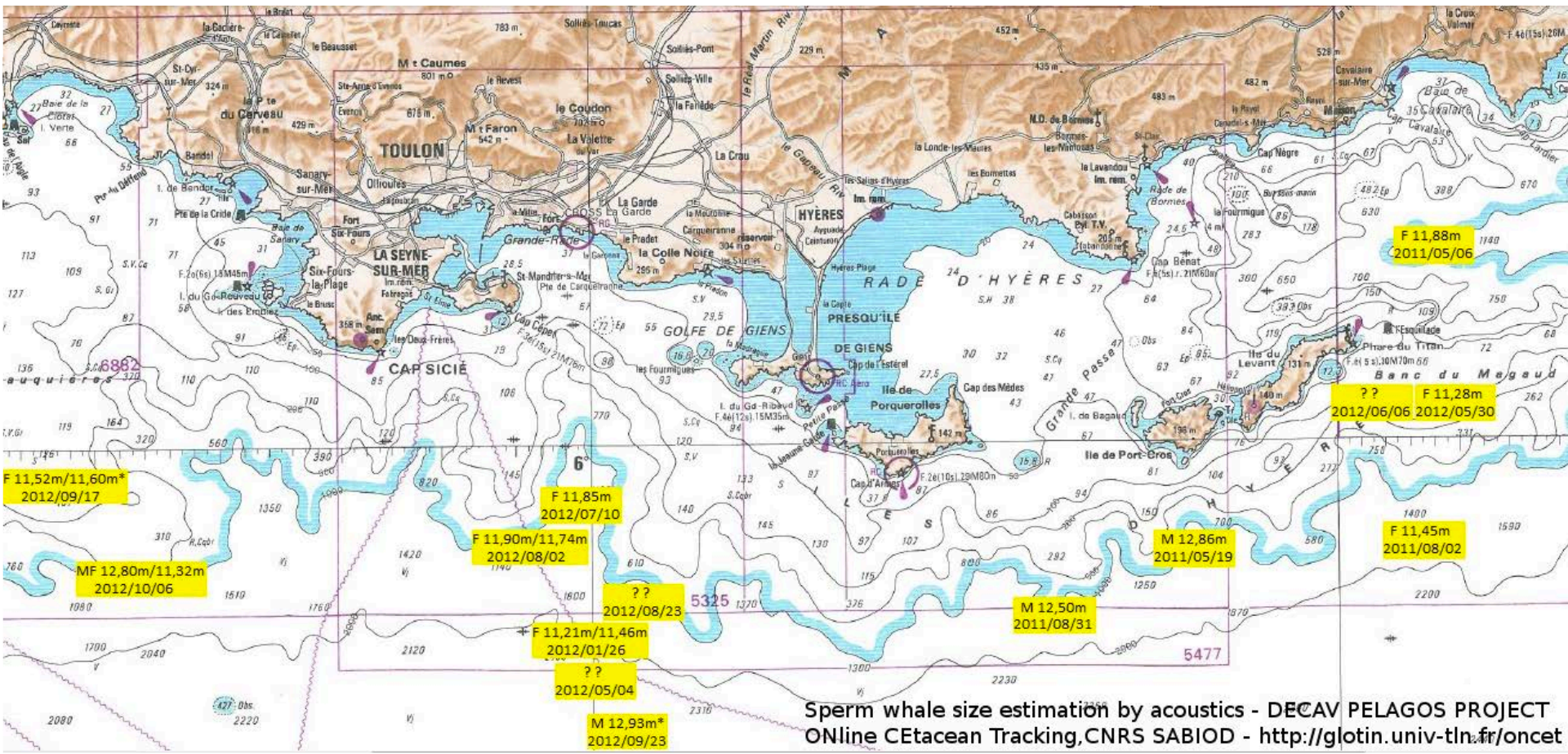


Interpretation : full moon light could result in a higher prey concentration at small depth water layers.

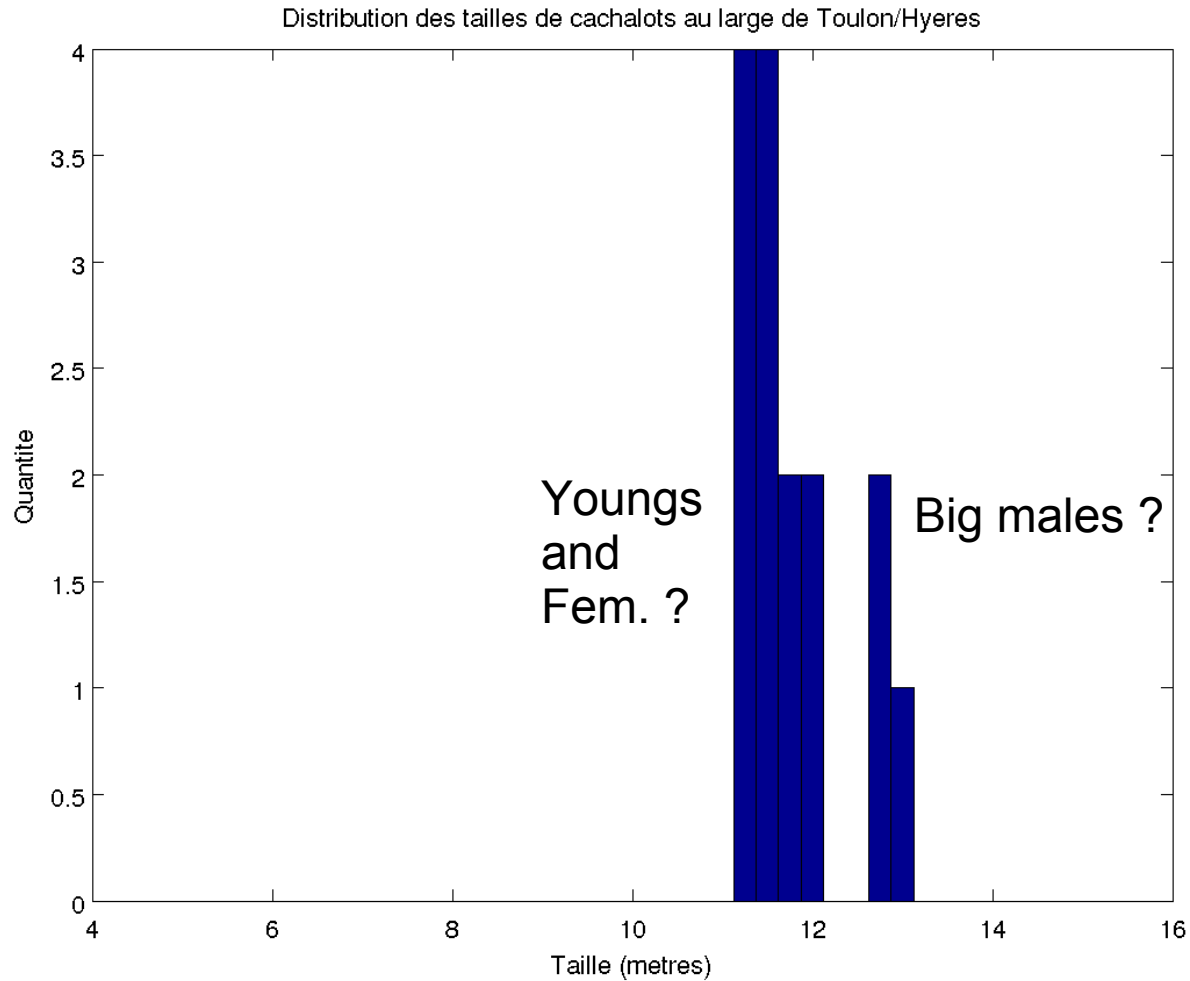
Thus, sperm whales are more often predated in this higher prey density at full moon, than at new moon.

? Moon effect on social dialects ?

Inter Pulse Interval : proposition for robust IPI estimator application on 2011-2012 DECAV PELAGOS project (each detection has its size est.)



Allometric rules on IPI => Sizes distribution



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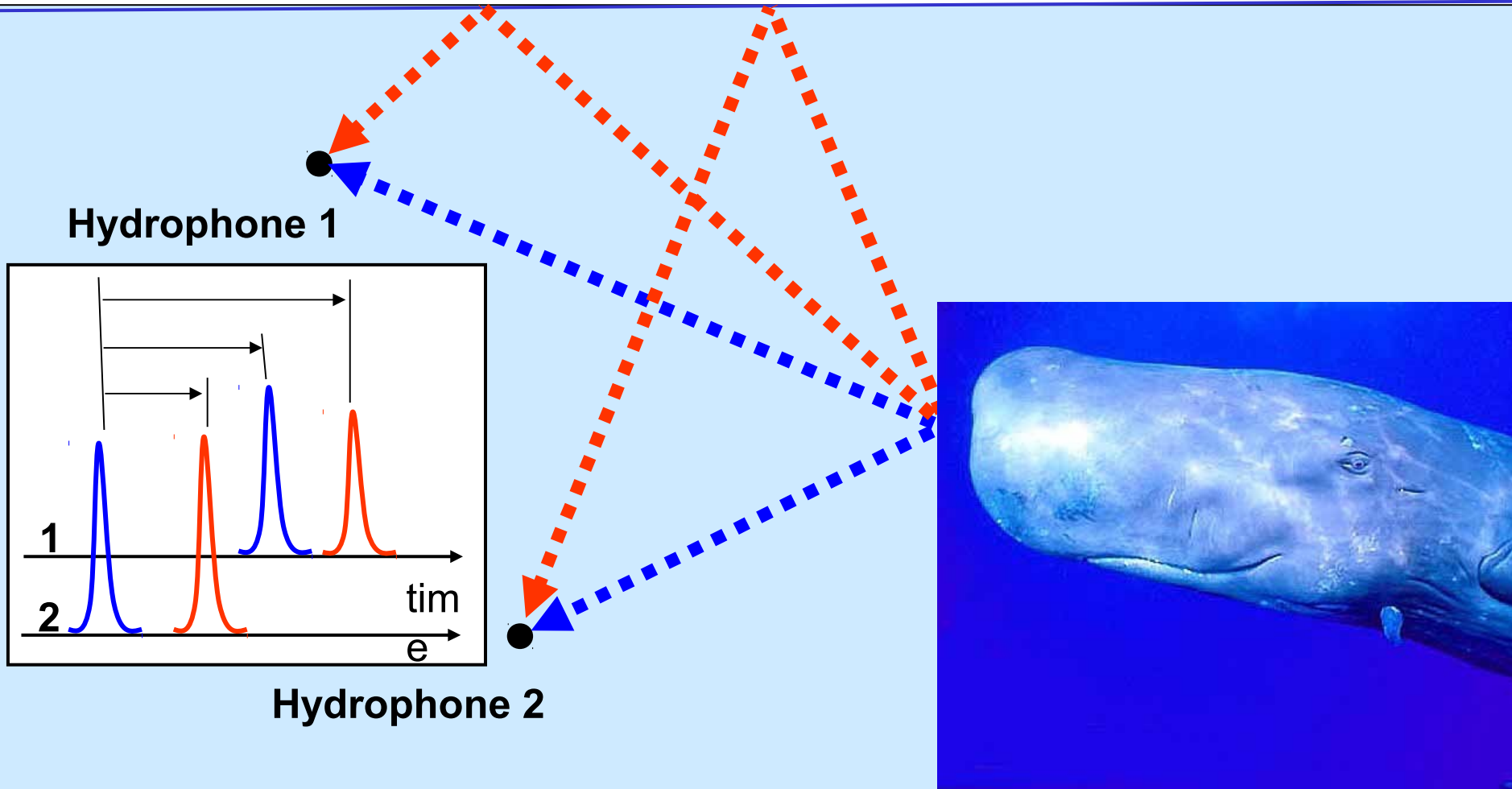
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TDOA *Time Delay of Arrival*

But multi-reflections (surface...) => **directs** + **indirects**

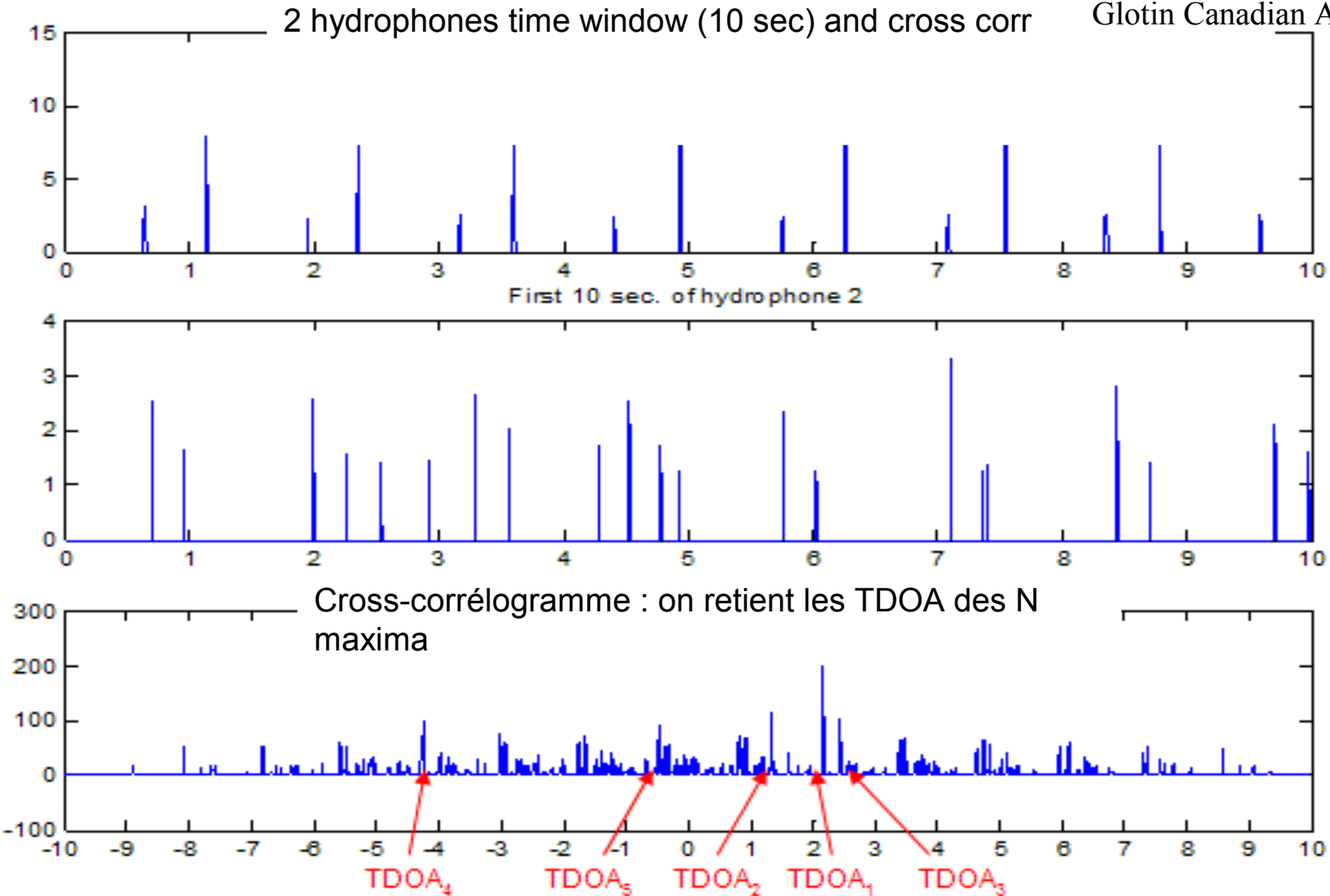


TDOA filtering ? Filtering the combinations between N local max

Criteria : MSE on the residual of TDOA transitivity system

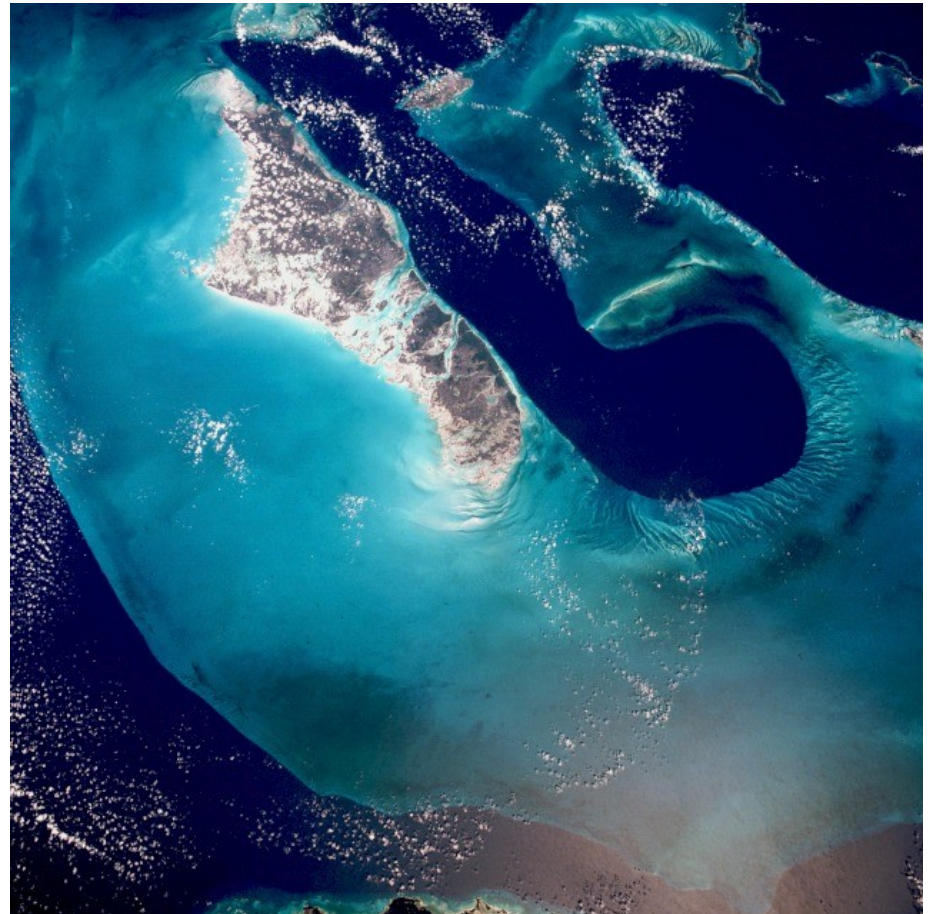
[Glotin Giraudet Bénard patent 2007, PCT 2009-2011, USA, EU.]

