Chair of Research & Teaching in artificial intelligence

202101

Acronyme	**ADSIL**
Project title	**ADvanced underSea Intelligent Listening**
Chair	Hervé GLOTIN, University Toulon, LIS UMR CNRS
Grant	570 240 € Dates : De juin 2020 à juin 2024
Topics	Passive Acoustic Monitoring, Acoustic Recognition, Machine listening, Deep Learning, Inversion, wavelet learning
topics IDA	x Data processing from various sensors x Distributed processing and applications for network communications

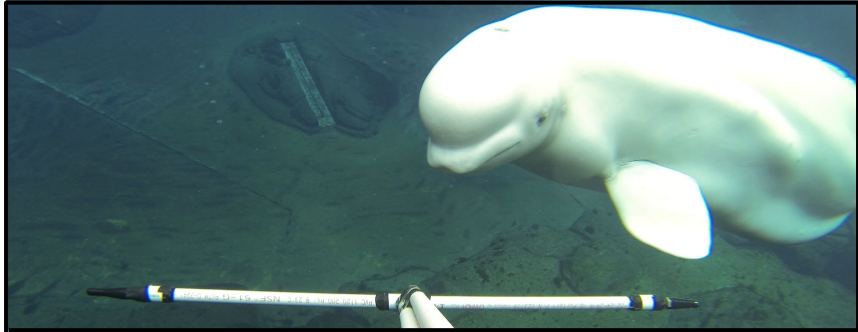
LAMFA INRIA LMA
PNPC PELAGOS
SMIoT IM2NP
IN2P3 CPPM
PREMAR CROSSMED
MIRACETI

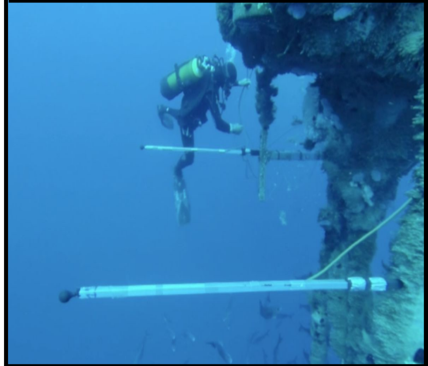
Equipe : 31 + 3 partenaires industriels
13 titulaires = Paris, Paiement, Gies, Giraudet, Razik, Marxer, Patris, Malige, Asch, Cristini, Liutkus, Ourmières, Glotin.
+ 2 Ing = Barchasz, Prevot
+ 2 Postdocs (Ferrari & Poupard) = oct 2020, janv 2021
+ 4 Thésards (Thellier, Jenkins, Best, Marzetti) = nov 2020
+ 3 Stagiaires (Gros-Martial, Trin, Juliette) = mars 2021
+ coll internat : Pavan, Roch, Symonds, Sousa-Lima, Bucchan
+ 3 indus : SEAPROVEN, SEMANTICTS, OSEAN

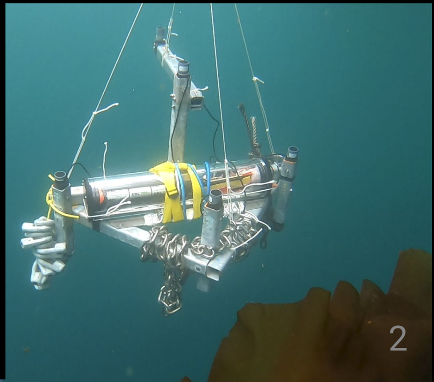
The team DYNI

We are research group of the Laboratoire d’Informatique et Systemes (LIS) UMR 7020 CNRS hosted at the Univ. Toulon (UTLN).

In ADSIL, we aim to innovate in methods of machine learning, signal processing and data analysis in order to improve our knowledge and understanding in physical, natural subsea acoustics.



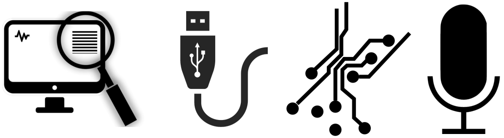


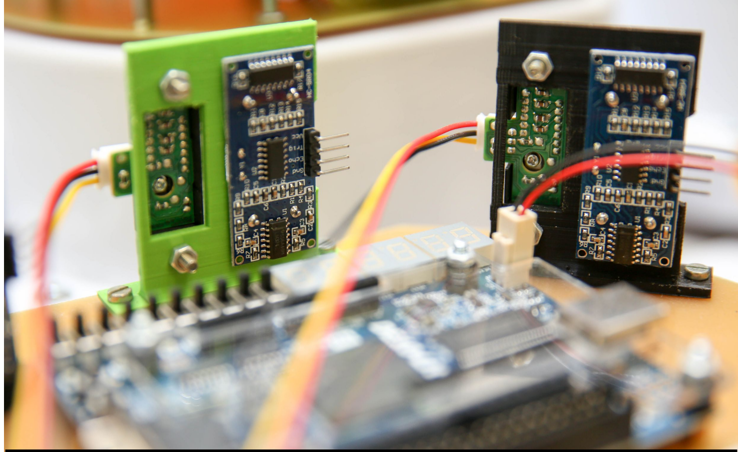


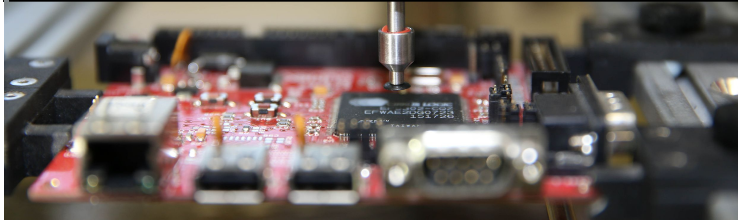
SMIoT: Scientific Microsystems for the Internet of Things

Design of electronic hardware (conception et routage des PCB), front-end, RF.
Assembly and testing of electronic prototypes
Industrialization of connected objects

Design, Test and Construction of the
HIGH BLUE MONO system





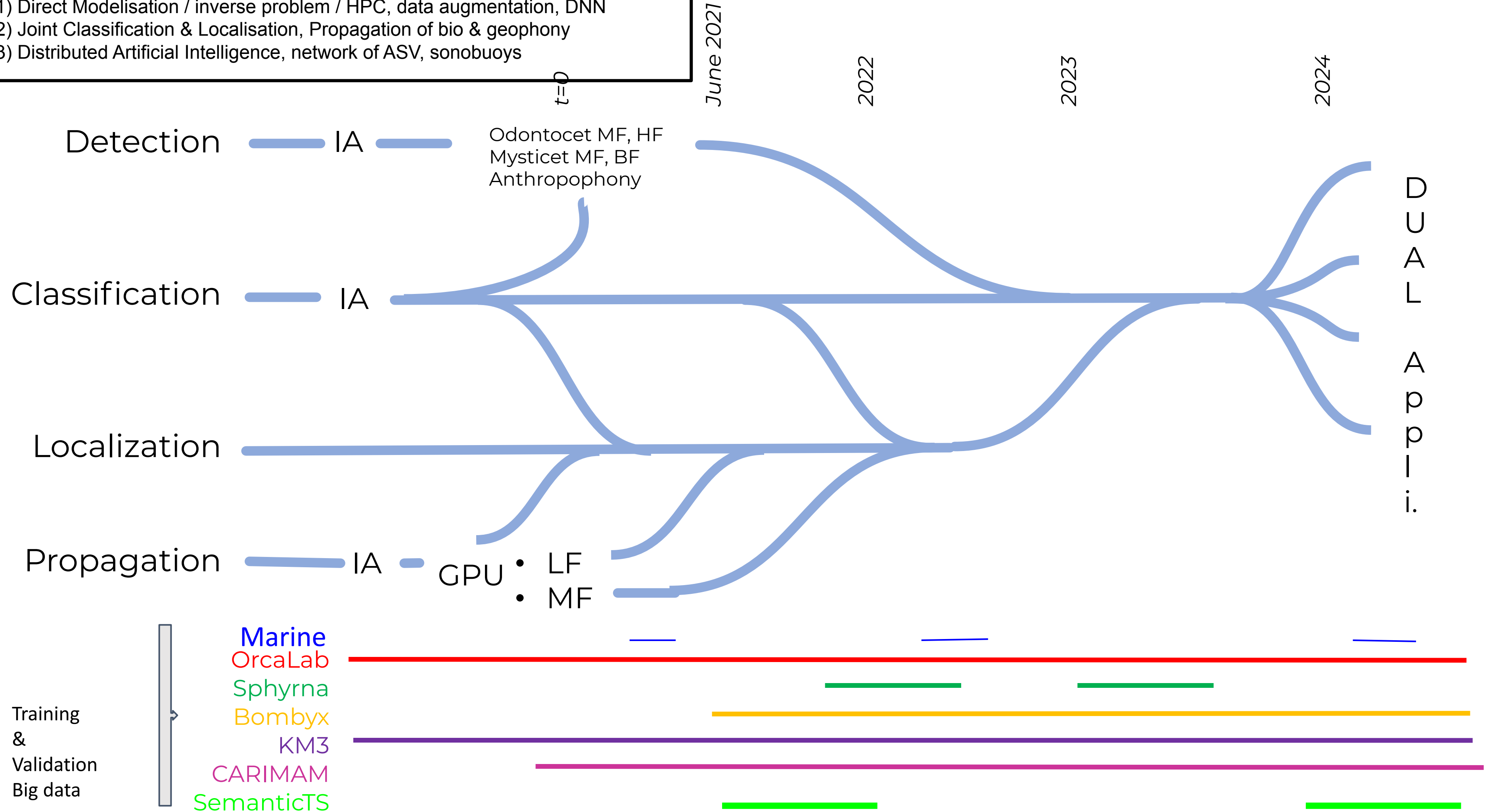


Map of the DYNI collaboration

hydrophones/microphones

Tara Ocean

Workpackages :
T1) Direct Modelisation / inverse problem / HPC, data augmentation, DNN
T2) Joint Classification & Localisation, Propagation of bio & geophony
T3) Distributed Artificial Intelligence, network of ASV, sonobuoys



Workpackages
T1) Direct Modelisation / inverse problem / HPC, data augmentation, DNN
T2) Joint Classification & Localisation, Propagation of bio & geophony
T3) Distributed Artificial Intelligence, network of ASV, sonobuoy

A) Biosonar (T1,T2)

Classification of biosonar (MF HG RM SP NT)

Matching pursuit nD of biosonars (HG NT PG)

Strategy of groups of hunters (HG NT MF PG)

Long survey (MP PB HG)

Bio-multistatism (HG SP)

Ecosystem and Bioacoustics (HG AP YO MP)

B) Classification of voicings (T1,T2)

Individual call tracking (Orca) (MP HG)

Whale songs and evolution (FM, PB, JP, JR, HG)

Source separations, dialect, individual signatures (MP, HG)

HF voiced pulse classification (PB HG RM SP)

LF voiced pulse classification (PB HG JP FM)

C) AI & propagation (Explanable IA) (T2, T3)

Propagation & DNN / GPU RTX (MF PC HG)

Stream modelisation, forecasting HD (AP, JJ, HG, YO)

D) IA online, network IoT / Embeded IA (T3)

Online Bombyx2 (PB, MF, HG, SP, RM)

Online KM3 (MF, PB, HG)

Online Orcalab (PB, HG, RM)

Emb. IA (PB VG HG SM) HF et BF

ULP (SM VG VB HG)

E) Maximisation of observation for classification & localisation (T1,T2, T3)