Glotin Canadian Acoustics 2008

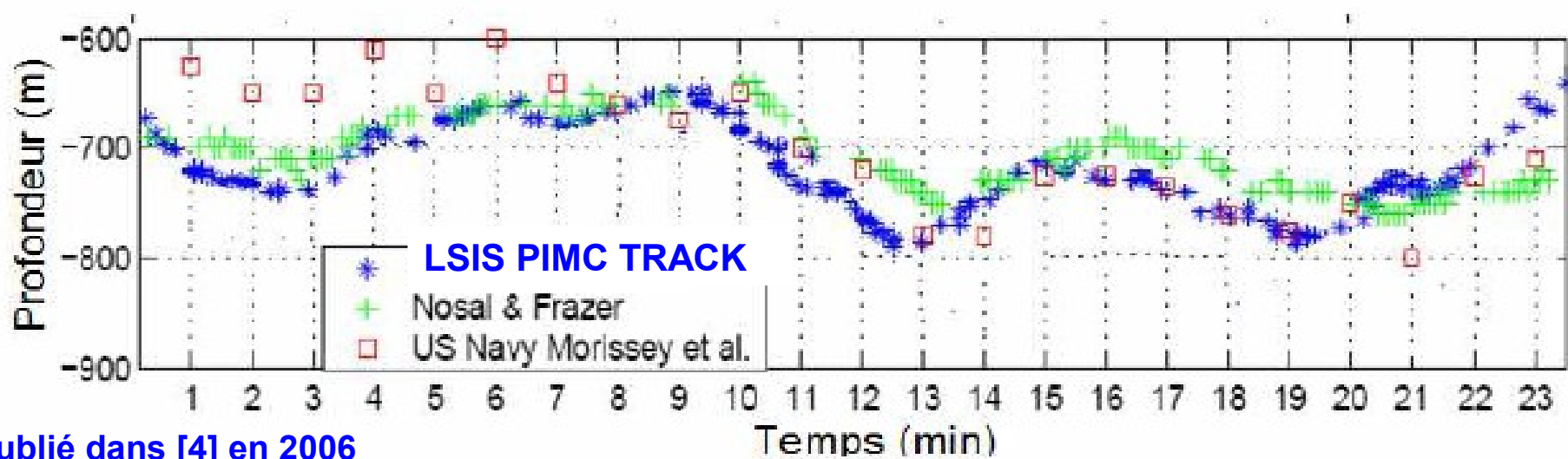
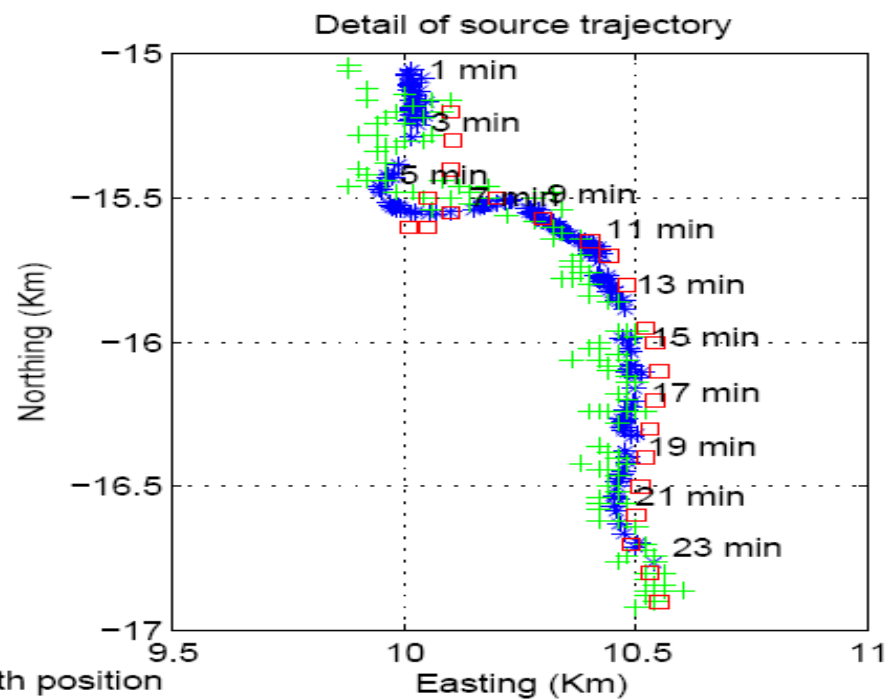
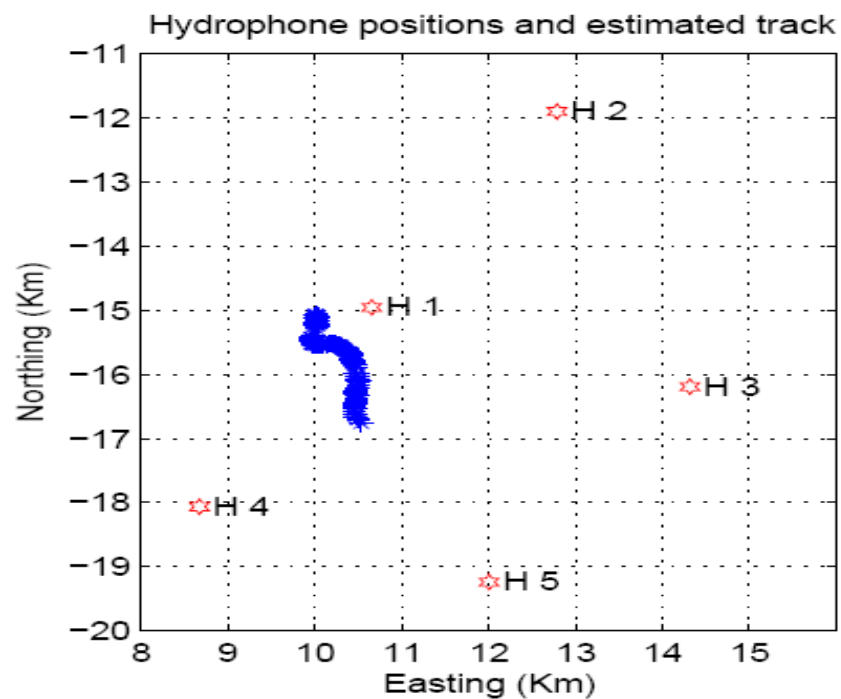


AUTEC NATO data set

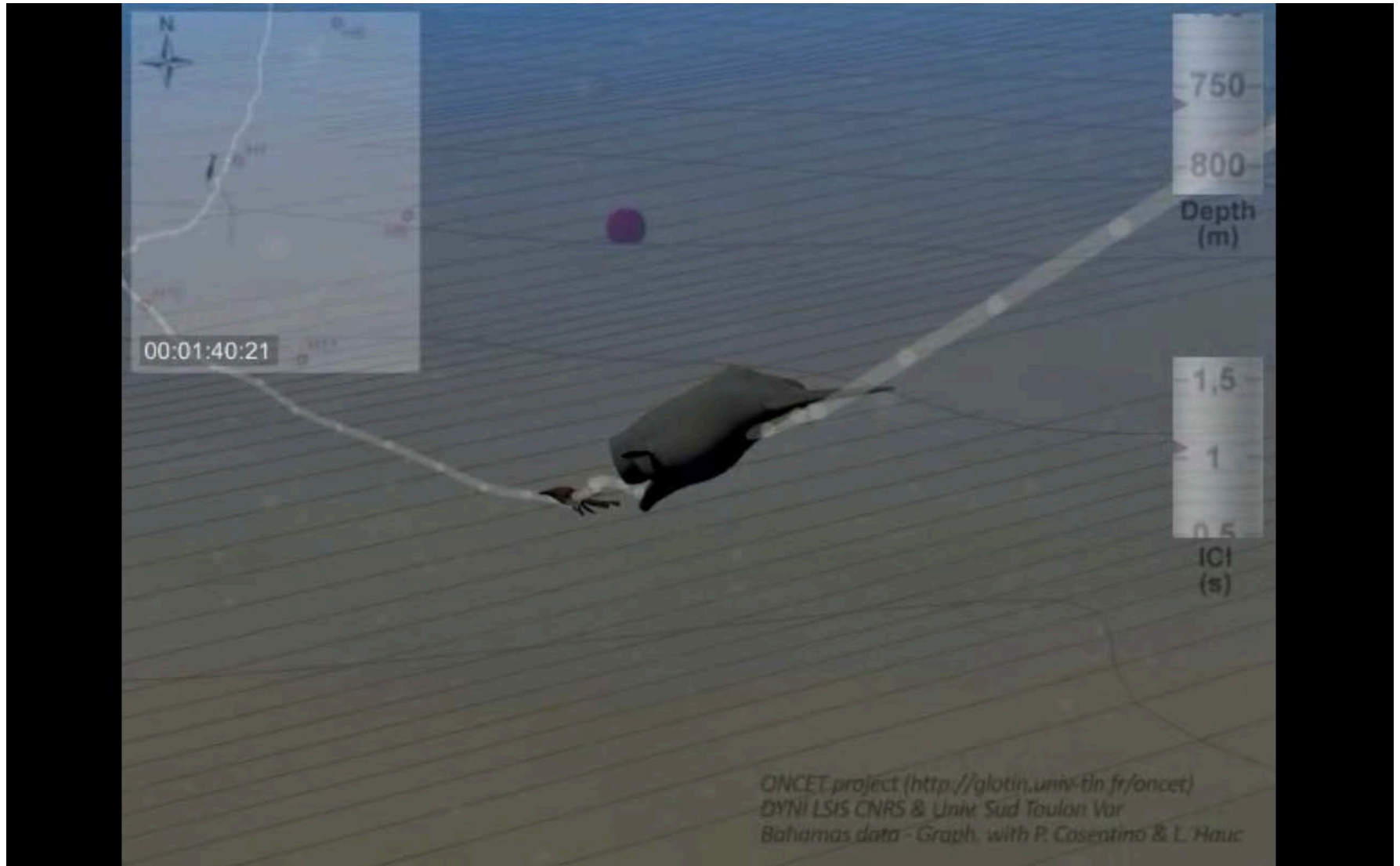
Atlantic Undersea Test & Evaluation Center (AUTEC)
Tongue Of The Ocean (TOTO)



RESULTS



ONCET : Online Cetacean Tracking = Etho-acoustics ?



[Patent Glotin et al. Multiple whale tracking PCT USA,... 2008-2012
Glotin et al. Whale Cocktail Party, Canac Acoustics, 2008
Bénard Glotin, Neutrino whale tracking, Applied Acoustics 2011]

Online demo at <http://sabiiod.org>
RANGE [500 to 5000 m] prec :15m

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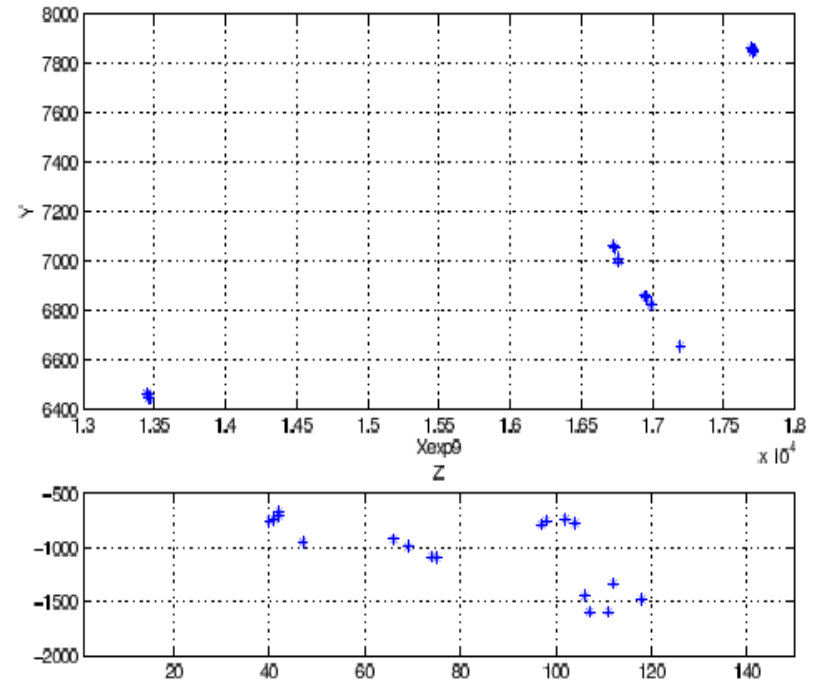
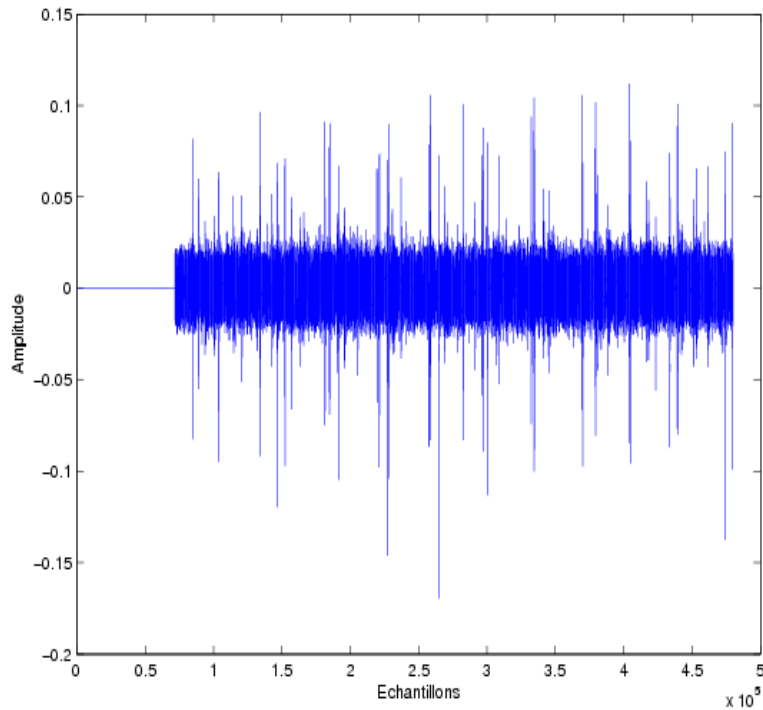
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2nd Challenge : Simultaneous clicking whales...

— First results 2005 :



- 4 whales localization without TDOA selection ...

Second step 2006 : DYNi vs SOEST Hawaiï (abandon US Navy)

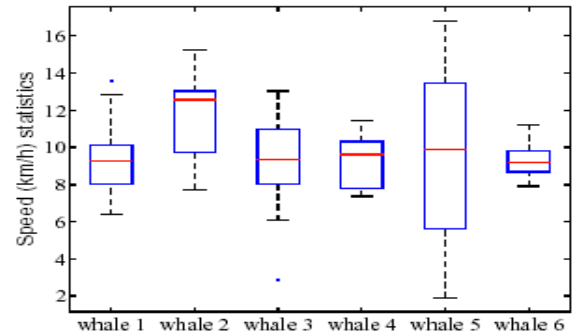
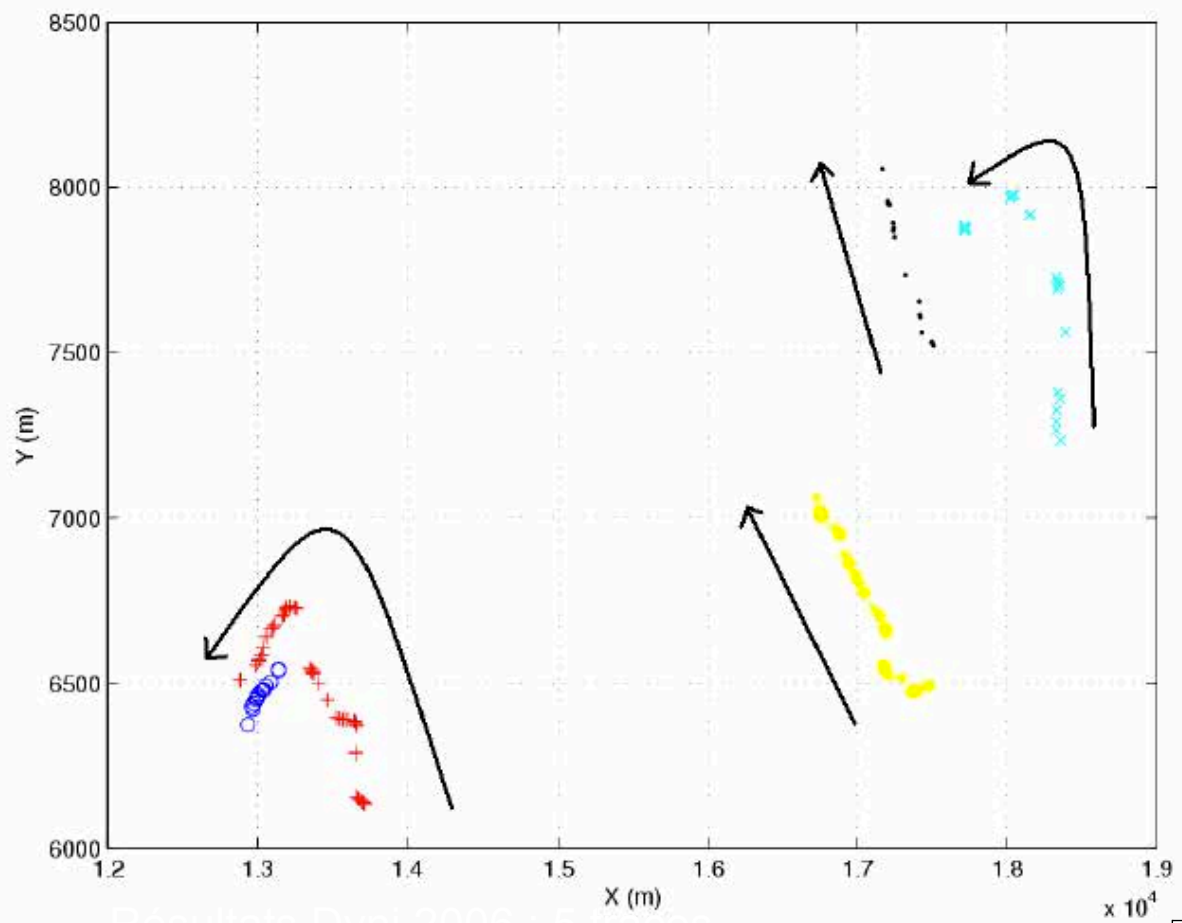
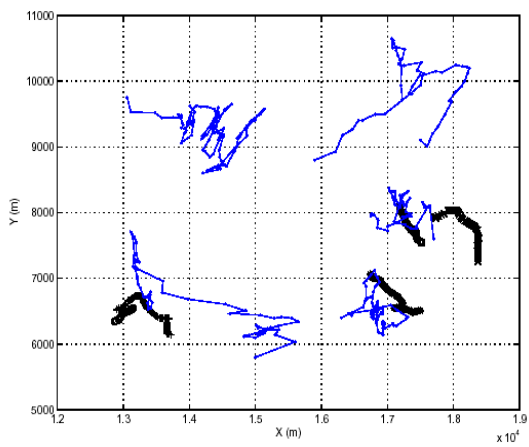


Figure 8: Speed (averaged on 30s windows) statistics on the whole track for each whale in D1 (whales 1 to 5) and D2 (whale 6). The central line of the box is the median of speed and the lower and upper lines are the quartiles. The whiskers show the extent of the speed. Whale 5 seems to stop a moment at the end of the track (See Figure 7).



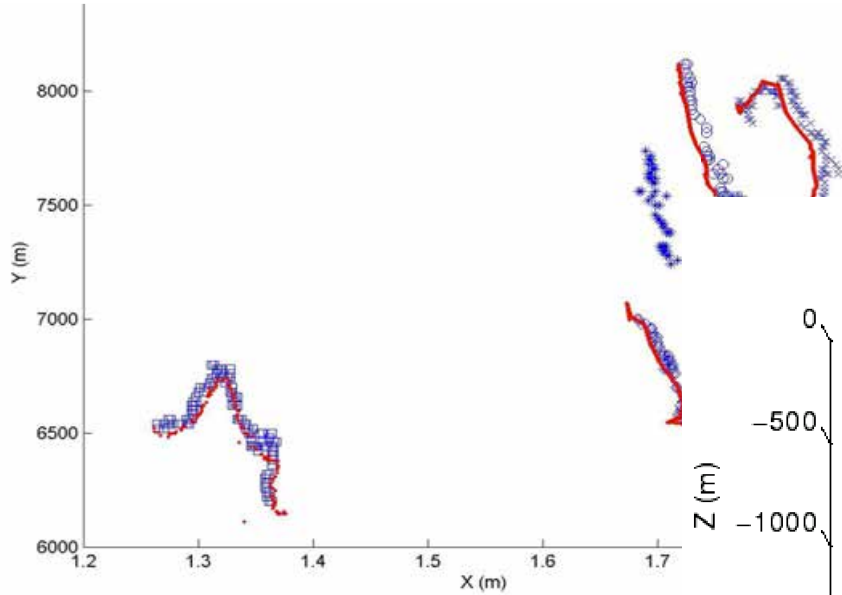
Résultats Dyni 2006 : 5 traces

Dyni (BLACK) VS SOEST (Hawaiï)
Blue (V > 100km/h)

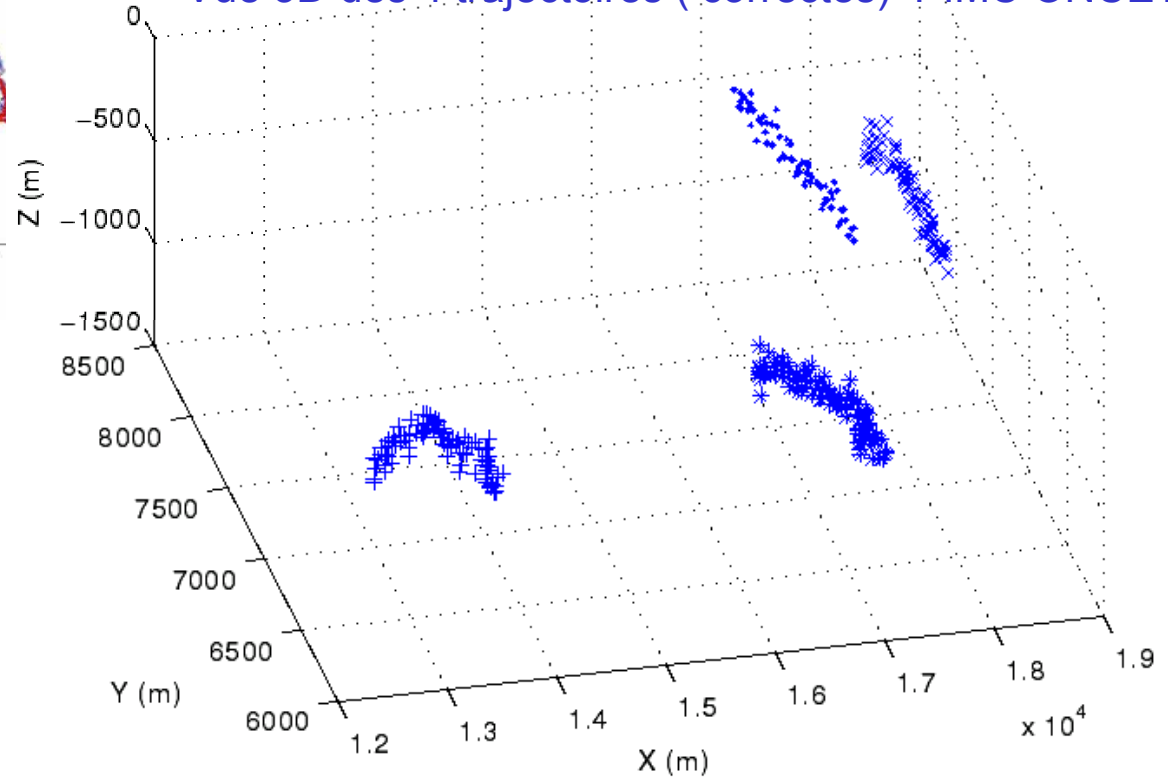
2009 : final ONCET model (Stochastic Adaptive Filtering)

PIMC-DYNI (rouge)

SOEST Hawaï contenant des fausses détections

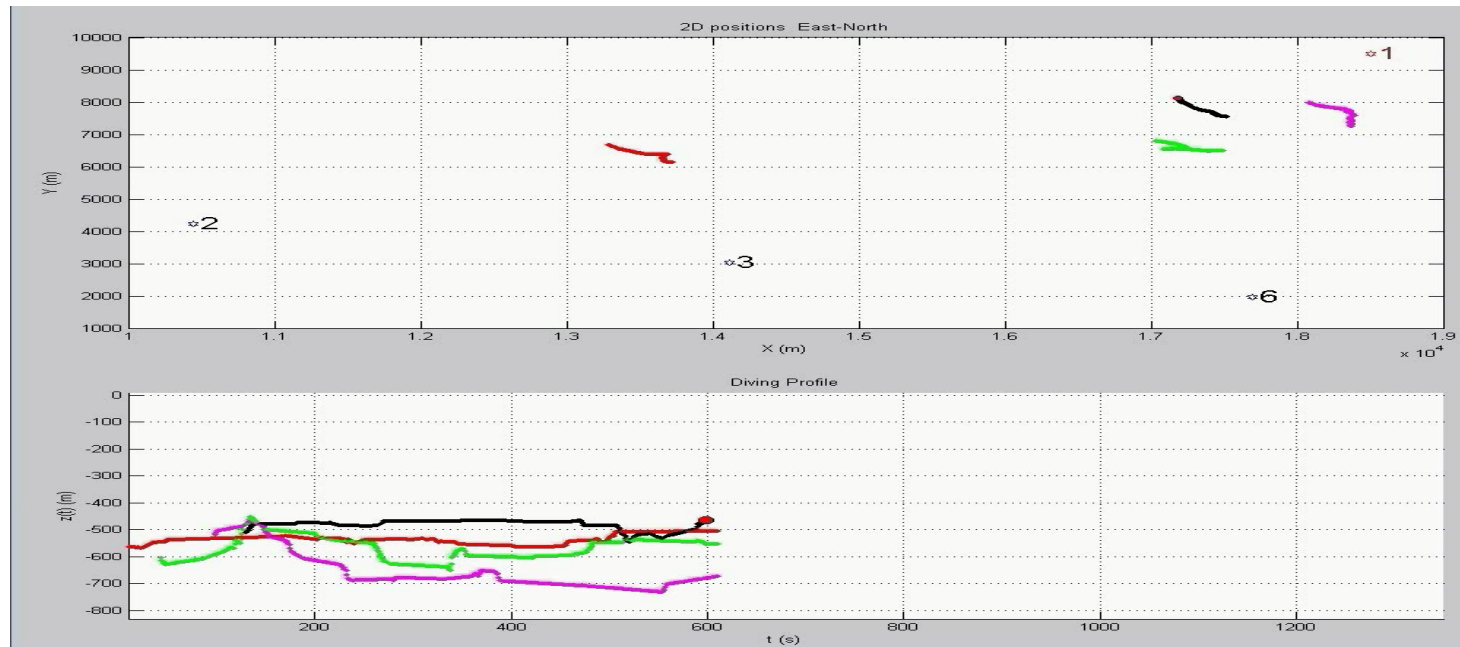


Vue 3D des 4 trajectoires (correctes) PIMC ONCET



Demonstrations on line at :

<http://sabiiod.univ-tln.fr/oncet>



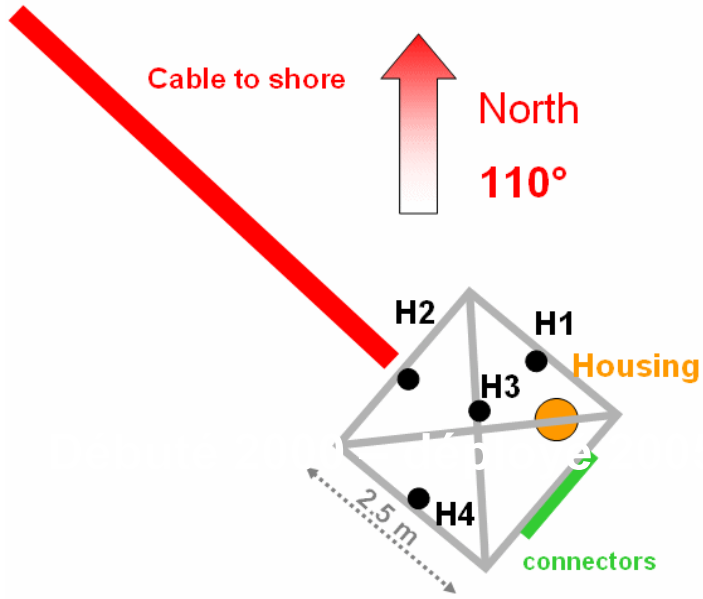
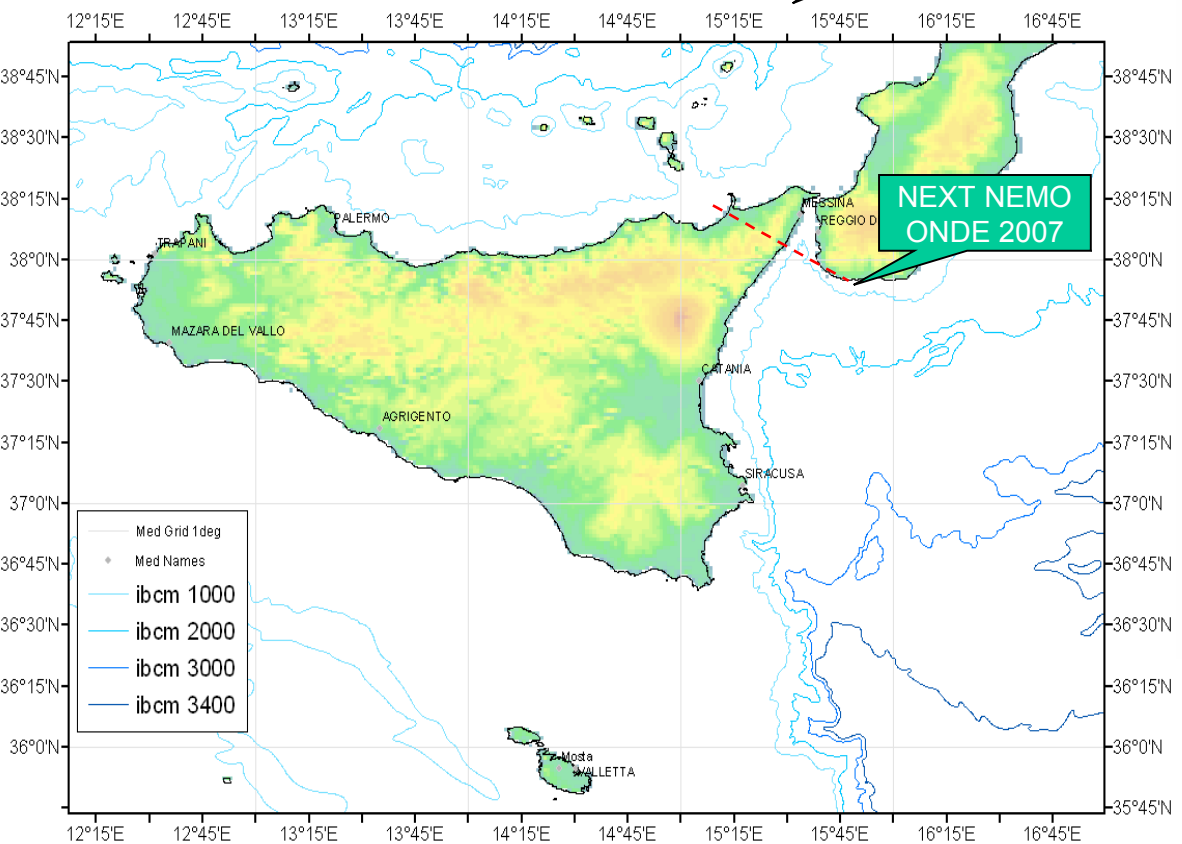
Astrophysics meets bioacoustics