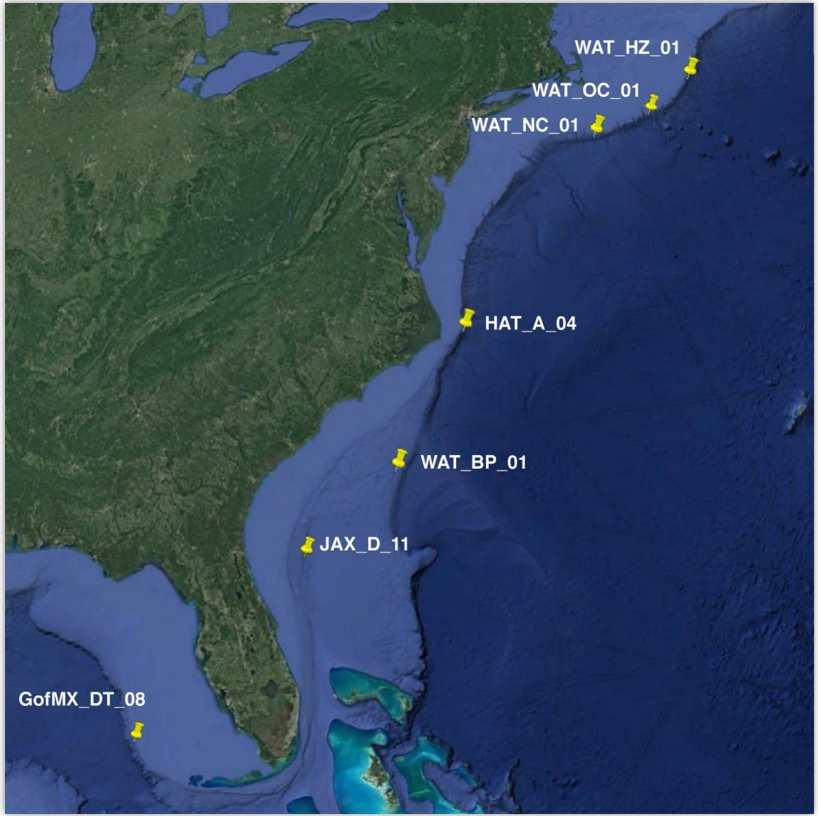
GIAS (2 Bombyx2) Feder2 / Region & projet LML

KM3ENV / Mission Patagonie BF / MF / HF ; Carimam ; Maurice et Orcalab (*COVID) ; Sphyrnas

SERIOUS GAME

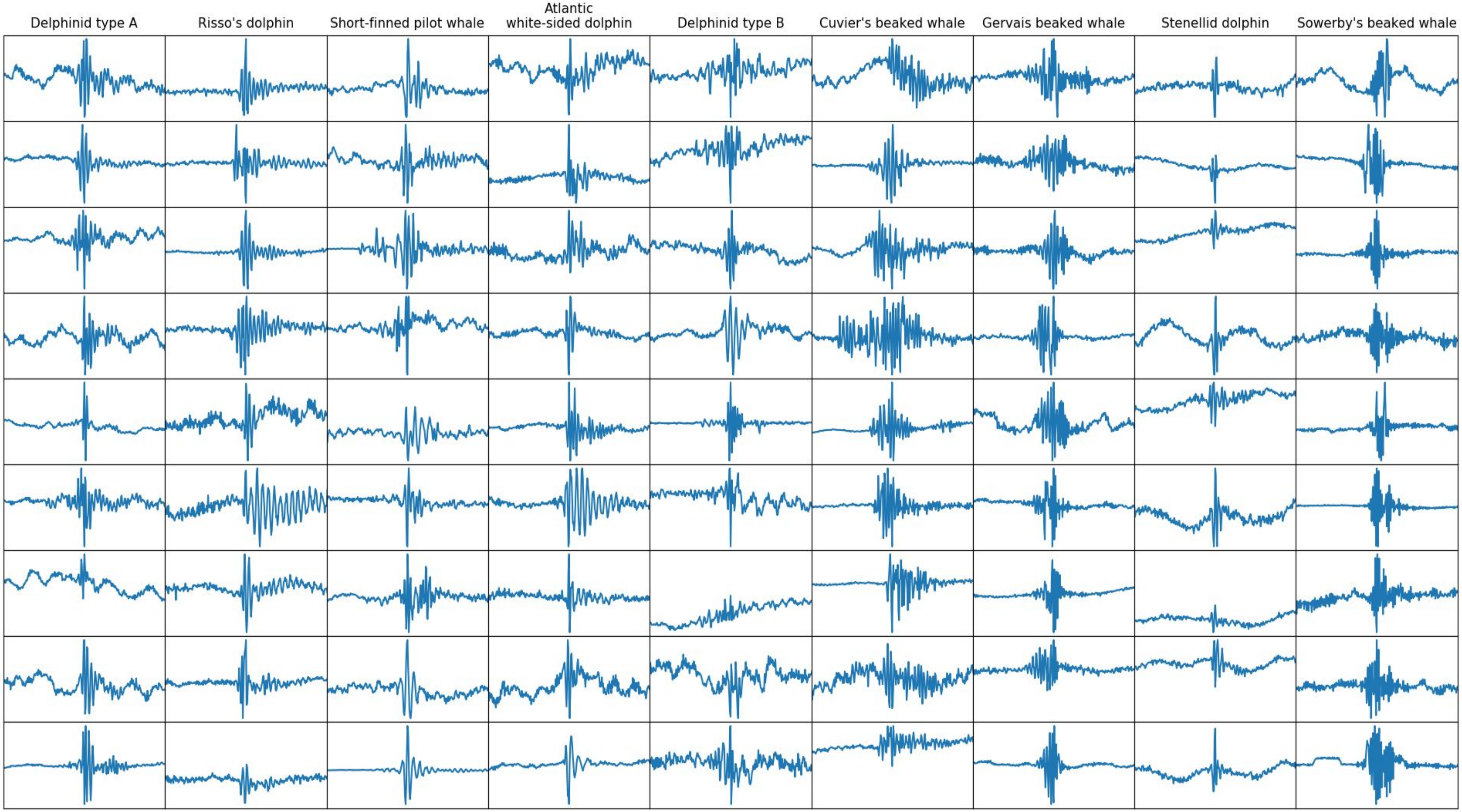
A) Biosonar (T1,T2)

IA model used for classification



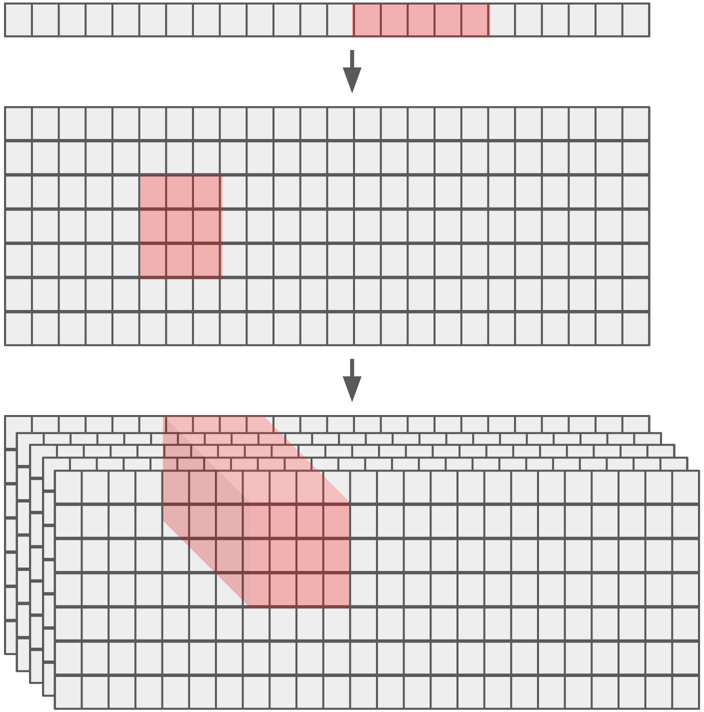
- DCLDE 2018
- 134 080 samples
- 10 classes

Abbreviation	**Species**
Me	*Mesoplodon europaeus*- Gervais beaked whale
Zc	*Ziphius cavirostris*- Cuvier's beaked whale
Mb	*Mesoplodon bidens*- Sowerby's beaked whale
La	*Lagenorhynchus acutus*- Atlantic white-sided dolphin
Gg	*Grampus griseus*- Risso's dolphin
Gma	*Globicephala macrorhynchus*- Short-finned pilot whale
Ssp	*Stenella sp.*Stenellid dolphin
UDA	Delphinid type A
UDB	Delphinid type B
Pm	*Physeter macrocephalus*- Sperm whale


Delphinid type A
Risso's dolphin
Short-finned pilot whale
Atlantic white-sided dolphin
Delphinid type B
Cuvier's beaked whale
Gervais beaked whale
Stenellid dolphin
Sowerby's beaked whale

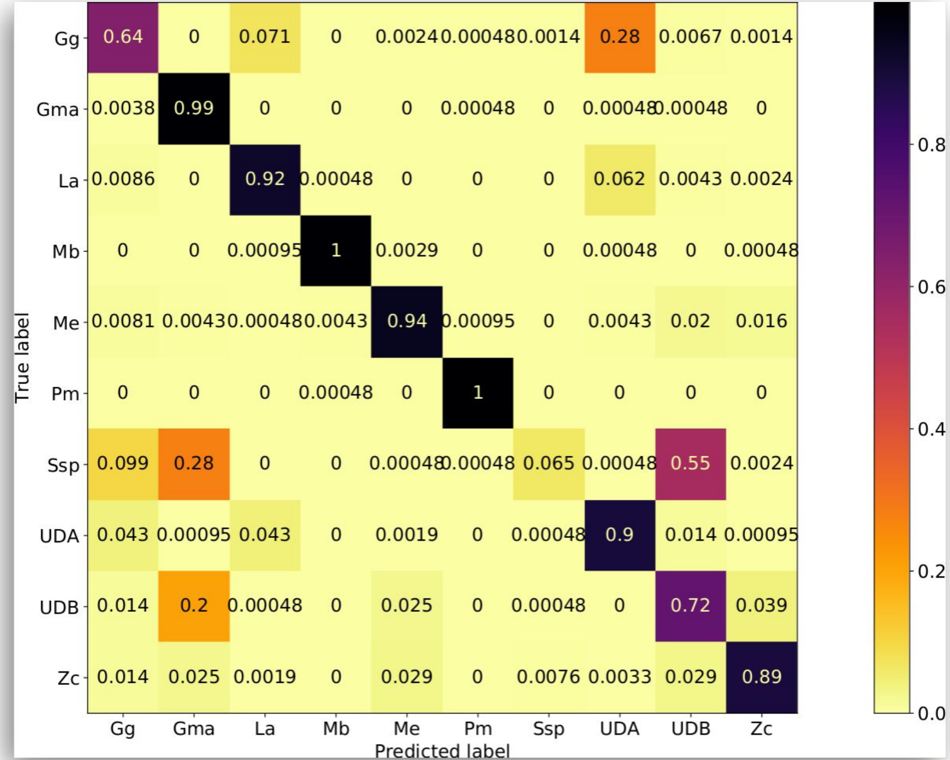
Multiscale Hierarchical Convolutional Networks

- Have the advantage of **invariance** to translation
- Map the symmetry group to the translation group
- Increasing dimension helps to deal with more complex **symmetries**

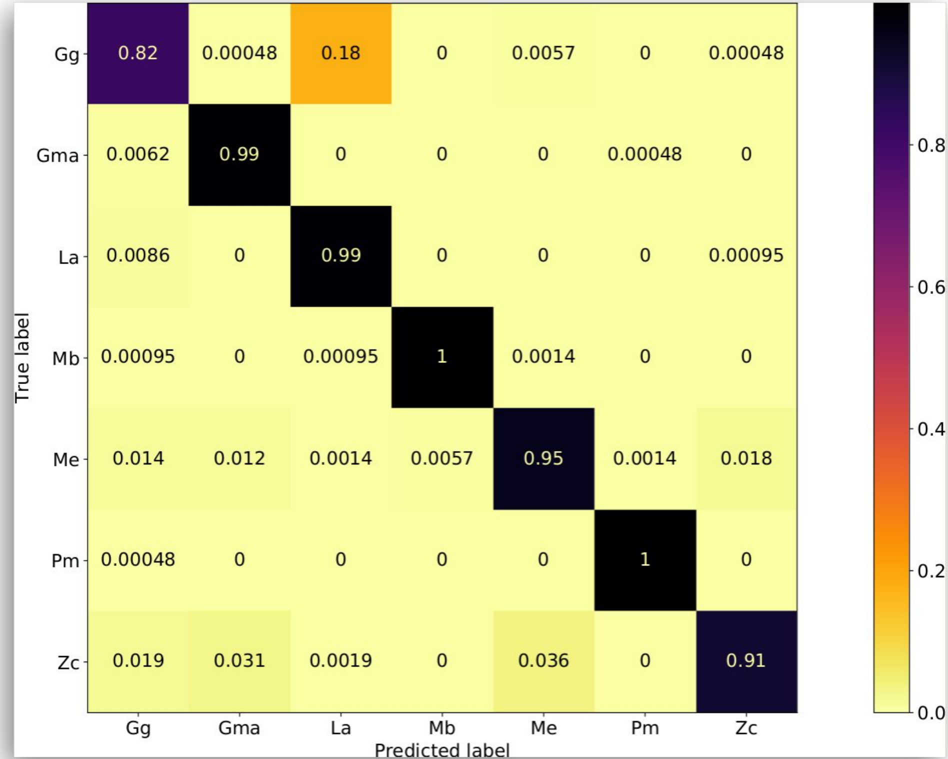


S. Mallat, “Understanding deep convolutional networks,”Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, vol. 374, no. 2065, p. 20 150 203, 2016
J. Jacobsen, E. Oyallon, S. Mallat, and A. W. Smeulders, “Multiscale hierarchical convolutional networks,”arXiv preprint arXiv:1703.04140, 2017.