Run 3D tracking on NEMO

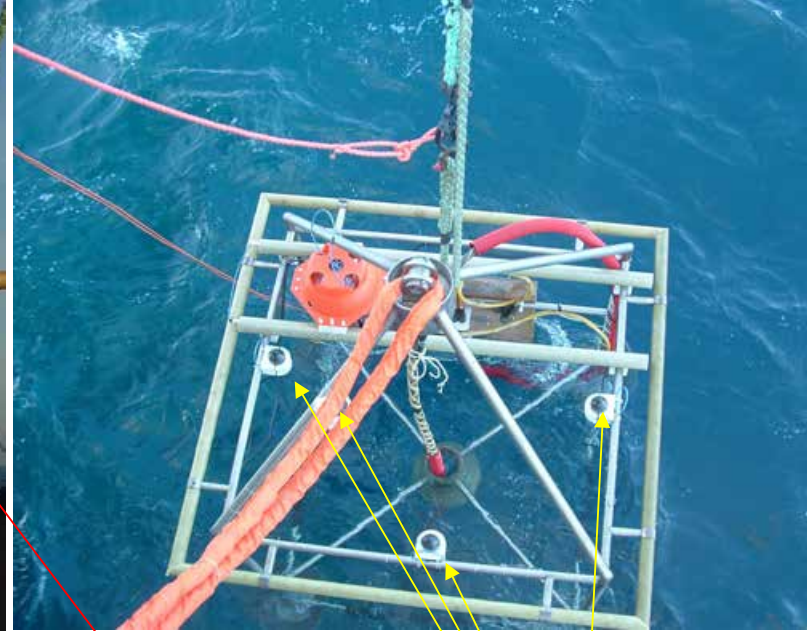
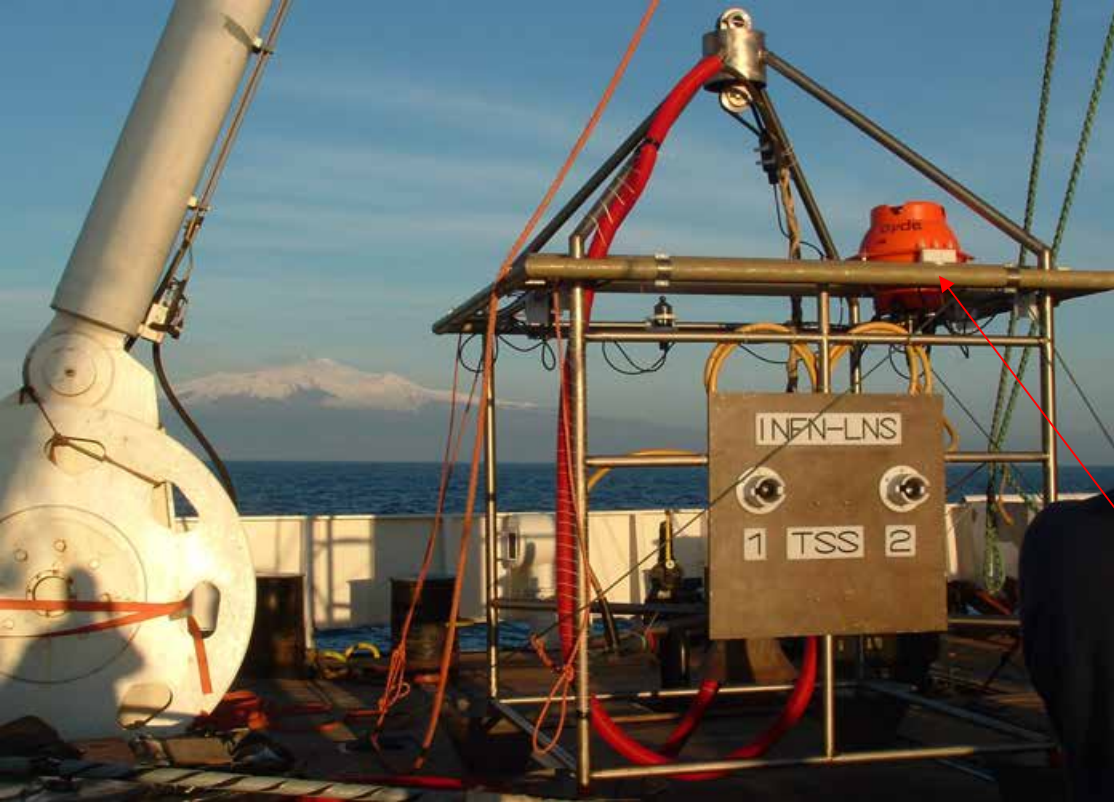
Lat: 37° 32.681' N Depth: 2050 m
 Long: 15° 23.773' E

NEMO

NEXT NEMO ONDE 2007



Height from seabed :
 H1, H2, H4: ~ 2.6 m H3: ~ 3.2 m
 Array = Only 2 meters long



Acoustic module

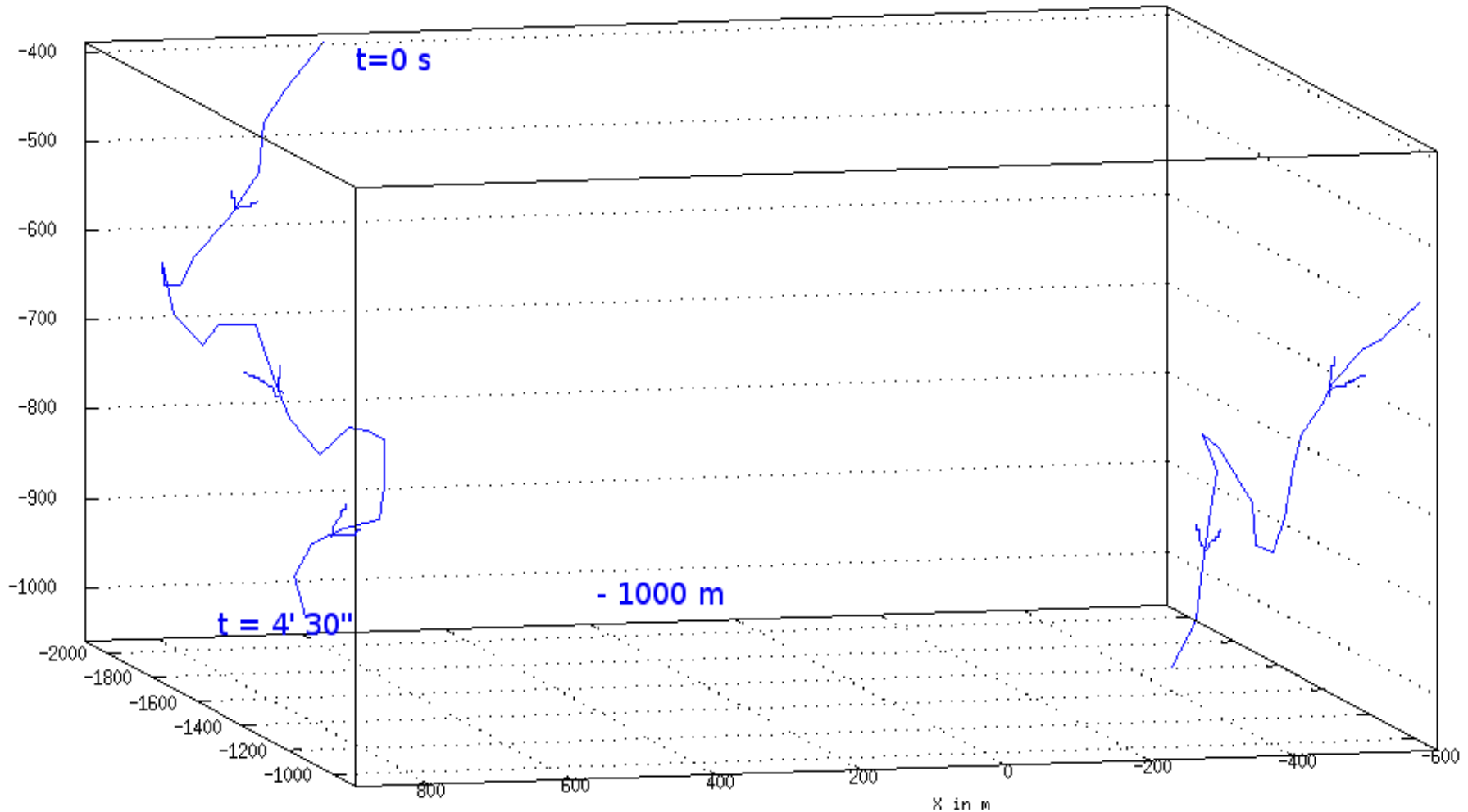
Hydrophones



Once deployed on the sea floor the frame was connected to the optical cable by a ROV (Remotely Operated Vehicle)

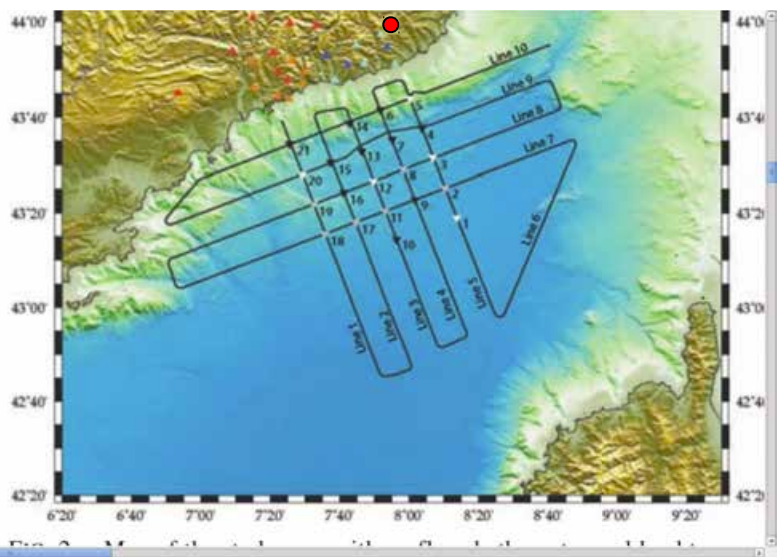
We thank INFN, NEMO, Ricobenne and G. Pavan for the record samples

LSIS results : 15 august 2005 15h00, Sicile Est :
2PC dive together from -400 m to -1000 m in 5 minutes



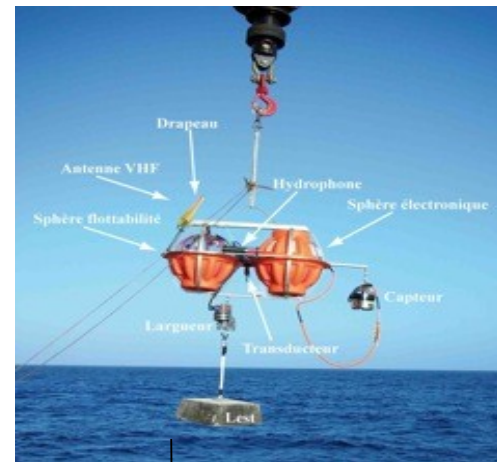
[Benard Glotin Applied Acoustics 2011]

Application to fin whales on fixed recording in Toulon area...

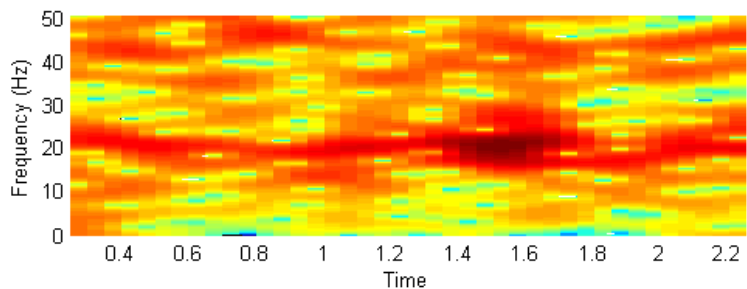
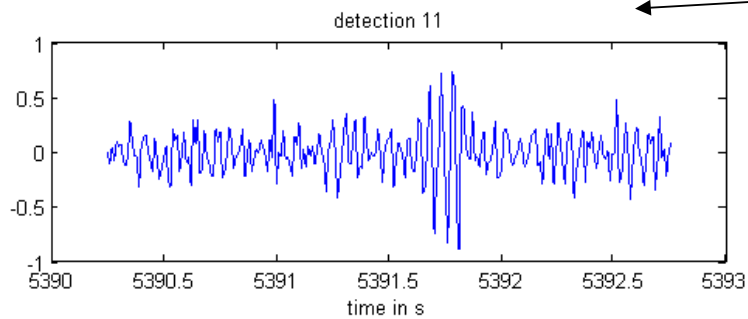


Raw recording from a single hydrophone fixed on the OBS at the sea bottom ~2500 m

Sampled at 100 Hz

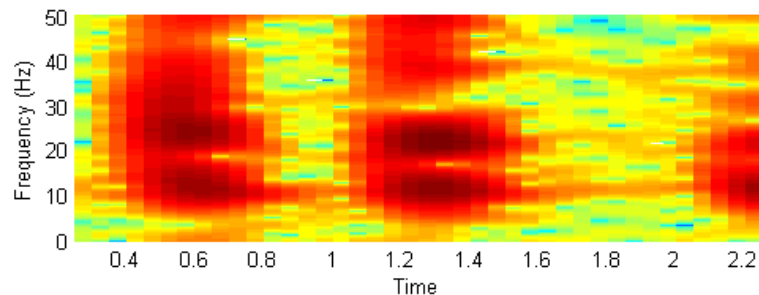
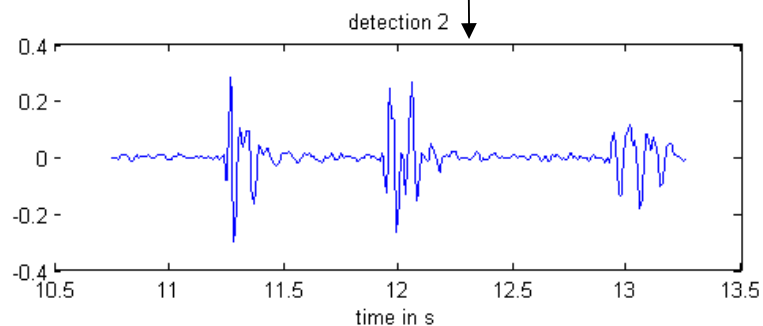


Detection processing



High spectral density around 20 Hz

Possibly rorqual sound emission



Wide band spectrum

Possibly sperm whale sound emission

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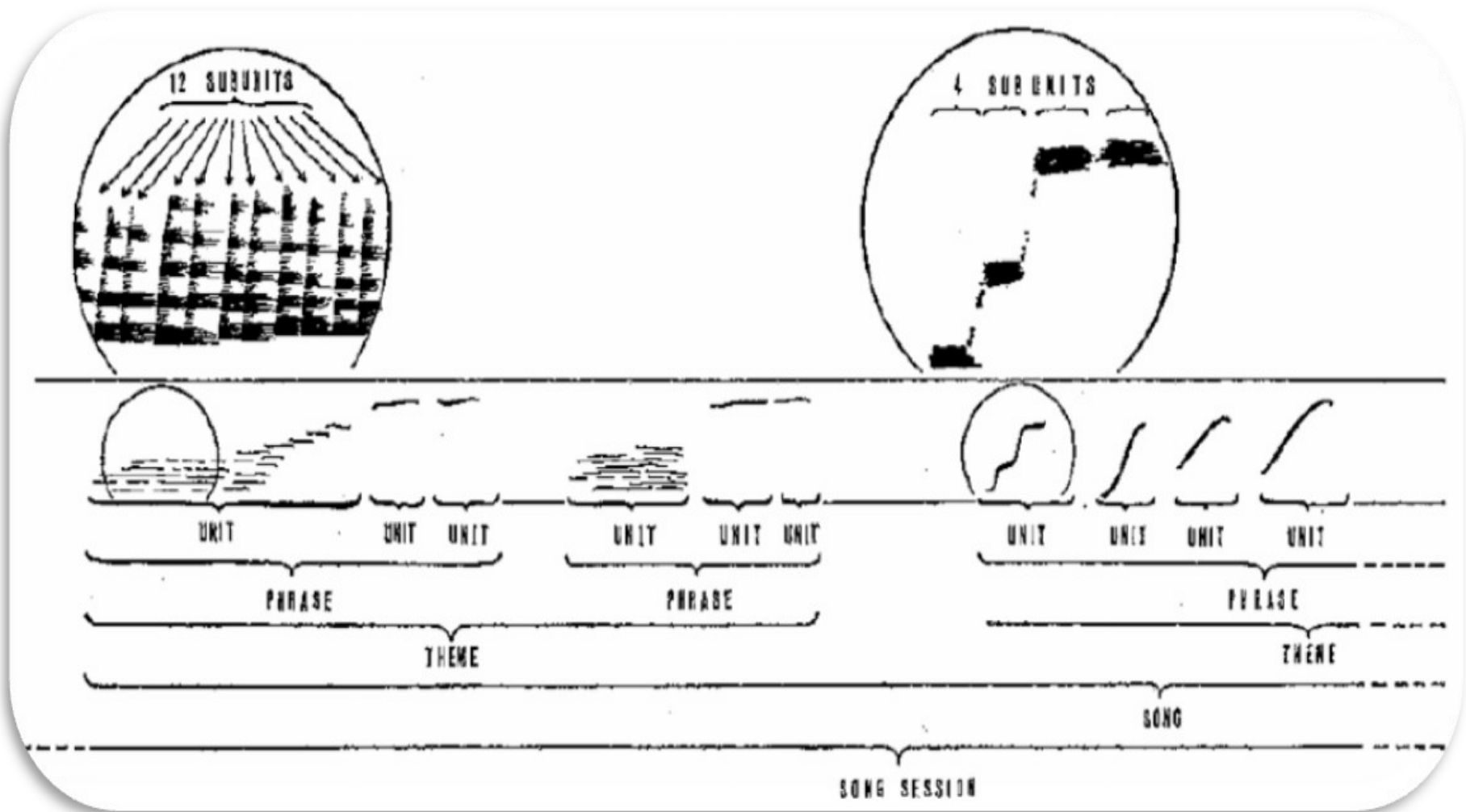
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Humpback whale song sparse coding : exploring song components

- Humpback songs are structured, but most of their decomposition algorithms are using a priori information
- An usual way to determine recurrent patterns in a data flow in an unsupervised manner is to cluster the data. However, the main drawback of k-means clustering is that the centroids of each cluster may not cover all the space and unfortunately do not suit the data.
- In this study we investigate the hypothesis of « subunit » and we propose a method to automatically identify these subunit components of the song.

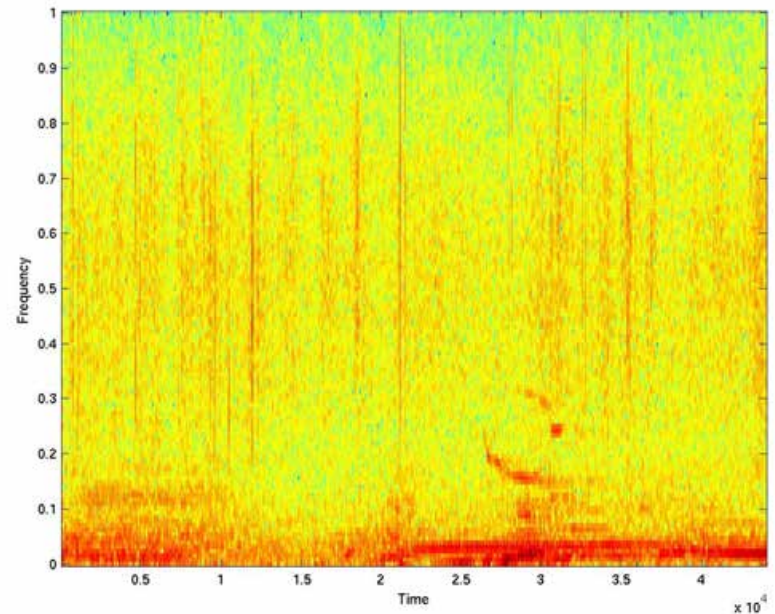
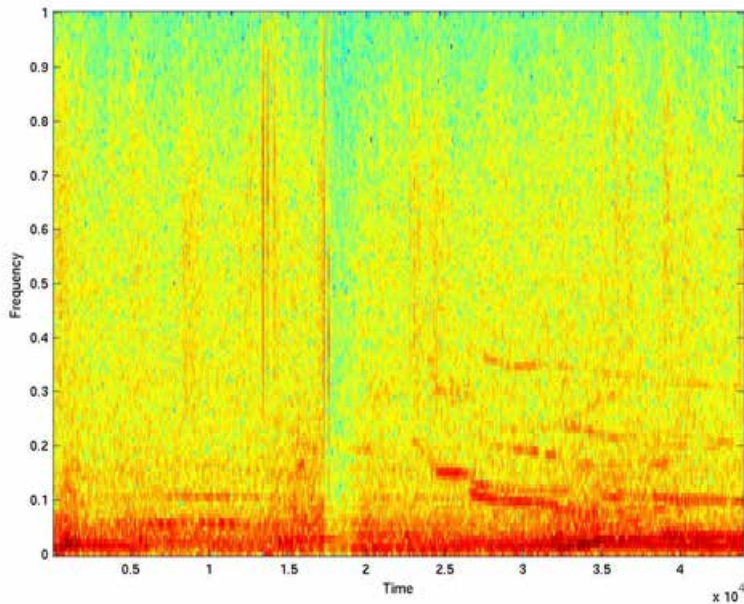


Humpback whale songs' structure : [Payne 1970]

Two song spectrograms : mostly unit of one second.

=> Unit patterns last nearly .1sec

=> The dictionary is learned on 1 sec.frame window.



Sparse Coding ?

- Sparse Coding (SC) : unsupervised dictionary generated from the complete data set
- SC may be more adapted to the differentiation of natural acoustic sources
- Development of methods for selecting and classifying relevant dictionary atoms
- Applications :
 - Supervised classification of whales
 - Discovering spatio-temporal / 4D behavior patterns for (un)known species

Sparse Coding by Lasso and K-SVD

Why Sparse Coding ? : More discriminative
Better generalization for new data
Reduction of the reconstruction error

And **Data compression**

– Each data vector \mathbf{x}_i is expressed as a c_i linear combination of a dictionary \mathbf{D} of size \mathbf{K} (only one in usual K-means)

– Formulation :

$$\arg \min_{\mathbf{D}, \mathbf{C}} \sum_{i=1}^N \|\mathbf{x}_i - \mathbf{D}\mathbf{c}_i\|^2 + \lambda \|\mathbf{c}_i\|_{\ell^1} \quad s.t. \quad \|\mathbf{c}_i\|_{\ell^1} = 1$$

introduces sparsity (regularization constraint : some contribution are non zero)

$$\lambda \|\mathbf{c}_i\|_{\ell^1}$$

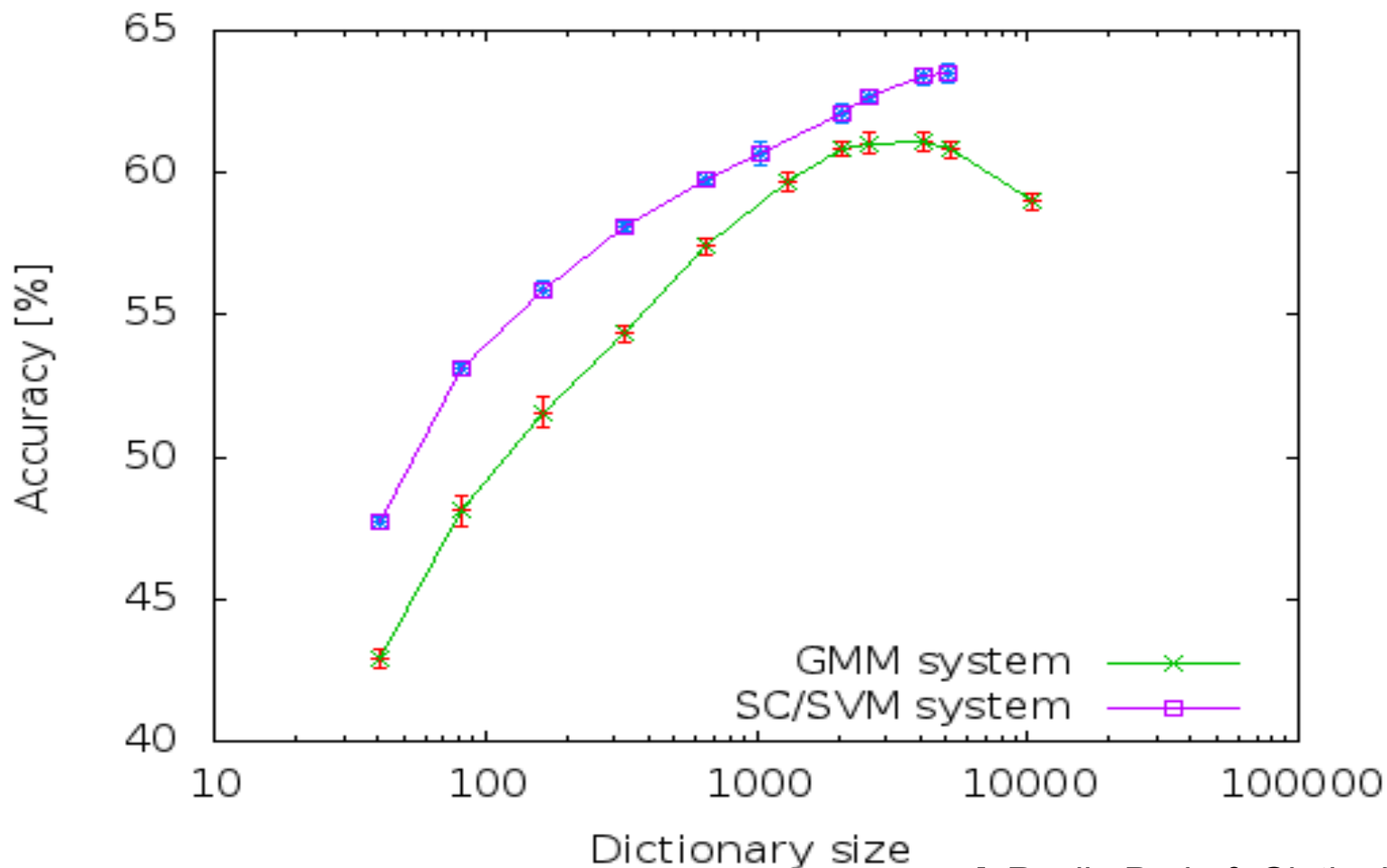
Iterative learning of \mathbf{D} and \mathbf{C} until convergence by LASSO and K-SVD algorithms

Complexity for projection in $\sim \mathbf{O}(\mathbf{K} \mathbf{n} \mathbf{n}_{nz})$, \mathbf{n} the number of vectors to project,

\mathbf{n}_{nz} the average non-zero coefficients

SC vs state of the art :

SC improves automatic speech recognition



Material

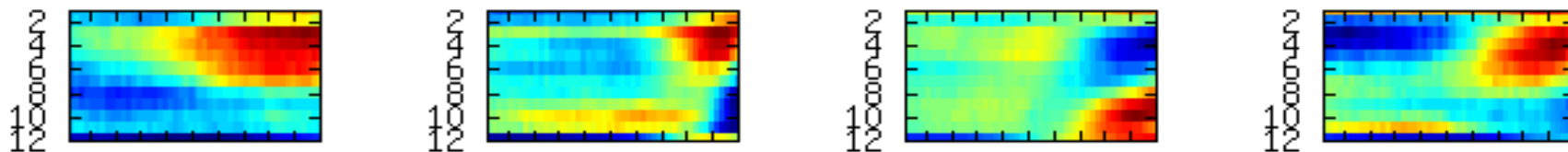
- Songs have been recorded at Hawaii (Lammers), Tonga (Clark), Madagascar (Adam & Doh), Reunion (Darewin), Guadeloupe (Adam),...
NewCaledonia (Glotin et al., Bachet et al.)...
- Each set contains clear song sequences of at least 10min, 44 kHz

Features extraction

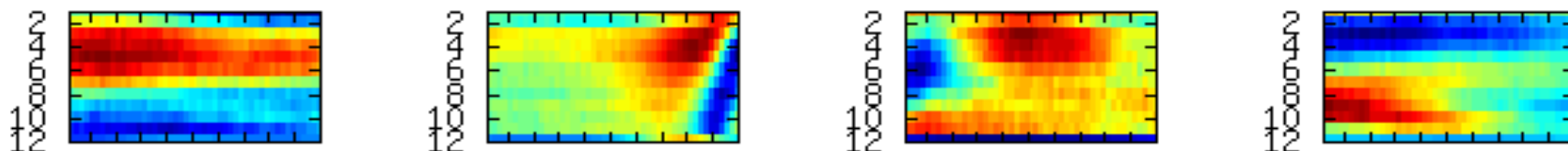
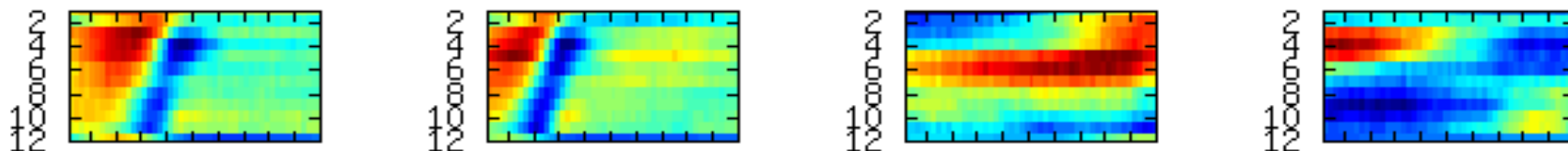
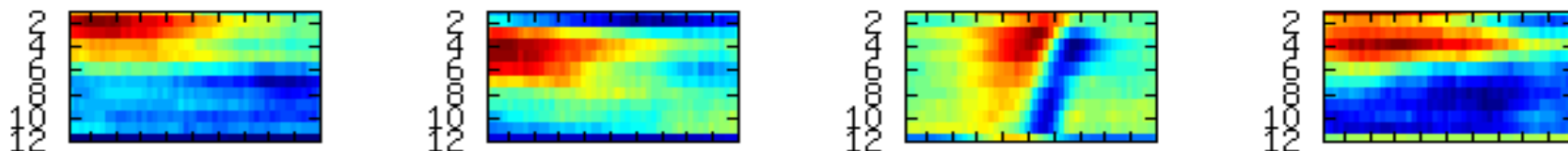
- 13 MFCCs
 - 10 ms frameshift,
 - 32 ms frame length.
- N windows are concatenated to get the desired scale (e.g. N=25 for 250 ms).
- On those vectors we :
 - Learn **Unsupervised** Dictionary : one codebook of 1024 words
 - Filter these words (units) according maximum quefreny movement (articulation).
 - Project the song sets using this codebook.