Accuracy = 80.6% on the 10 classes



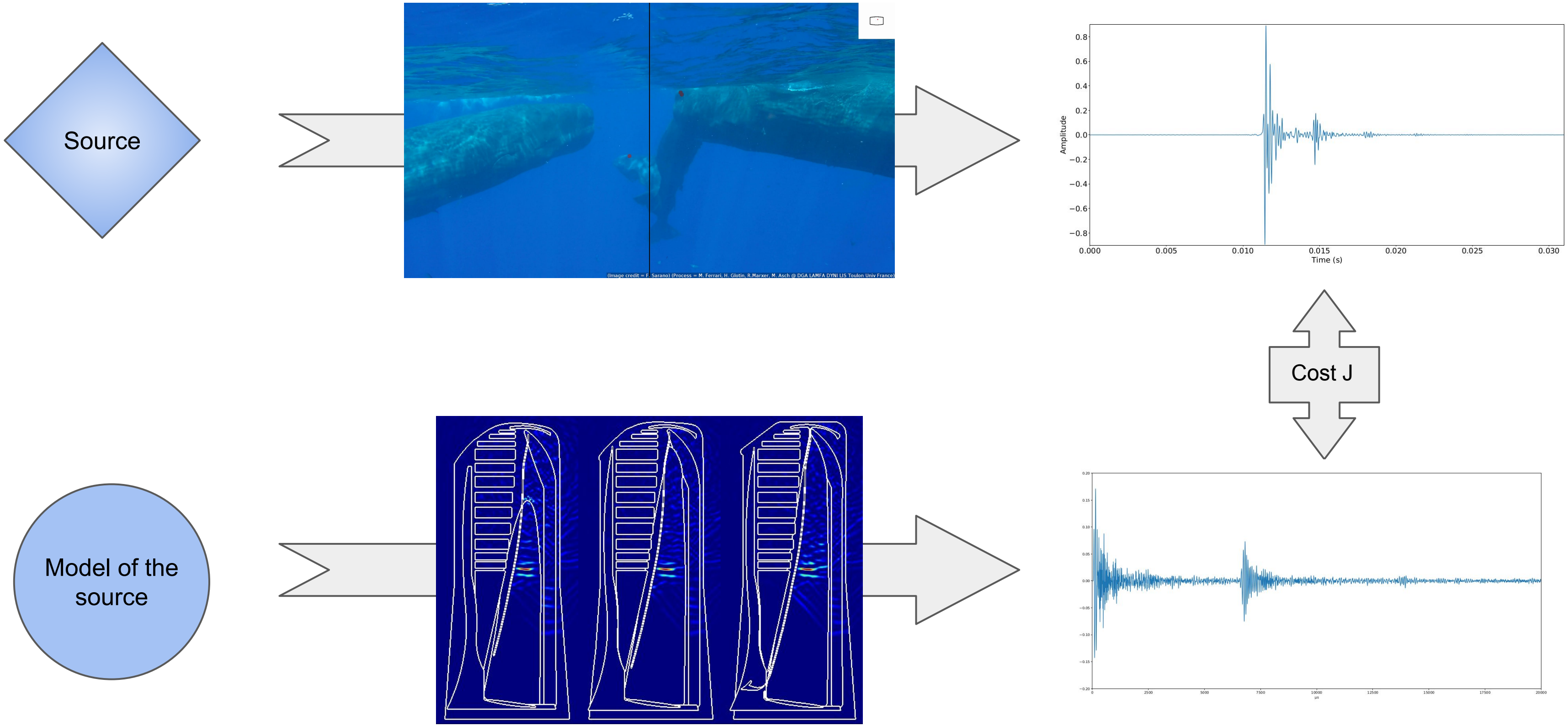
Accuracy = 95.1 % on the 7 classes



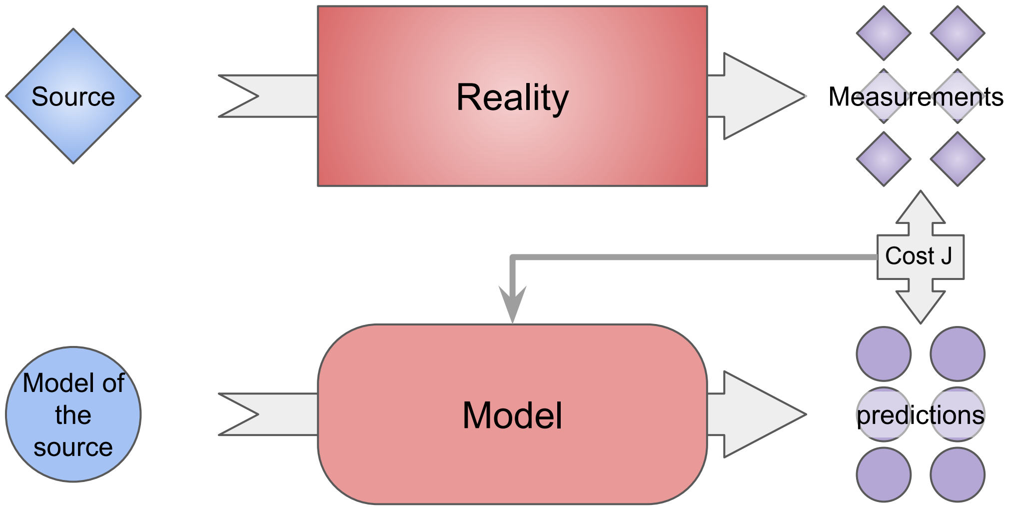
Other models for classification

- Passive acoustic monitoring in Quebec
  - 186 bird species, 207 species in total (frogs/mammals, etc.)
  - 11000 labeled samples
- Classifying orca vocalizations
- Detection and classification of fin whales and sperm whales

Inverse Problem of Parameter Estimation



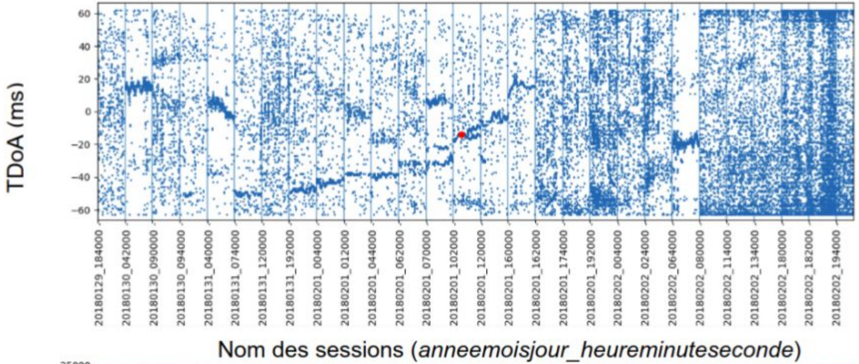
Inverse Problem of Parameter Estimation

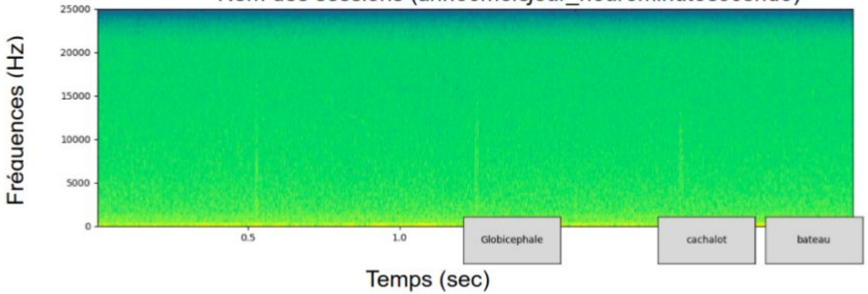


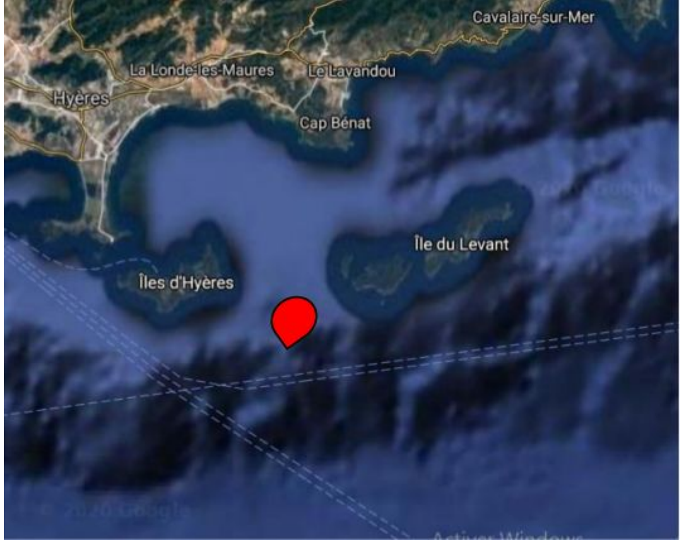
- Define a **cost function** J which
  - represents the **error** between the **prediction** and the **measurements**
  - depends on the **parameters** of the model
- Find an **explicit** formula of the **gradient** of J with respect to model parameters
- Minimize J

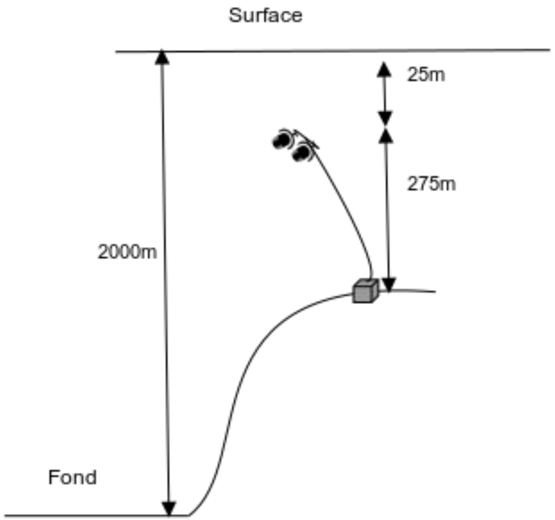
The BOMBYX station

- Bombyx station, stereophonic
- 25 of depth
- Env 2700 hours of recordings, stereo
- Detection of sperm whales clics on Bombyx
- Data for future training









The BOMBYX station

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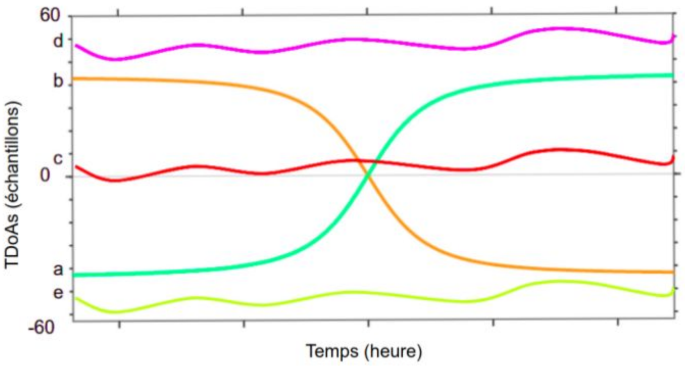
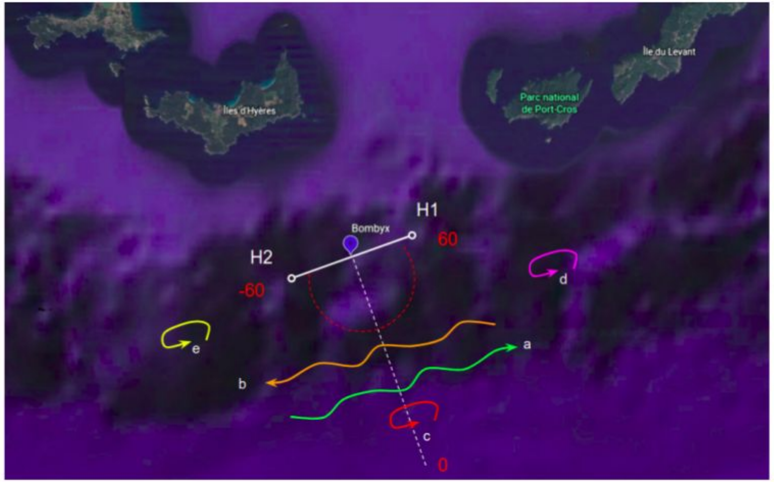
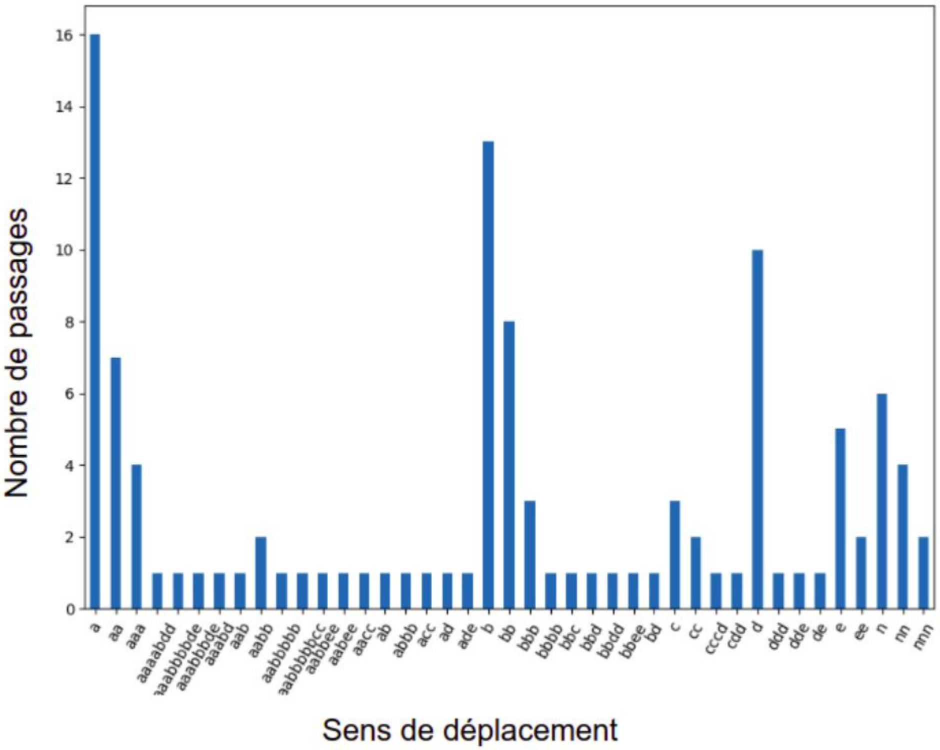
The BOMBYX station







Matching poursuit & tracking 3D

Missions Sphyrna 2018, 2020, 2021…

Bio-Multistatisme ?

=> corpus & AI

Det Class Loc & Propagation joints

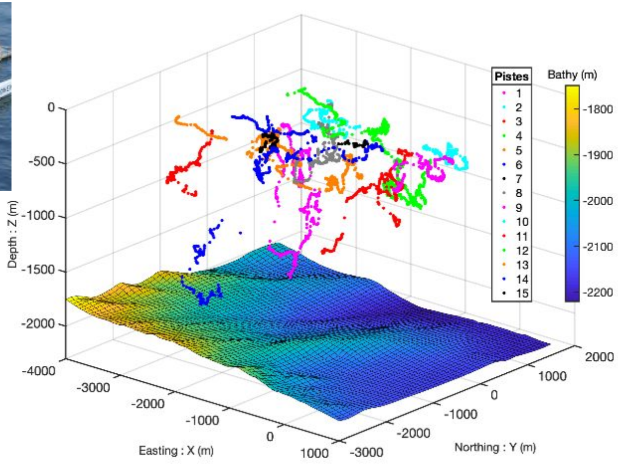
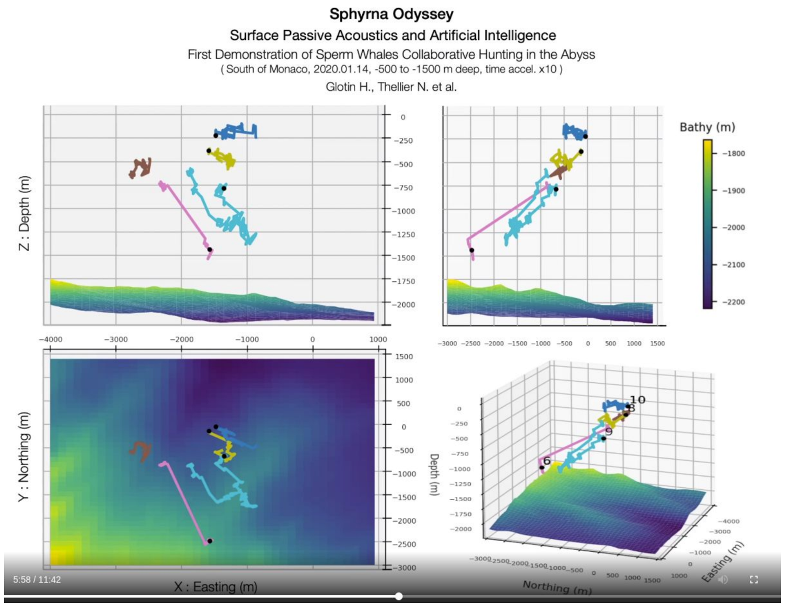
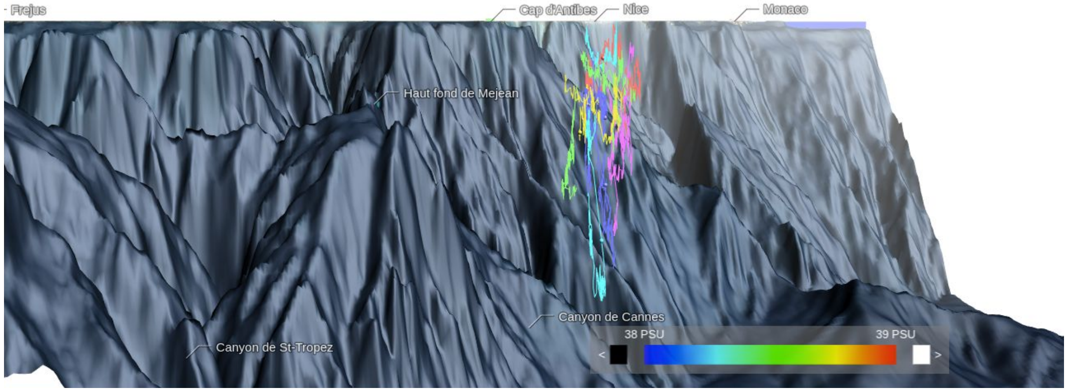


Figure 3.1: Traces 3D des déplacements des 15 pistes (record entier)

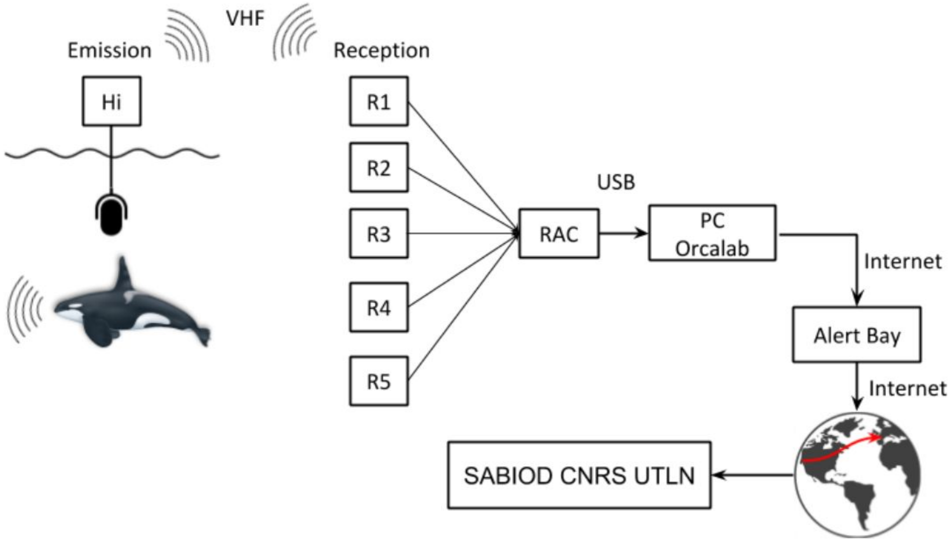


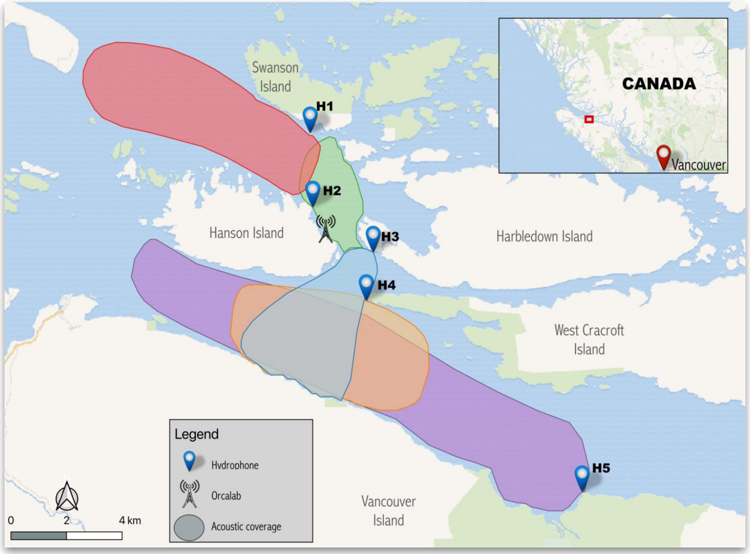


B) Classification of voicings

Orca Vocalization Detection
Context - OrcaLab

- Northern resident orcas community
- In situ observatory since 1970
- 5 Hydrophones (recording at 22kHz)
- Full time recording since 2015 (50 TB)





Hydrophone layout in Johnstone Strait

Orca Vocalization Detection
Models architectures

Input	1x346x80
Conv2D(3x3)	32x345x78
Conv2D(3x3)	32x343x76
MaxPool(3x3)	32x114x25
Conv2D(3x3)	32x112x23
Conv2D(3x3)	32x110x21
Conv2D(3x19)	64x108x3
MaxPool(3x3)	64x36x1
Conv2D(9x1)	256x28x1
Conv2D(1x1)	64x28x1
Conv2D(1x1)	1x28x1
GlobalMax	1

Spectral Model [3]
309,825 parameters
Input : Mel Spectrogram

Input	1x1x1x110250
Conv1D(5)	1x1x32x55125
Conv2D(3,5)	1x32x32x27563
MaxPool	1x32x32x13781
Conv3D(3,3,5)	8x16x16x3446
Conv3D(3,3,5)	32x8x8x862
Conv3D(3,3,5)	64x4x4x431
Conv3D(2,2,5)	128x3x3x216
Conv3D(1,1,1)	128x1x1x216
MaxPool	128x1x1x1
Linear	64
Linear	1

End to End Model
294,497 parameters
Input : raw signal

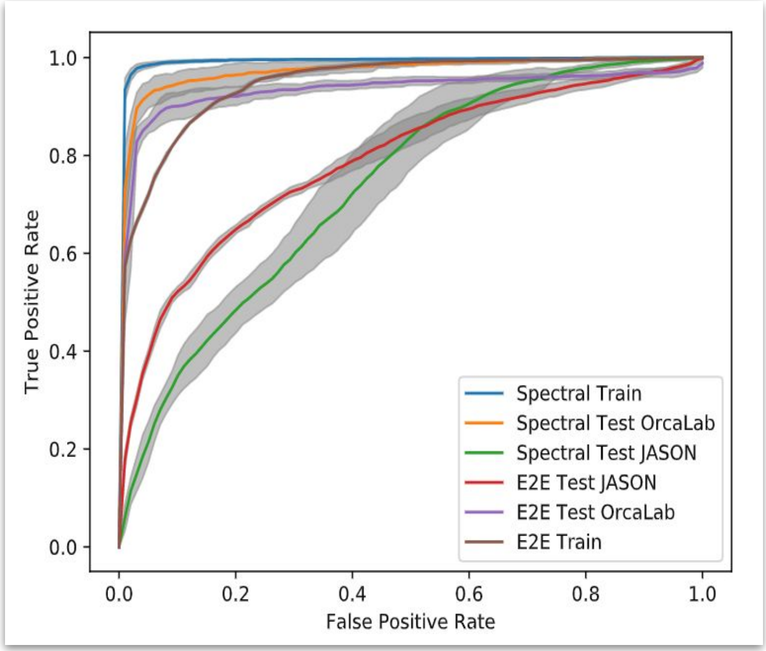
[3] Grill, and Schlüter. "Two convolutional neural networks for bird detection in audio signals." 2017 EUSIPCO. IEEE, 2017.