SPARSE MFCC CODE :

Samples of the 1024 word dictionary, some are coding sea noise

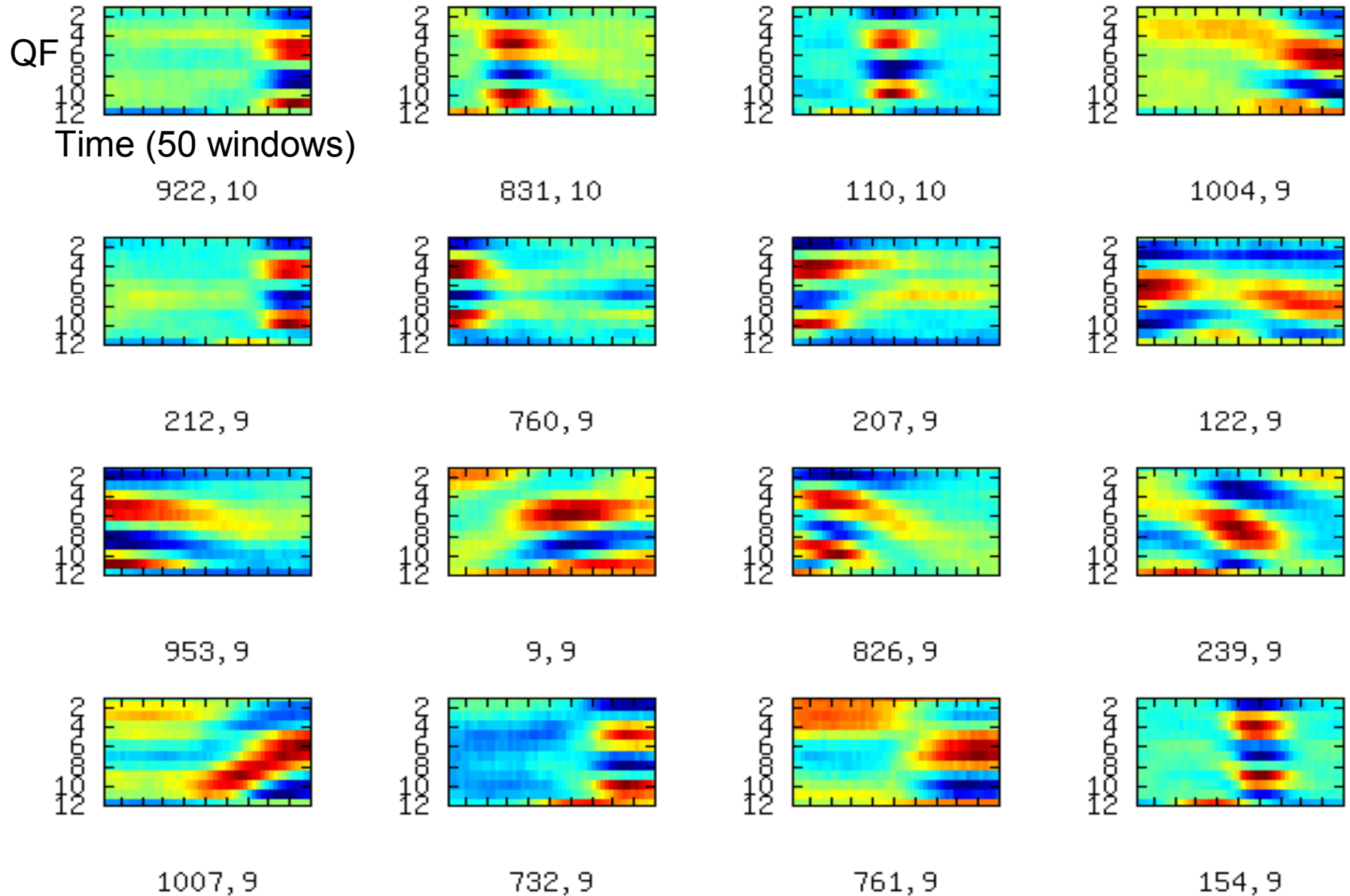


Time per patch = 250 ms , ordinata = 12 MFCC

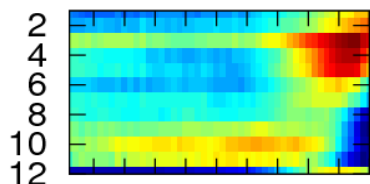


CODE SELECTION : the 16 most 'articulated' units

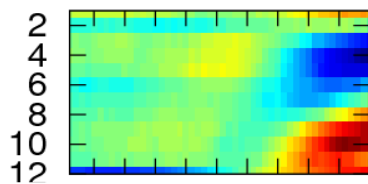
criteria : selected by gabor filtering



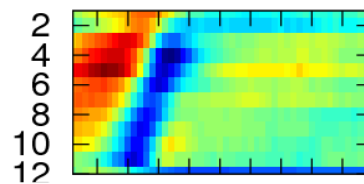
The 16 most 'articulated' words according to max variance in time and quefreny => whale ARTICULATIONS



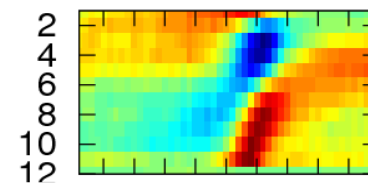
275,10



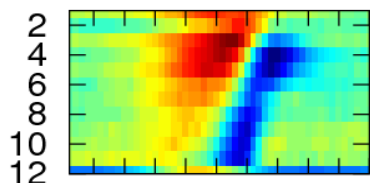
959,10



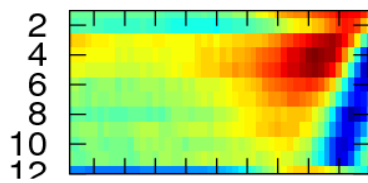
59,10



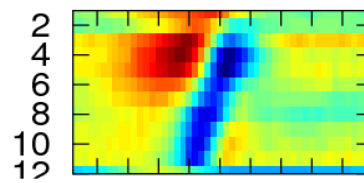
574,9



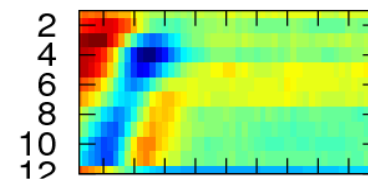
406,9



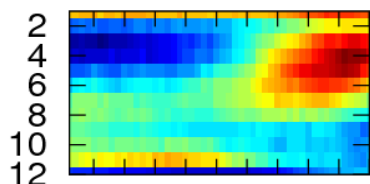
340,9



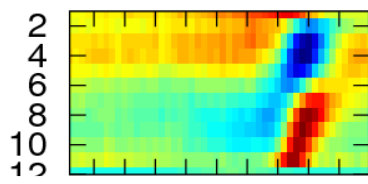
476,9



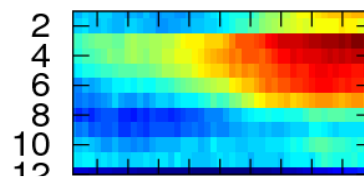
363,9



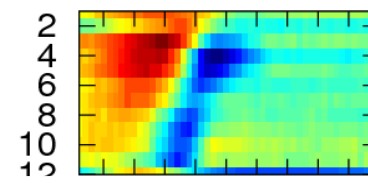
514,9



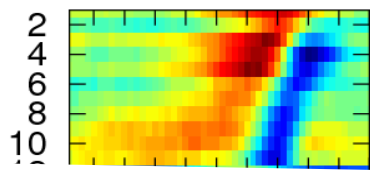
802,9



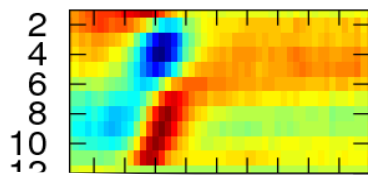
611,9



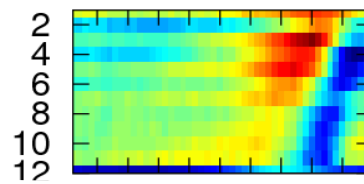
675,9



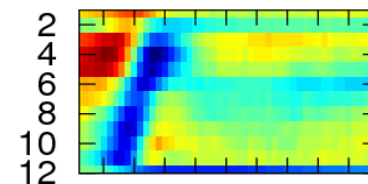
719,9



486,9



297,9



835,9

WHALE SONG CLASSIFICATION (preliminary results)

Song representation : filter 16 'most articulated codes' : C1...C16

Considering vector of N word couples = [. C(i,t)... C(j,t')...]

Build bigrams B(i,j) in a short time window (10 seconds)

Song = Histogram of bigram mean activity B(i,j) into time window 10 sec.

sim(Sp,Sq) = Cosine similarity between Sp and Sq representation

Validation :

Songs classification by:

Material :

Hawaii

Tonga

Guadeloupe

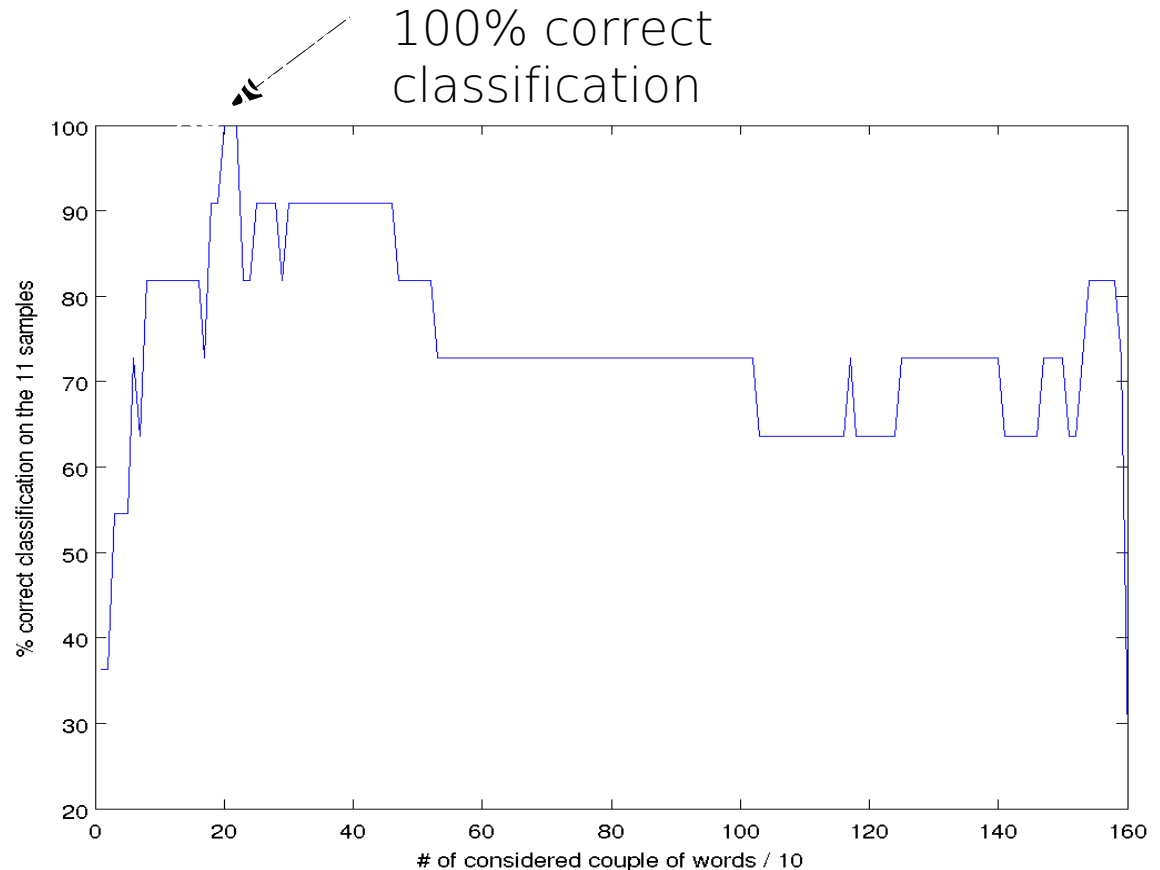
Madagascar

Reunion

Task :

20 files of few min,

5 classes



Submitted to JASA Razik et al.

Conclusion

- We presented an algorithm to create by unsupervised dictionary learning a proto-lexicon of the song of the humpback whale.
- These representations are more generic than manual segmentation
- Different unit types have been learned on MFCC vectors.
- Long term units that are variously composing the songs from one year to another may be extracted **systematically**
=> WORLD SCALE BIOPOPULATION ANALYSIS

Perspectives

- Within this new song decomposition method, we find common patterns through time (subunits) and discover song differences considering long time units.
- By computing these features on different recordings through several years, we expect to find more efficiently stable patterns, and patterns here between different whale groups.
- Our approach is naturally applicable to any marine mammals, and will be tested on dolphin whistles.

I. Introduction

II. Single hydrophone 'ethoacoustics'

III. 3D RT Single whale tracking by PA

IV. 3D RT Multiple whale tracking by PA

V. Classification by sparse coding

VI. Fast Tracking by sparse coding

VII. Conclusion : Scaled Acoustic Methods SABIOD

Sparse coding for
Very fast TDOA
estimation
application to Hawaii



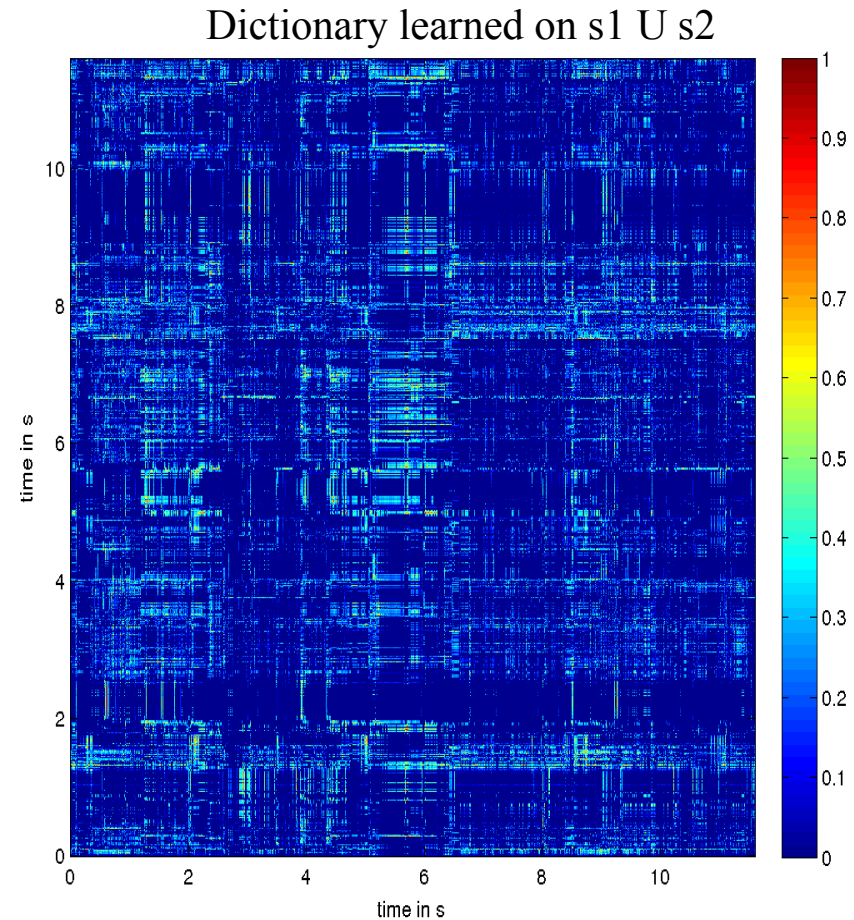
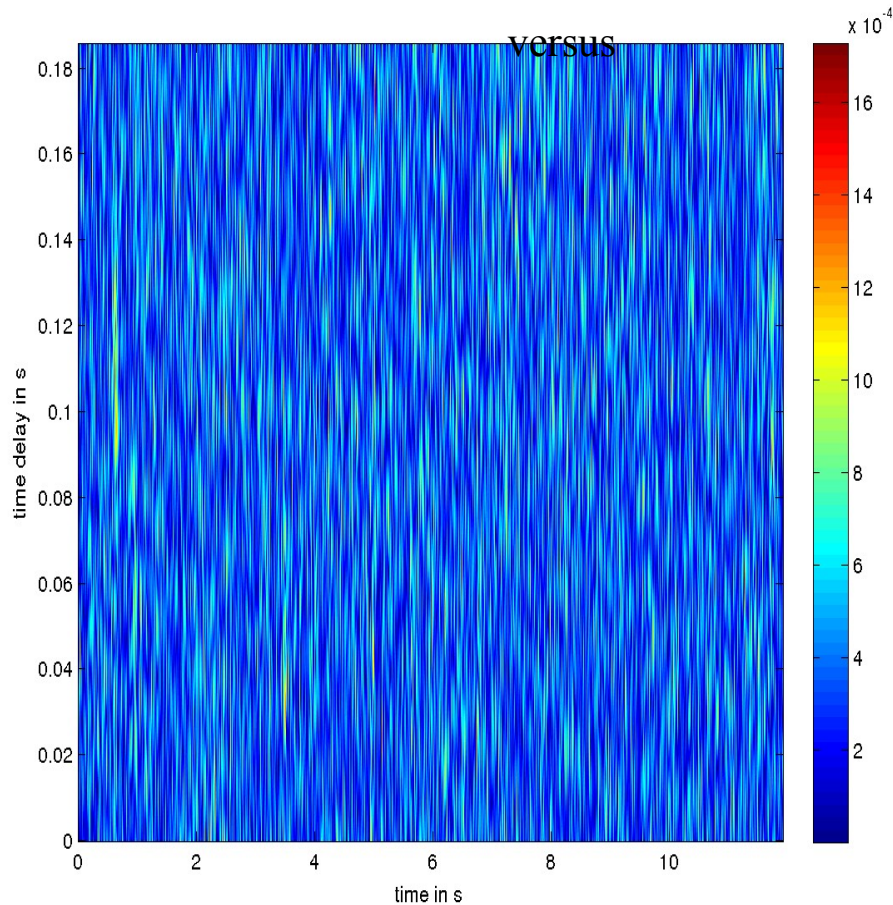
- 1. Objectives
- 2. Why and how to learn sparse dictionary ?
- 3. Sparse matching of Minke whale boings in Hawaii
- 4. Time delay estimations
- 5. Tracking results
- 6. Conclusion and perspectives