Orca Vocalization Detection
Models' Performances

Averaged over 10 runs

Spectral Model			
	Precision	Recall	AUC
Training	0.91 ± 0.017	0.97 ± 0.005	0.99 ± 0.001
Test OrcaLab	0.91 ± 0.105	0.90 ± 0.044	0.98 ± 0.010
Test JASON	0.51 ± 0.04	0.87 ± 0.030	0.74 ± 0.027

End-to-end Model			
	Precision	Recall	AUC
Training	0.63 ± 0.004	0.87 ± 0.002	0.95 ± 0.002
Test OrcaLab	0.50 ± 0.019	0.96 ± 0.005	0.94 ± 0.008
Test JASON	0.63 ± 0.023	0.70 ± 0.032	0.79 ± 0.010

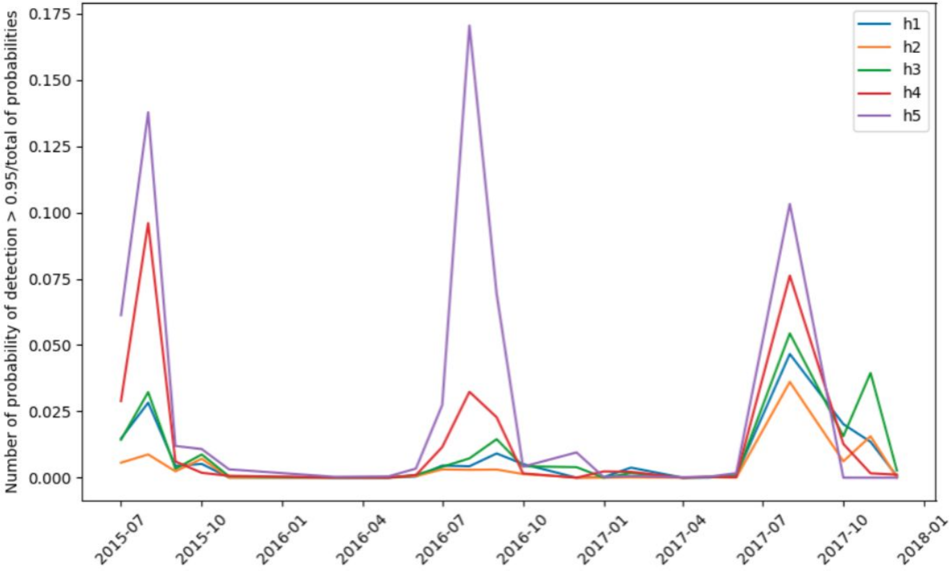


Recieving operator curve

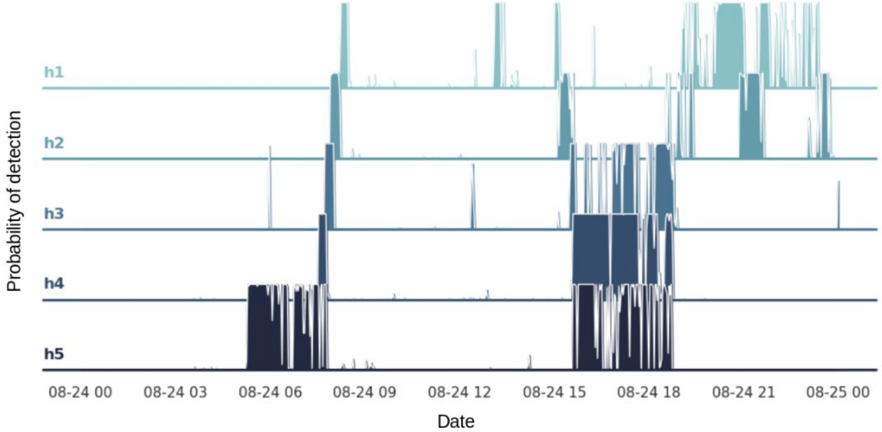
Best et al. 2020, IJCNN

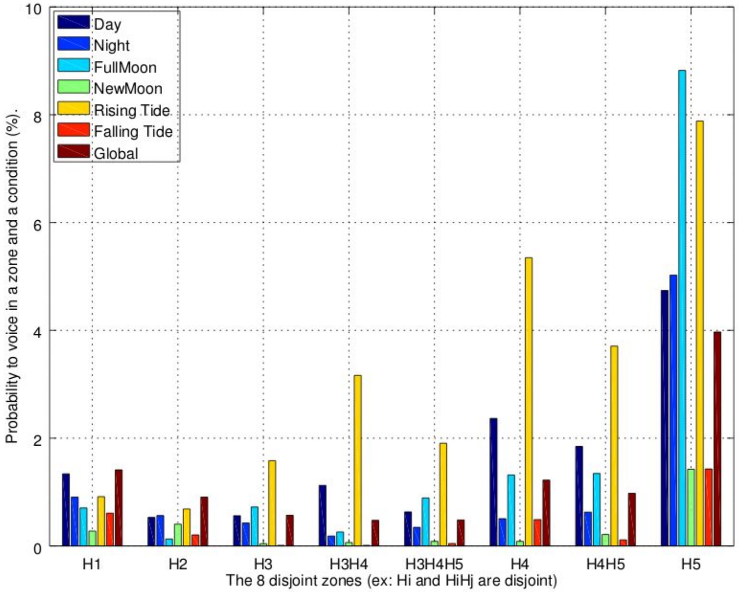
Orca Vocalization Detection
First Results

- Run over 3 years (2015 to 2017)
- Over 420k detected vocalizations



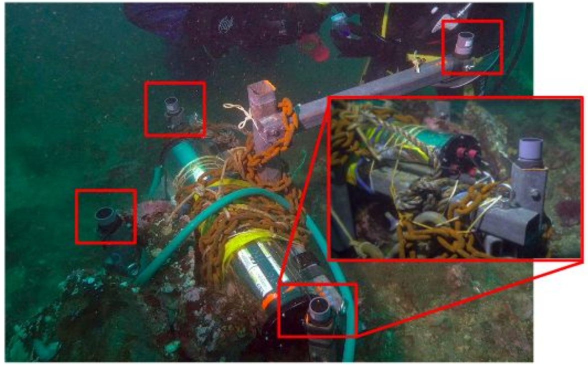
Probability of vocalization detection through time

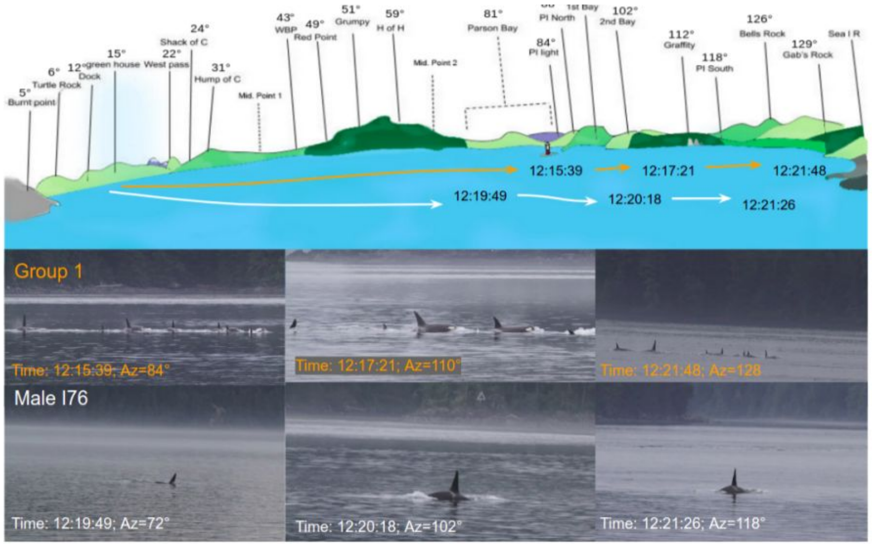


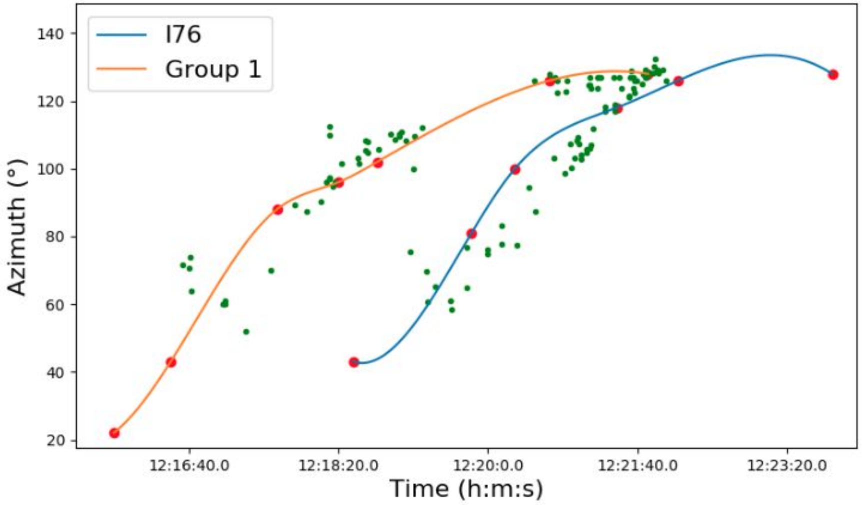


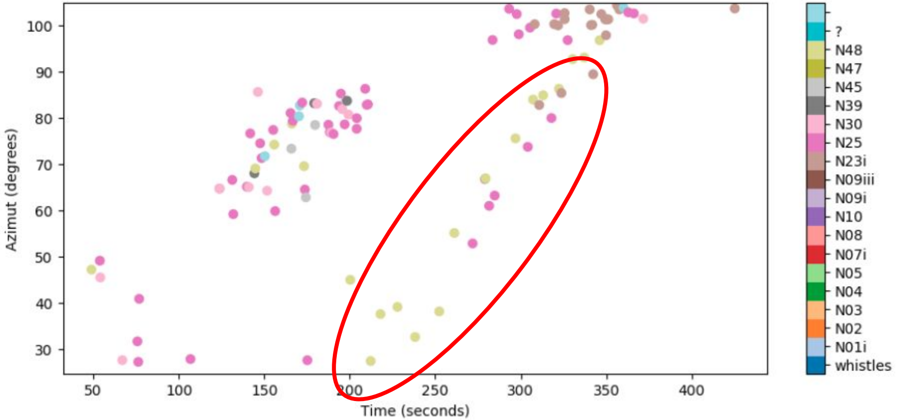
Best et al. 2020, IJCNN; Poupard et al. Ocean 2019

Individual separation and identification of orcas calls in the wild: Individual signature learning ?



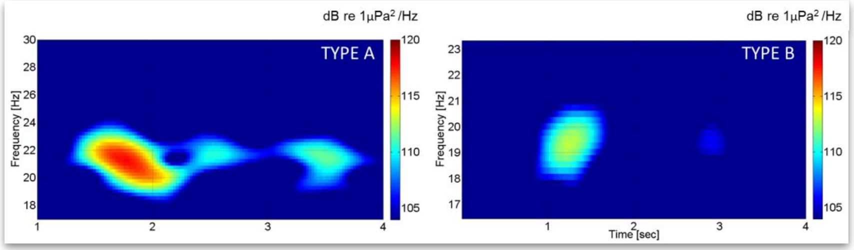






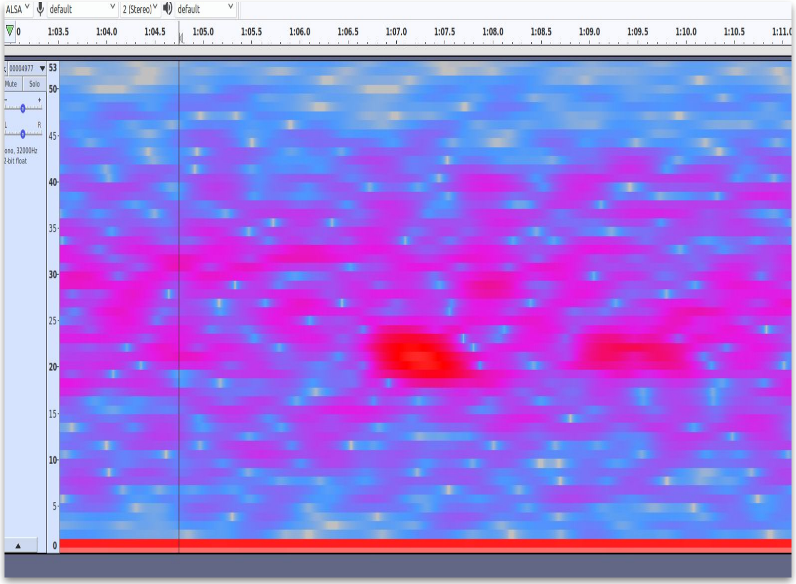
Poupard et al, in Sub to SR

Fin whale pulse detection
Context - Fin whale pulse



Monitoring fin whale (Balaenoptera physalus) acoustic presence by means of a low frequency seismic hydrophone in Western Ionian Sea - EMSO site. Gianni Pavan

- Centroid frequency : 20Hz
- Bandwidth : 5-7Hz
- Length : 1sec
- Periodicity : 15-40sec



Sample from Boussole dataset

Fin whale pulse detection
CNN binary classifier

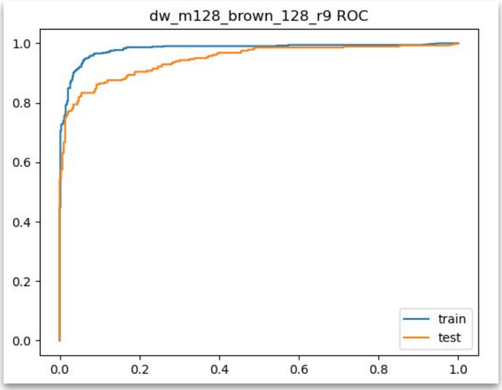
Dataset :

set	source	annot	
test	bombyx	False	292
		True	282
train	boussole	False	430
		True	430
	giani	False	100
		True	100

Trained with +3dB brown noise

Test AUC : 0.946

Train AUC : 0.981



- Sampling frequency = 200Hz
- STFT (winsize=256, hopsize=16)
- Mel (128 features from 0 to 100Hz)
- Log
- Conv 128 - 128
- Conv 128 - 128
- Conv 128 - 1
- MaxPool

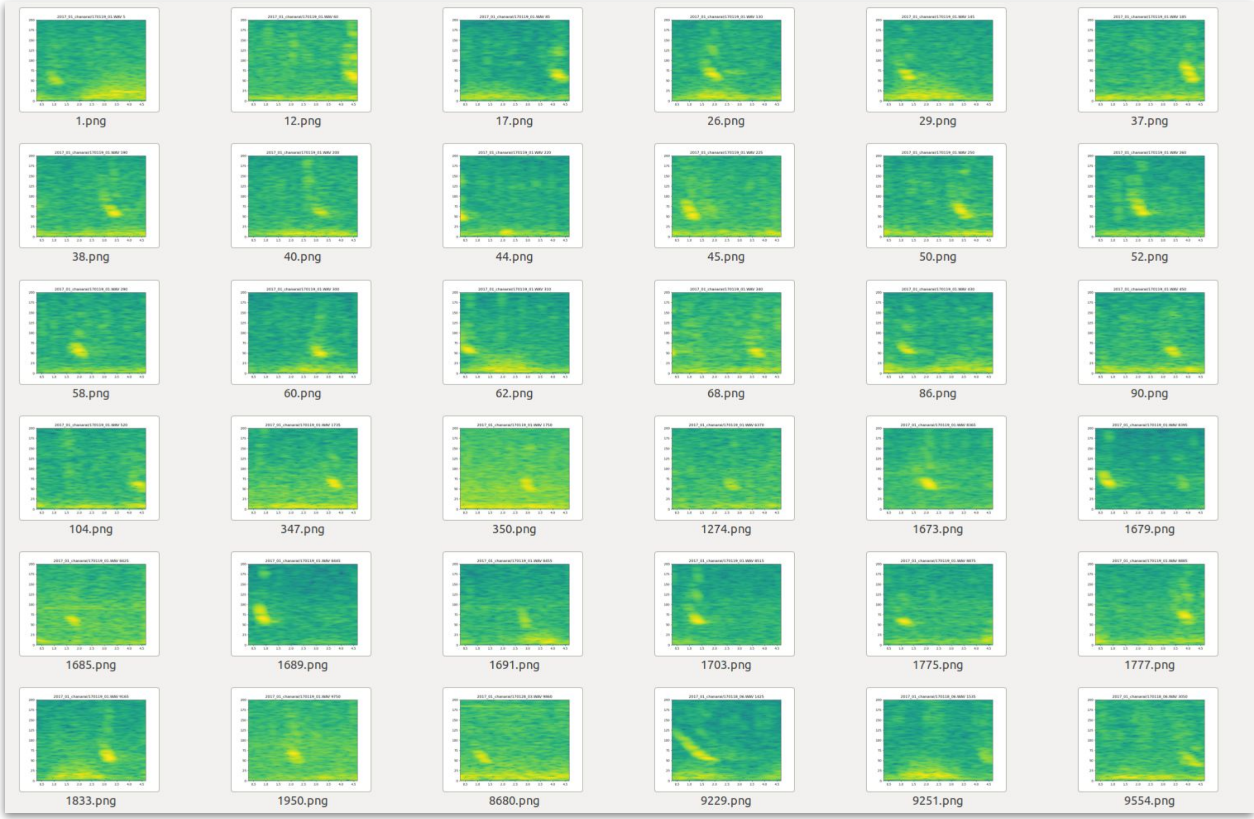
Conv = batch norm, depthwise conv, dropout, Relu
Valid AUC = 0,94

Fin whale binary classifier

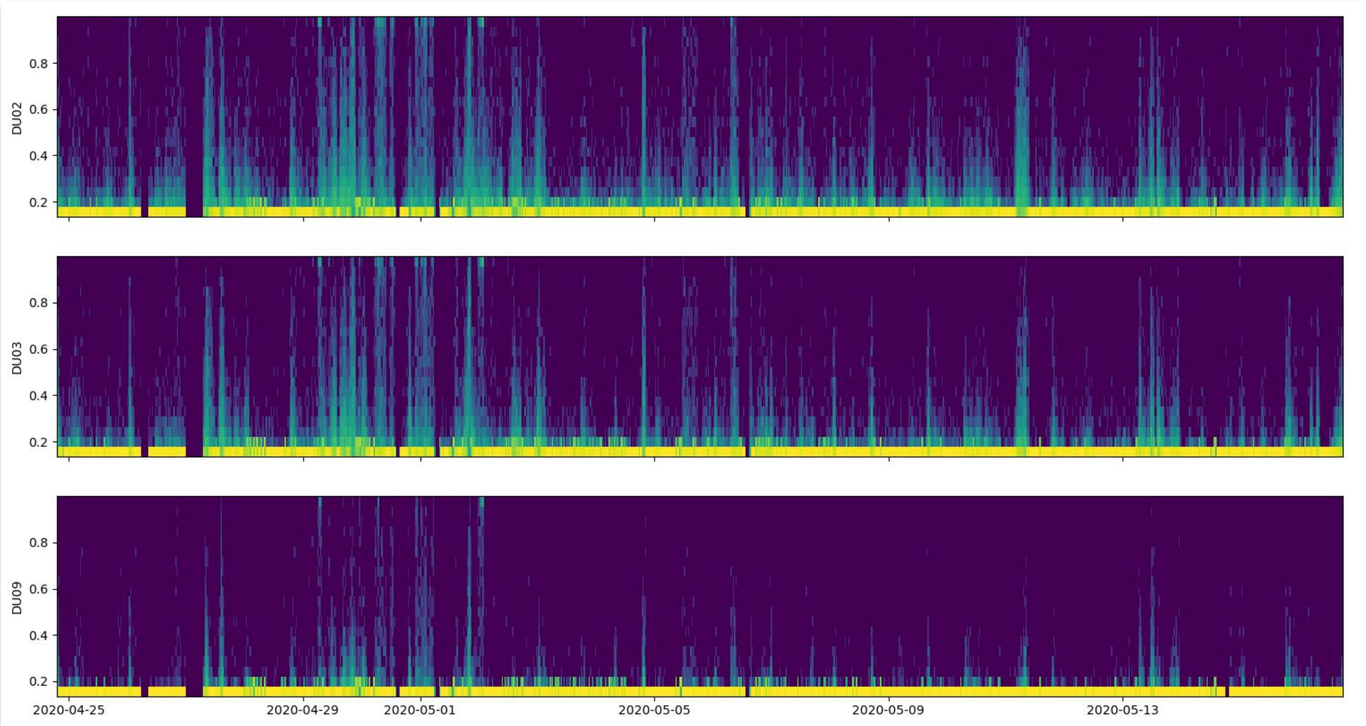
Low Frequency event classification : Fin whale pulse detection
Application to new datasets

- Easy to deploy architecture
- Trained for Chilian fin whales
  - 0.99 Test AUC
- Fine tuning / transfer learning
  - Low data needs
- Train for blue whale detection

Sample of high predictions over Chilian dataset
(rec. Patris, Malige, Glotin 2017, Chanaral, Humbold loop…)