Scaled Sparse Time Delay of Arrival estimations on stereo recordings

Humpback Whales, Madagascar recordings

Cosinus(SC(s1), SC(s2))

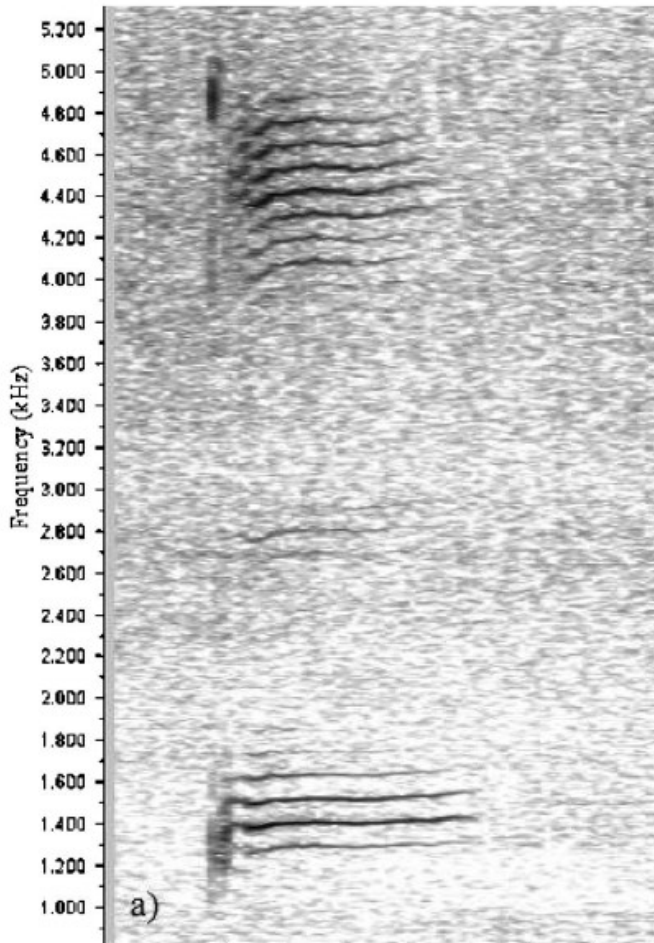
CrossCorr(s1, s2)



Objectives

- We propose in order to process efficient detection of minke whales (*Balaenoptera acutorostrata*), a sparse coding of their boings vocalizations.
- This sparse coding confers several advantages : it makes the structure in natural signals explicit and it represents complex data
- More generally, l_1 -norm yields to robust Time Difference Of Arrival (TDOA). Recently Yuanqing Lin has described a l_1 -norm sparse Bayesian learning for acoustic blind channel identification and provides dramatic improvement dereverberation and TDOA estimation in reverberant environments compared to conventional methods.
- Therefore we compute the projection of a MFCC vector into a sparse coding representation, which allows good properties for similarity computation.

Why Sparse Coding ?



Duration ~ 2 secondes

Sample of boing (from Rankin and al.)

- Sparse coding minimizes the reconstruction error and allows good generalization for undetermined data.
- No need for any knowlege on the target (the boing) : the Sparse coding shall reconstruct in priority the frequent and high SNR events (e.g. the boings).

⇒ We aim first to show that sparse coding will infer a simple boing matching process.

⇒ Autocorrelation may give similar matching patterns, but our sparse vector representation will allow very fast cosine similarity computation

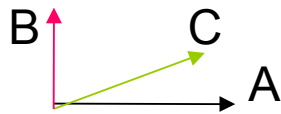
Features for minke boings detection

- 13 MFCCs
 - C0 to C12
 - 20 ms frameshift
 - 32 ms FFT
- 5 window length : 1/4, 1/2, 1, 2, 4 seconds
- Concatenation of the 5 vectors in one vector of 65 dimensions (non sparse).

Sparse projection of the MFCC

- On those 65 dim. vectors we :
 - Learn **Unsupervised** Dictionary : one common codebook of 1024 elements over the four hydrophones records and the three sets NN26, NN27, NN28 (4*30 minutes)
 - Project each hydrophones records using this codebook.
 - The resulting representation is very sparse : only 10% of the 1024 dimensions are non null.
 - This property allows relevant similarity measure between each projected signal window on different hydrophones.

Time Delay Estimation



$$\cos(A,B) = (A \cdot B) / (\|A\| \cdot \|B\|),$$

The cosine similarity measure (def.)

here $\cos(A,B) = 0 < \cos(A,C)$.

Higher the cosine is, the more the vectors are similar.

The multidimensional cosine between two hydrophones acoustic matrices, is very efficiently computed on parallel processing (much faster than correlation) :

$$\text{allcosines}(h1, h2) = (H1 * H2') / (\text{norm}(H1') * \text{norm}(H2)),$$

where H_i is the matrix of the 1024 by 10 minutes frames,

* is the matrix product,

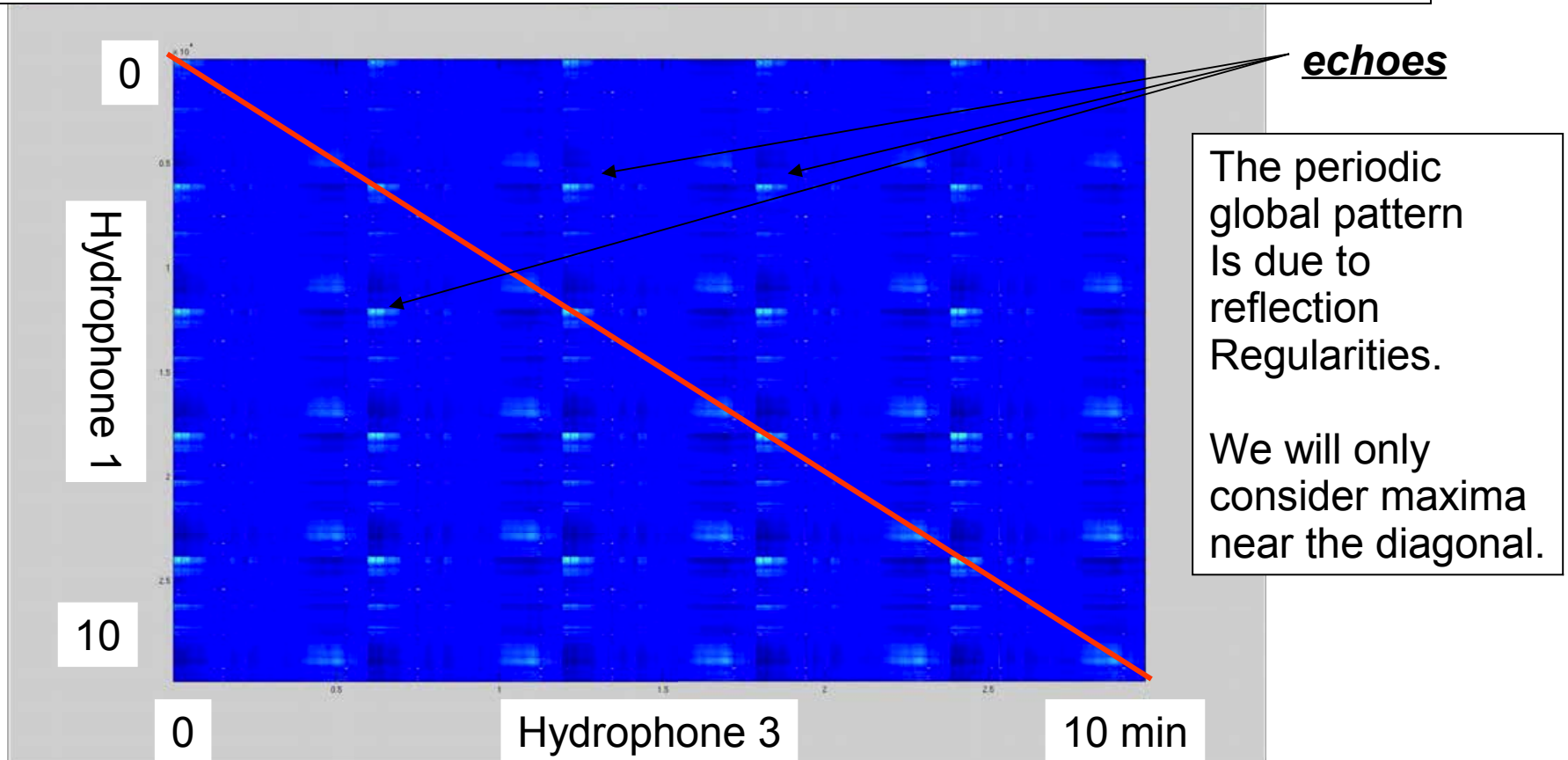
$\text{norm}(H_i)$ is the L2 norm of each frame vector of H_i .

Time Delay Estimation

We compute the cosine between each vector pair from h_i and h_j
This representation allows a global analysis (far echoes...)

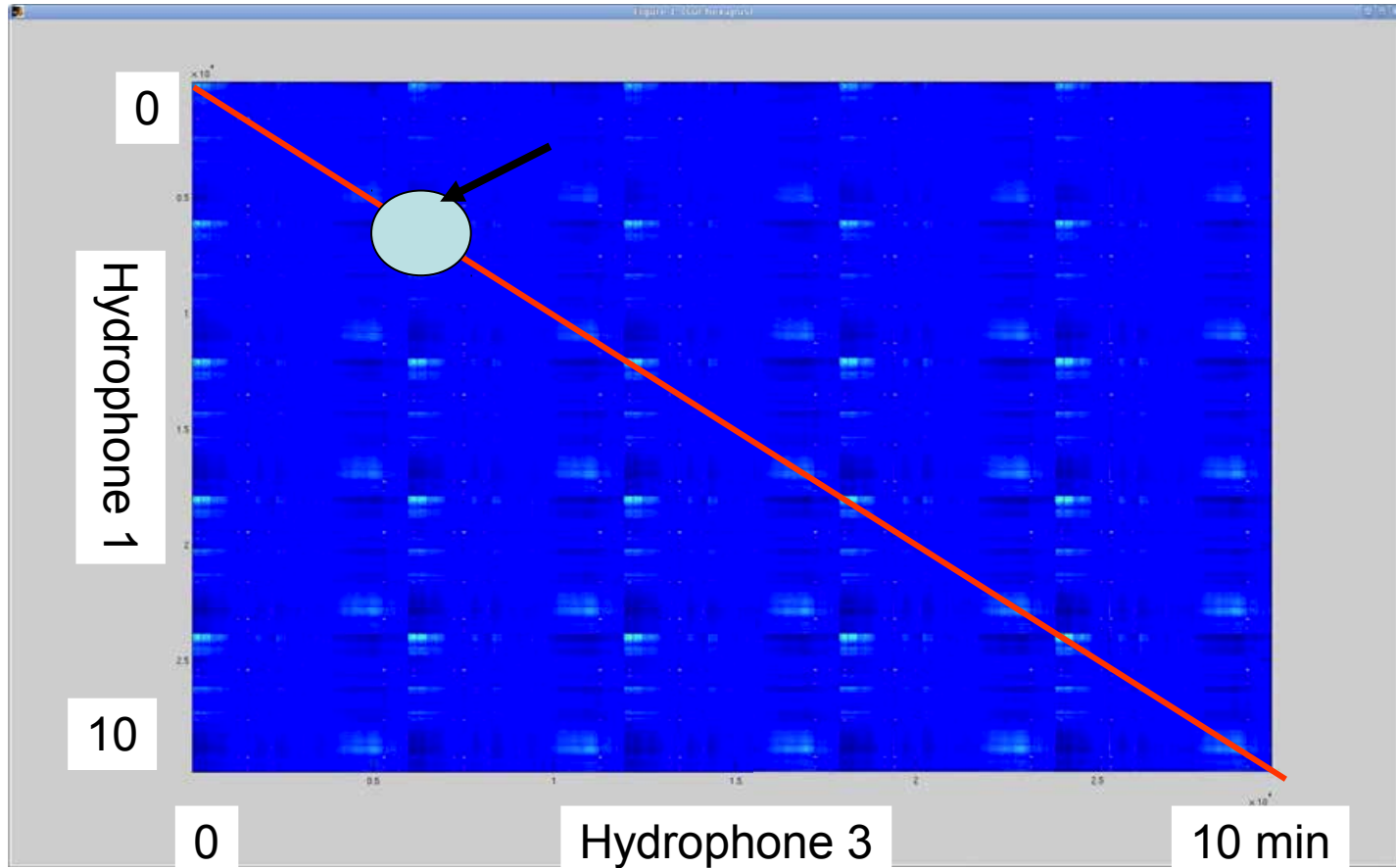
We figure out in red the 0 delay diagonal.

Similarities in (h1,h2) Hawaiiin data of 10 minutes (NN26, frame shift 20 ms)

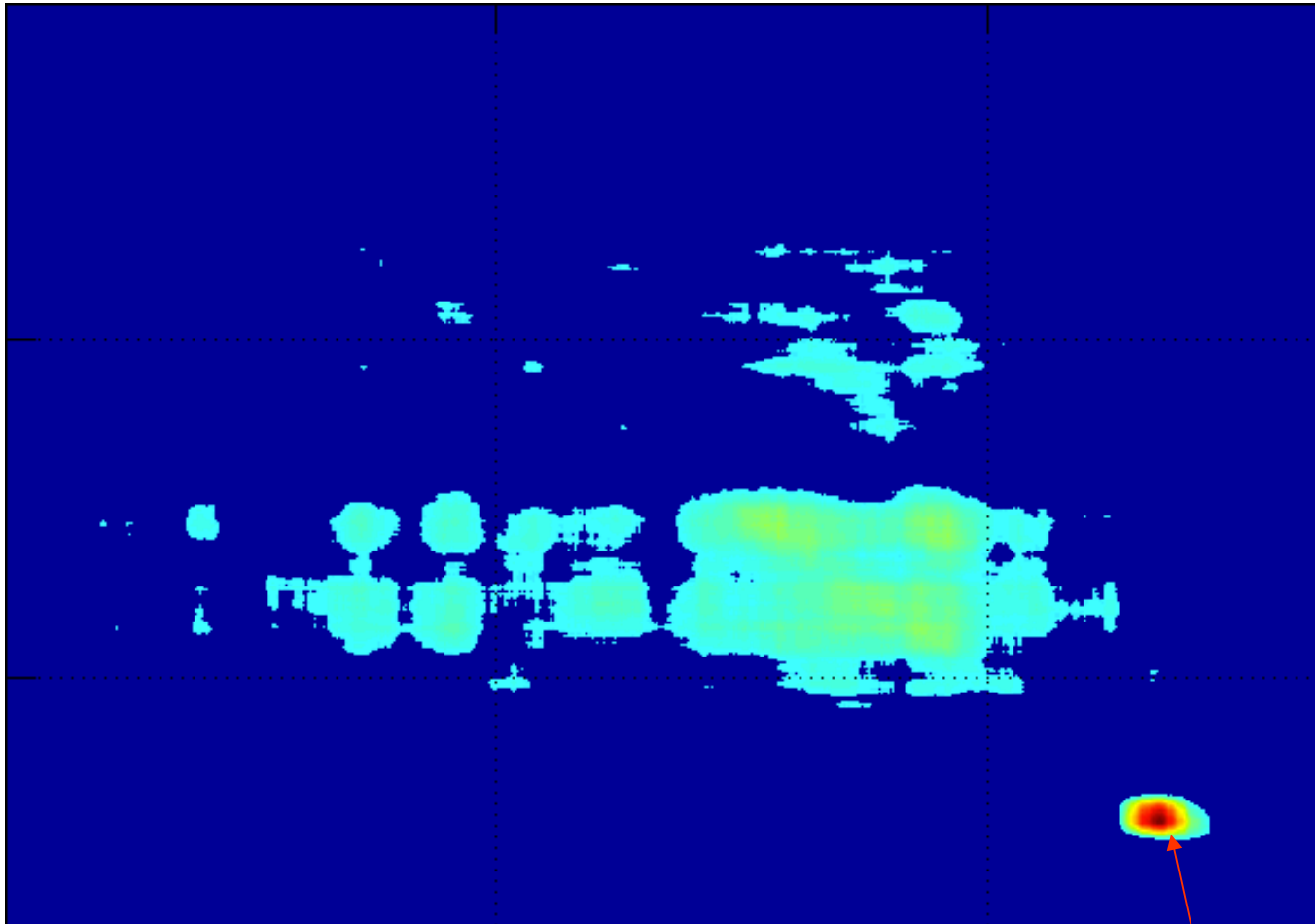


Time Delay Estimation

Zoom inside the map...