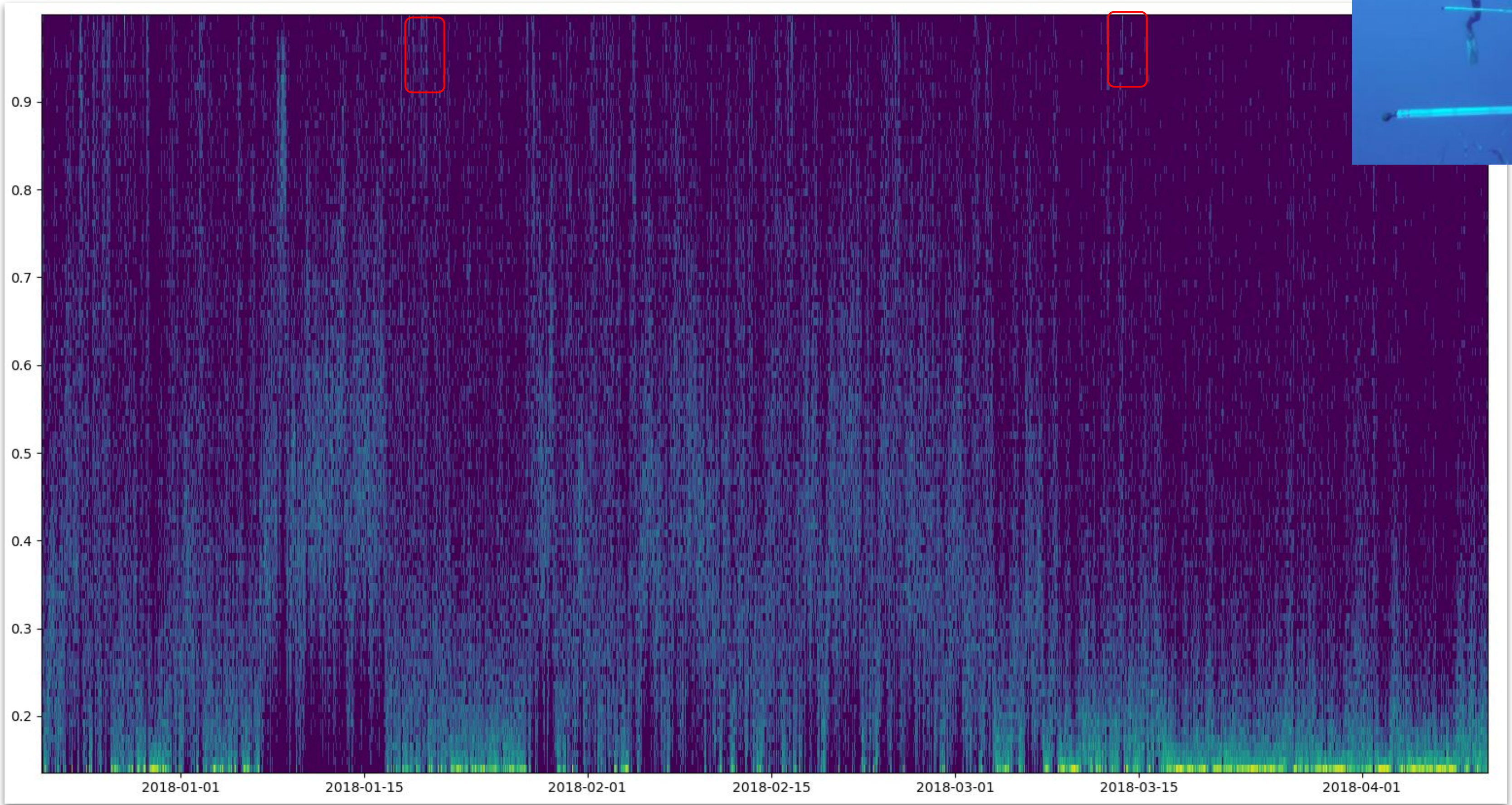


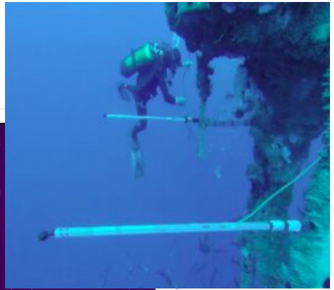
Fin whale pulse detection
KM3Net forward



2D histogram (x=date, y=prediction) over 3 weeks

Fin whale pulse detection **Bombyx1 forward**

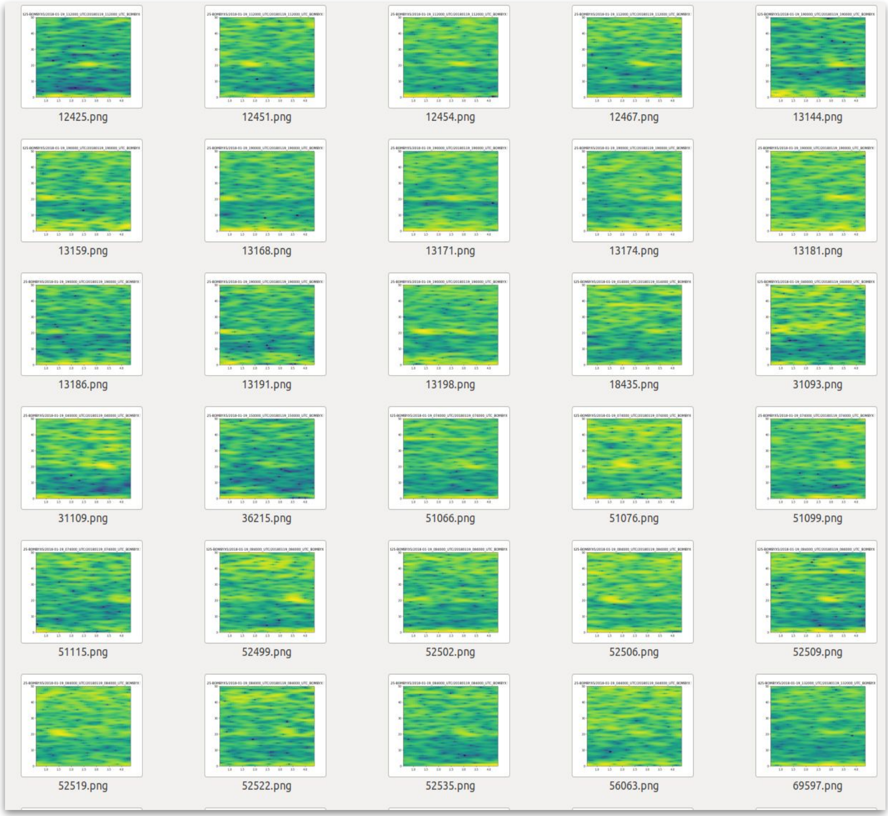




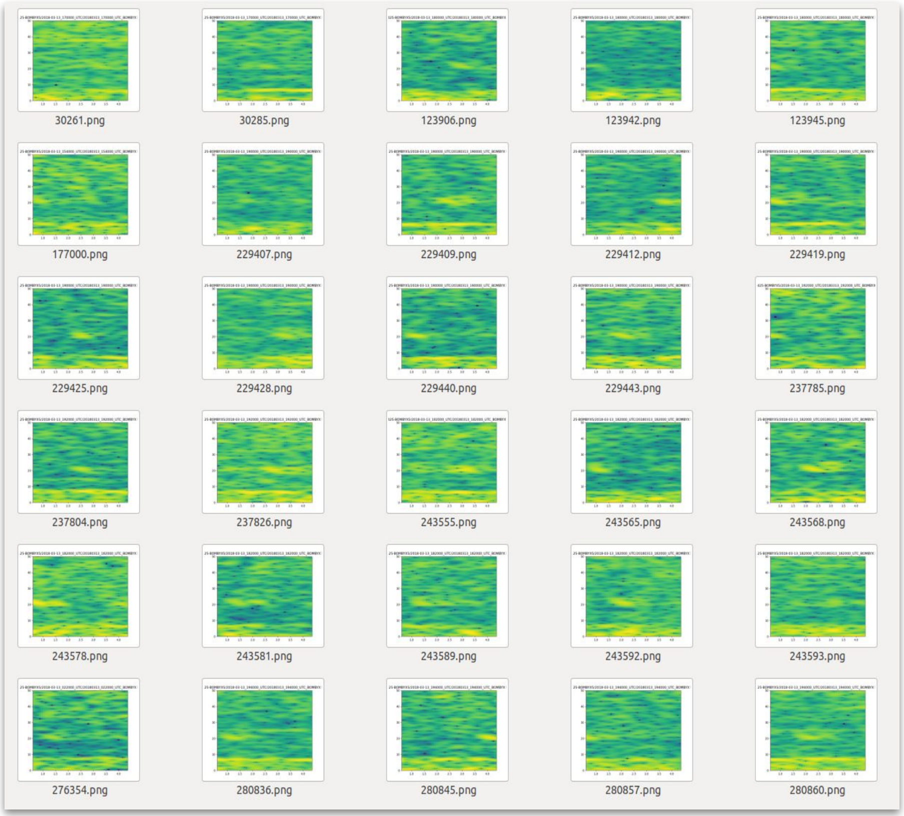
2D histogram (x=date, y=prediction) over 4 months

Fin whale pulse detection

Bombyx1 forward - Positive detections = True positives



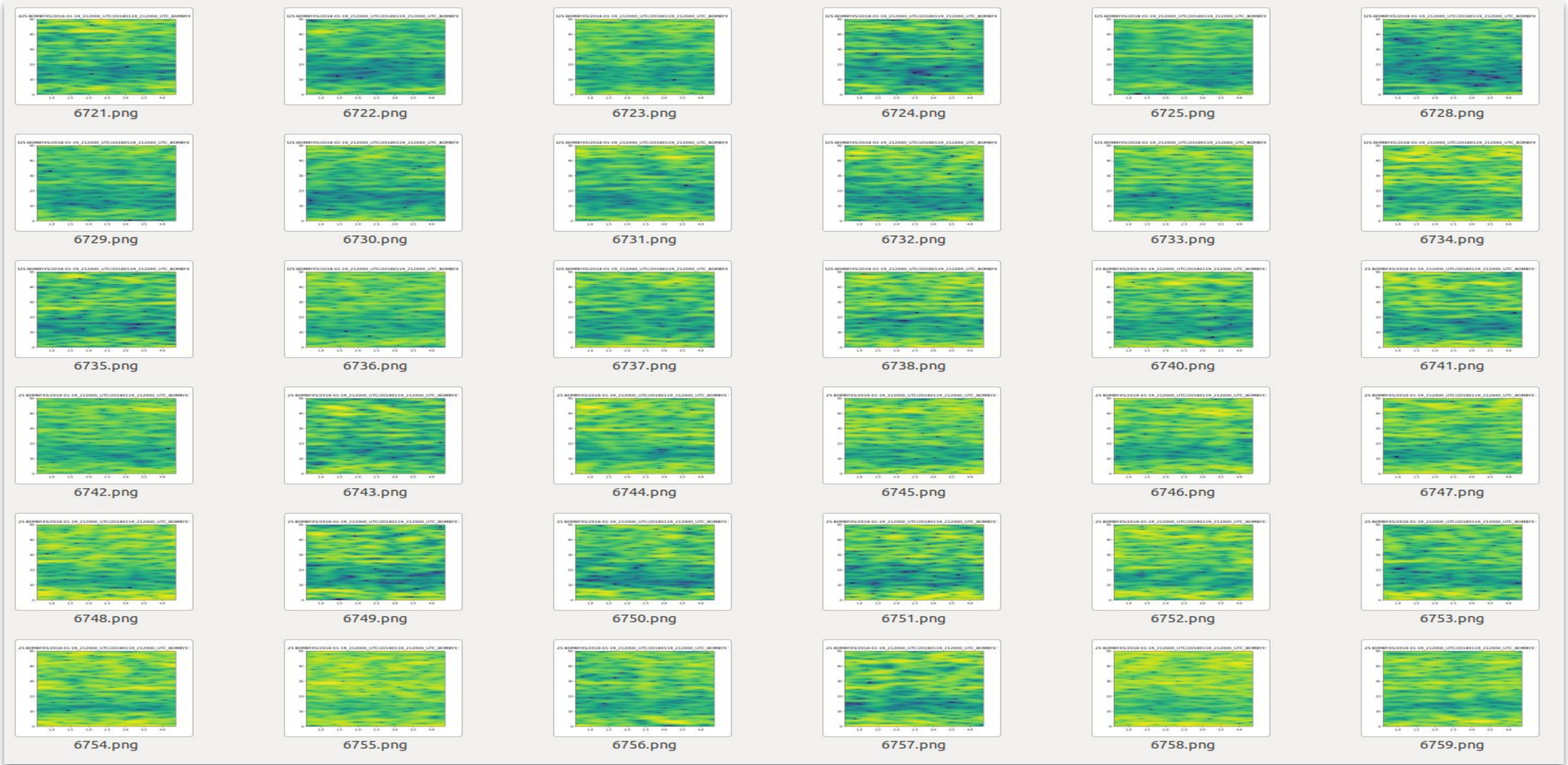
19/01/2018 pred > 0.95



13/03/2018 pred > 0.95

Fin whale pulse detection

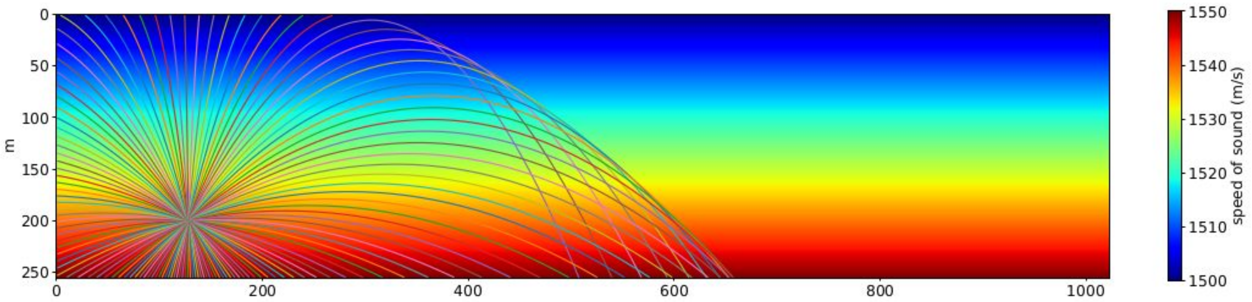
Bombyx1 forward - Negative detection = True negatives