Zoom of this map between h1 and h3
zoom to 1 minute, after 5% superior quantile selection to
remove the background noise

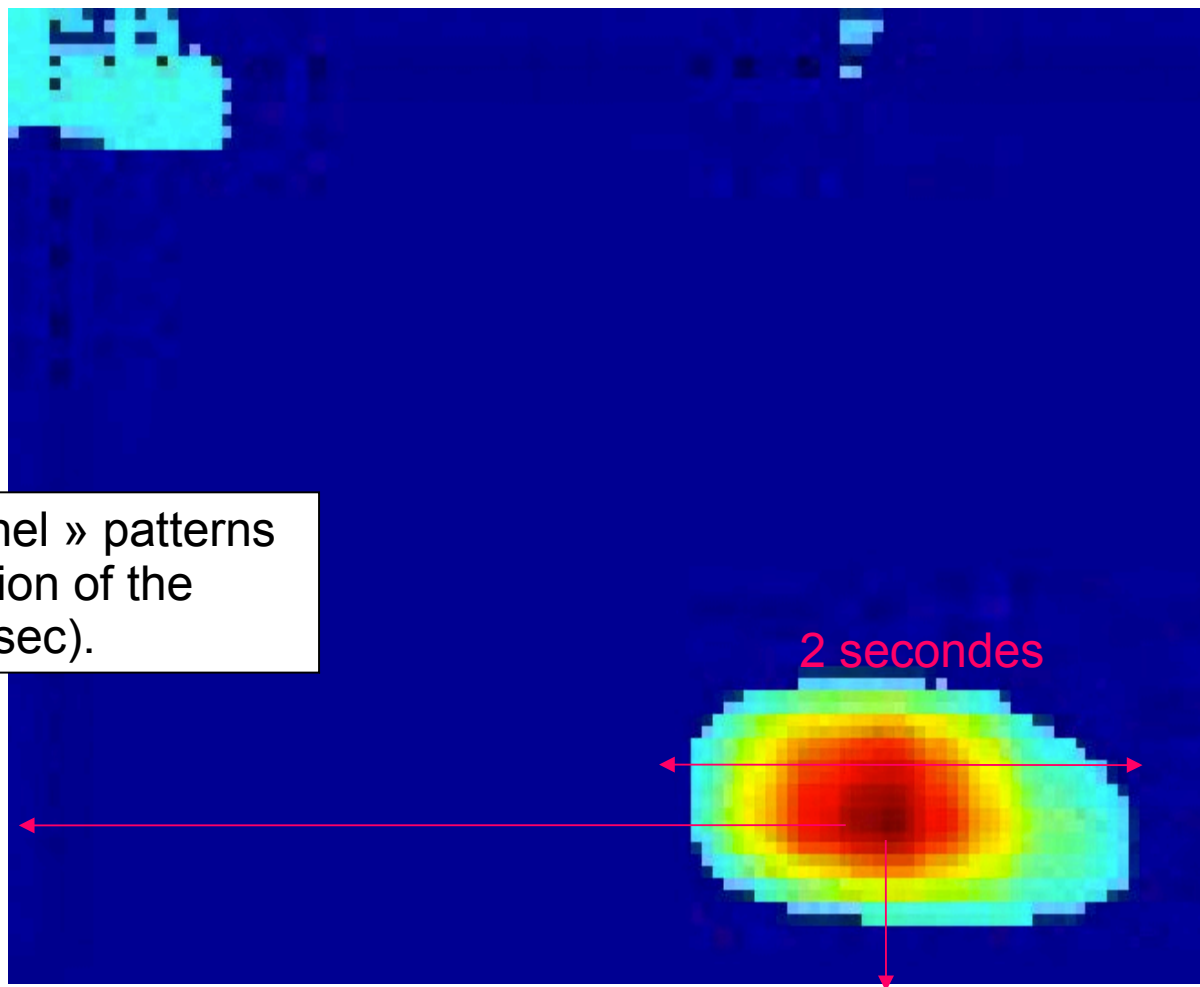


We see clearly some local maxima

Zoom of h1h3 map to 10 secondes

We get clear « kernel » patterns that have the duration of the boing sounds (= 2 sec).

T(h1)



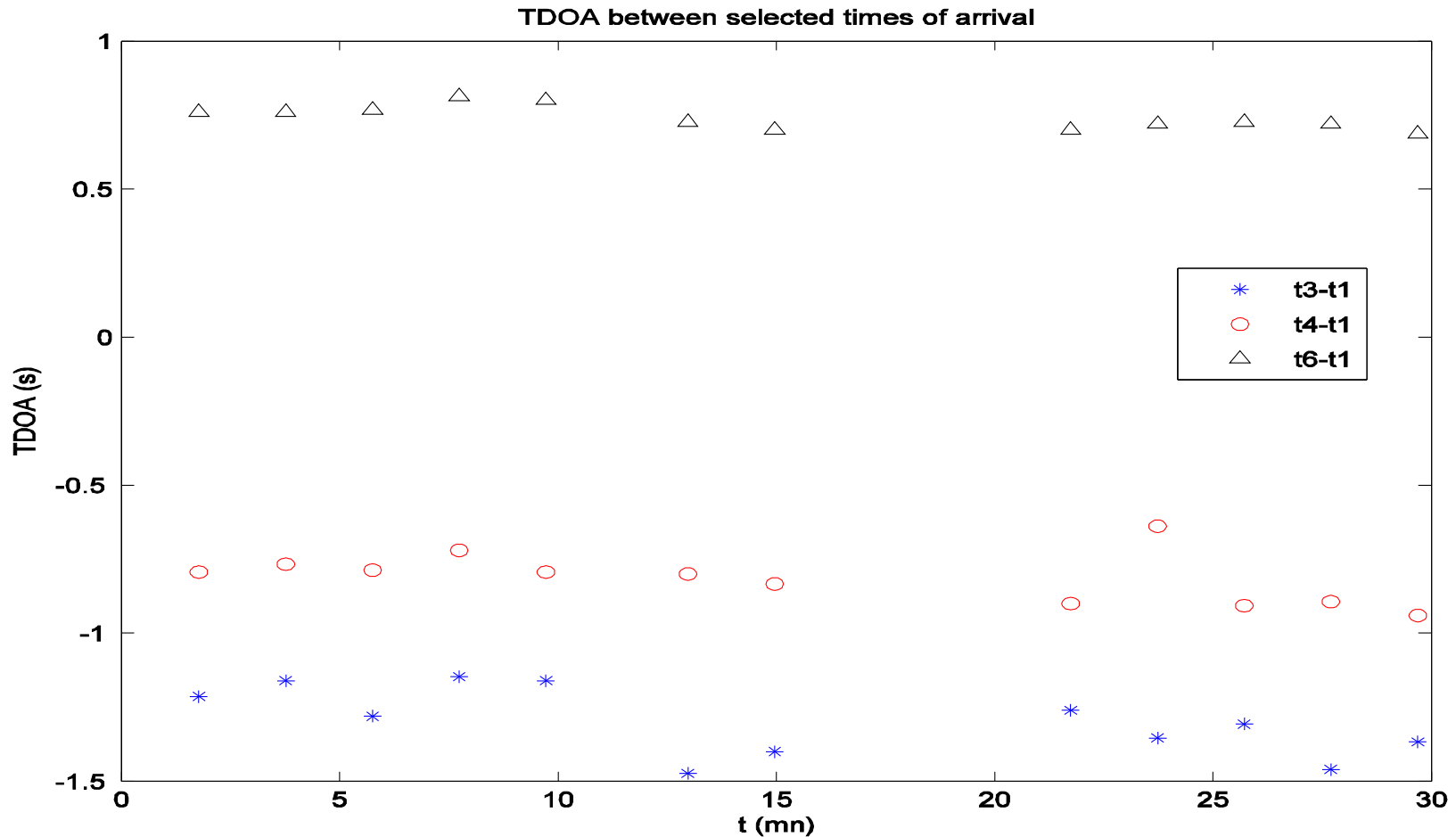
T(h3)

The maximum of each kernel are measured iteratively to get the times on h1, h2

Then : **$TDOA(h1,h2) = T(h1)-T(h3)$**

Time Delays Of Arrival Estimations

We extract 14 TDOA over these 30 minutes,
between h1,h3,h4,h6



=> Coherent and regular variations

Conclusion

- We efficiently matched, through cosine of sparse projections, **and without any target knowledge**, the minke boing sounds.
- We got **clear boing detection** on hydrophone pairs.
These TDOA generated straightforward **coherent track** with correct speed.
- Another set of TDOA has been detected (a second minke whale ?).
We work further on that question.
- Perspectives : we will process our algorithm in the whole array and consider virtual hydrophones.
We'll date also local max cosine similarities to extract the other present whales

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<http://sabiiod.org> ... join us in the SABIOD project !

- Ethoacoustic patterns extracted from SC statistics
- Biodiversity indexing may be easier based on SC
- 3D tracking may be accelerated using SC representations...

- Scaled detection and sparse decomposition

'Physeter catodon localization by sparse coding',

Paris, Glotin, Doh, Halkias, Razik, Workshop on Machine Learning for Bioacoustics, ICML4B, Atlanta 2013

- Whale localisation from SC

'Sparse coding for large scale bioacoustic similarity function',

Glotin, Razik, Paris, Halkias, POMA 19, 010015 (2013)

Report / paper available at <http://sabiod.org>

' Sparse coding for scaled bioacoustics: From Humpback whale songs evolution to forest soundscape analyses' H Glotin, J Sueur, T Artières, O Adam, J Razik,
The Journal of the Acoustical Society of America 133 (5), 3311-3311

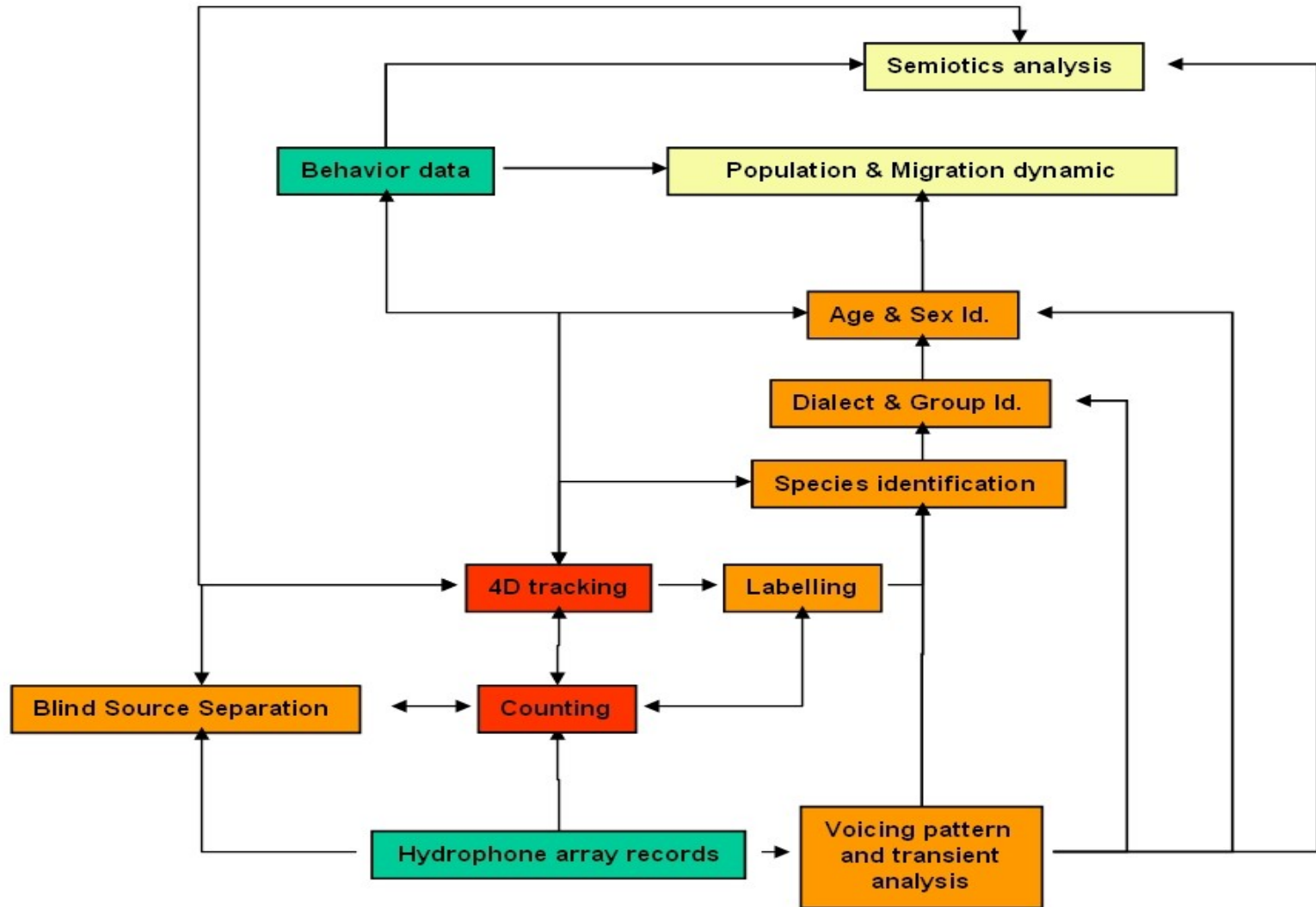
- Individual signature from SC of calls or transient

'Humpack sparse coding for group or individual identification',

Razik, Glotin, Paris, Adam, Doh, sub. in JASA

Acknowledgments : This work is supported by CNRS MASTODONS SABIOD and Institut Universitaire de France « scaled complex scene analysis project »

Global framework



LSIS PIMC framework since 2006 (Pole Mer PACA – SABIOD project Glotin <http://sabiiod.org>)



Join us to Scale Bio-acoustic Plateform

SABIOD

Scaled Acoustic BIODiversity platform

Home

NEW: Bioacoustic
Workshop @ NIPS,
Nevada, dec. 2013

ICML 2013 Workshop

Data Samples

Online CEtacean Tracking

Team

Media

Contact

Bioacoustic signaling is a primary mode of communication and exploration for most of the animals. It enables quick load and transfer of information without any visible contact with the target, tackling the reduced visibility of deep forest (insect, frogs, birds, mammals...), cave or night activities (insects, bats), and/or the long distances like in ocean (krill, fishes, whales...). Bioacoustics is also one of the factors in optimizing natural selection, playing a significant role in signalling resource qualities to potential partners. The SABIOD project aims to detect, cluster, classify and index bioacoustic big data in various ecosystems, at different space and time scales, in order to reveal informations on the complex sensori-motor loop, and on the health of an ecosystem, yielding to new biodiversity insights.

NEWS:

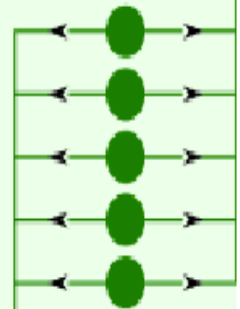
- [Int workshop Neural Information Scaled to Bioacoustics \(joint to NIPS 2013\) 10th dec - deadline ext. abstract 13th oct.](#)
 - [IEEE ATSP'14 last CFP - Special session on Bioacoustics Int. conf. on Ad. Tech. for Signal & Image Processing](#)
-

We open a a special workshop on Learning to Filter / classify for Bioacoustics

Neural Information Processing Scaled for Bioacoustics: NIPS4B

10th of dec. 2013 - Lake Tahoe, Nevada, USA

joint to [NIPS 2013](#) - Prog. Comm.: Glotin - LeCun - Mallat - Artieres - Tchernichovski - Halkias



Important Dates

[\[FLYER\]](#)

Objectives

Challenge 1:
Bird Song Classification

Challenge 2:
Whale Song Processing

NeuroSonar Session

Pre-schedule

Bioacoustic data science aims at analyzing and modeling animal sounds for neuroethology / biodiversity assessment. However, given the complexity of the collected data along with the different taxonomies of the different species and their environmental contexts, it requires original approaches. In recent years, the field of bioacoustics has received increasing attention due to its diverse potential benefits to science and society, and is steadily required by regulatory agencies as a tool for timely monitoring and mitigation of environmental impacts from human activities. The increased expectations from bioacoustic research have been coincident with a dramatic increase in the spatial, temporal and spectral scales of acoustic data collection efforts. One of the most promising strategies concerns neural information processing and advanced machine learning.

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 - <http://www.intechopen.com/articles/show/title/highly-defined-whale-group-tracking-by-passive-acoustic-stochastic-matched-filter>

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