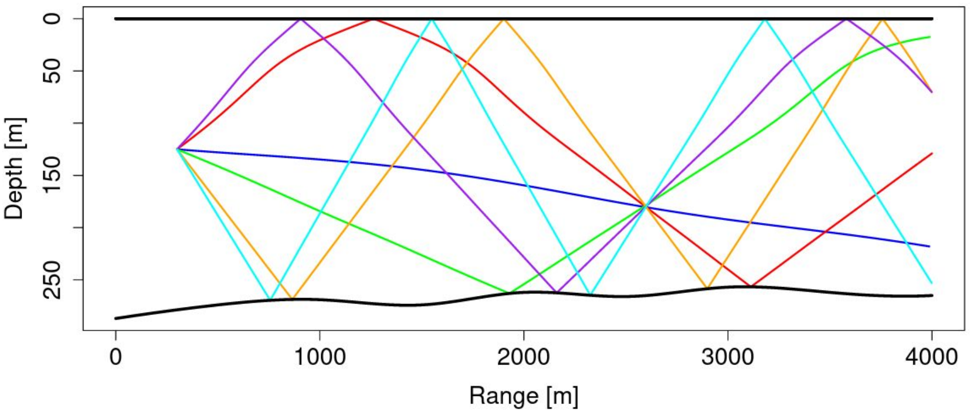
19/01/2018 pred < 0.5

C) Sound propagation GPU & DNN (Explanable IA) (T2, T3)

Use of GPU to speed up ray tracing models



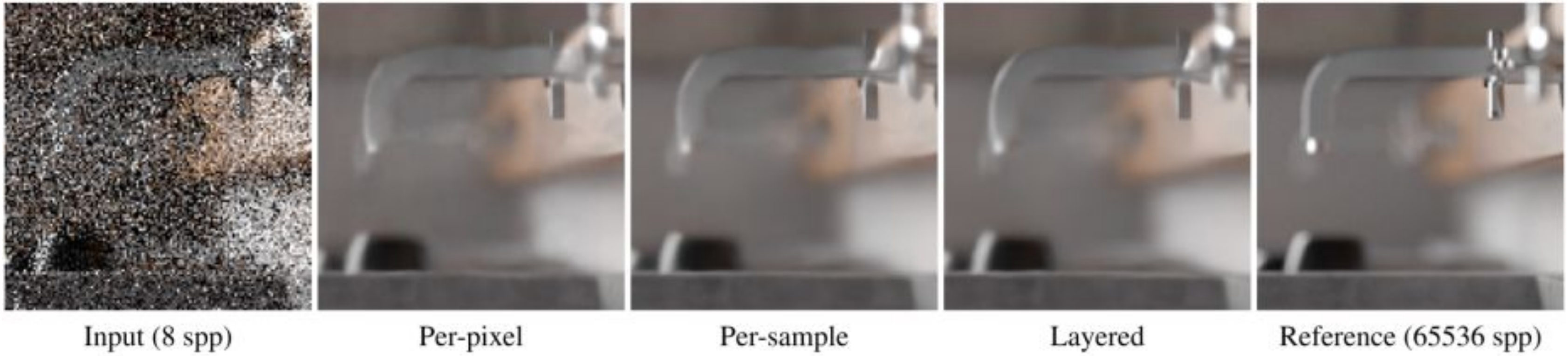
Example of multiple rays



All eigenrays from a source at coordinates (300, 125) to a receiver at coordinates (2600, 180). The different eigenrays are color-coded.

Ulmstedt, Mattias, and Joacim Stålberg. "GPU Accelerated Ray-tracing for Simulating Sound Propagation in Water." (2019). http://liu.diva-portal.org/smash/get/diva2:1352170/FULLTEXT01.pdf

Neural denoising: reducing the number of ray needed



https://research.nvidia.com/publication/2020-06_Neural-Denoising-with

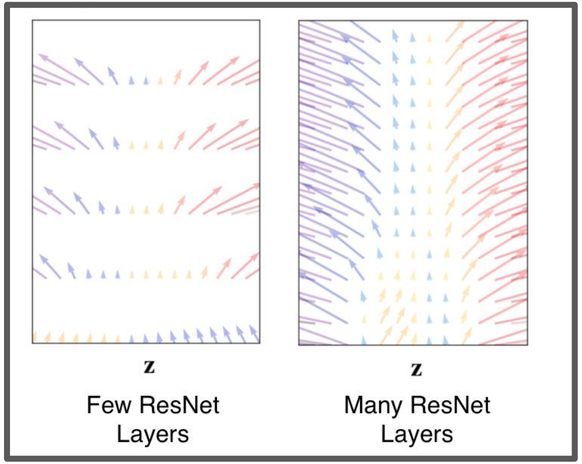
Neural ordinary differential equations (NODE)

- A framework for modeling acoustic propagation ?
- Idea: relaxing the concept of “layer” = time !

$$x_{n+1} = x_n + F(x_n, \theta) \Rightarrow dx(t) = F(x, t, \theta)$$

Impact for ADSIL, contributions envisioned:

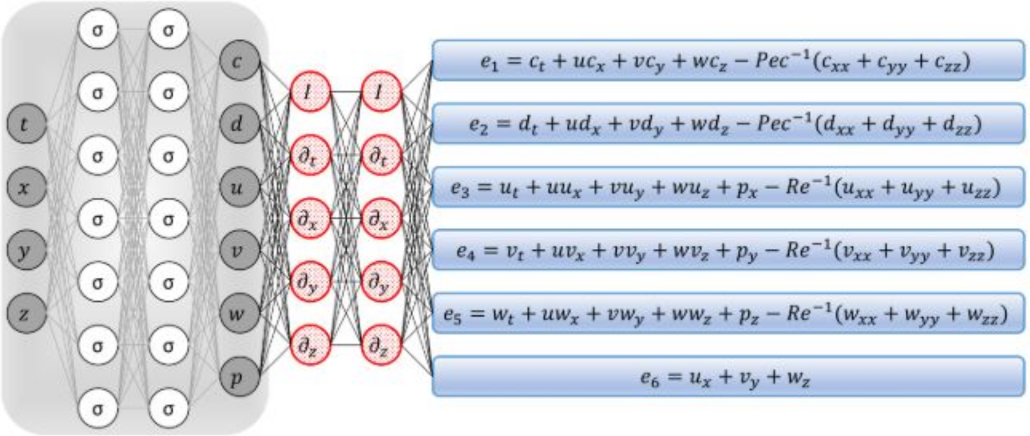
- In acoustics
- In machine learning: training NODE is difficult !



Chen, R. T., Rubanova, Y., Bettencourt, J., & Duvenaud, D. K. (2018). Neural ordinary differential equations. In *Advances in neural information processing systems* (pp. 6571-6583).

Integrating physics knowledge into DNNs for multiscale current modelisation (JJ, AP, HG, YO et al)

Starting point:
Physics-Informed Neural Networ[k]
(PINNs)



Raissi et al.: Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 2019

Raissi et al.: Hidden Fluid Mechanics: A Navier-Stokes Informed Deep Learning Framework for Assimilating Flow Visualization Data. ArXiv, 2018

D) online AI, emb. AI (T3)

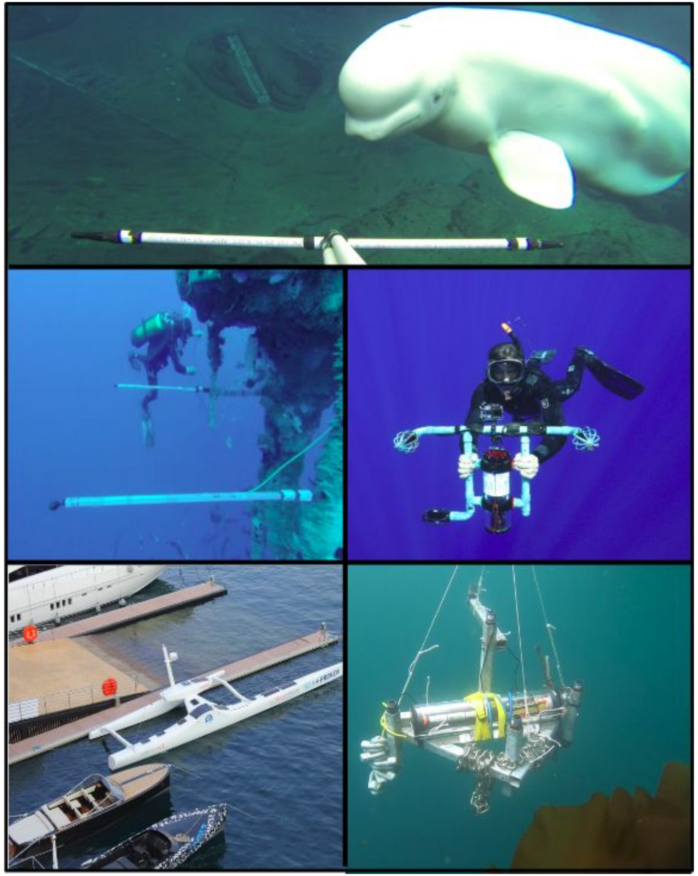
Online Sphyrna & Bombyx2 (PB, MF, HG, SP, RM)

Online KM3 (MF, PB, HG)

Online Orcalab (PB, HG, RM)

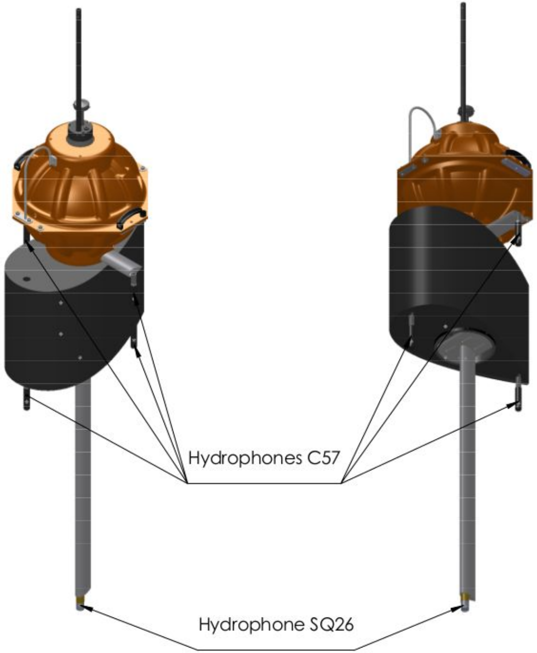
Def IA PIC (PB VG HG SM) pour HF et BF

IA ULP hybride (SM VG VB HG)



REDEX

SPHYRNA & BOMBYX2



REDEX JASON 2015-2020 : DAQ QHB (FA2020) http://sabiod.org/pub/QHB.pdf

A NOVEL LOW-POWER HIGH SPEED ACCURATE AND PRECISE DAQ WITH EMBEDDED ARTIFICIAL INTELLIGENCE FOR LONG TERM BIODIVERSITY SURVEY

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ABSTRACT

Acoustic monitoring is a key feature for studying biodiversity. Recent works on very high frequency animal sounds open new insights and challenges on biodiversity survey. In order to set a scaled monitoring, and to cover most of the frequencies of the present species, a novel multi-channel ultra high velocity recorder has been designed, called Qualilife HighBlue. This paper presents its architecture and characteristics. One of its most innovative features is an always-on ultra-low power wake-up, triggering recordings when temporal and/or spectral interesting events are detected. For this task, shallow neural networks are embedded for advanced pattern detection, as

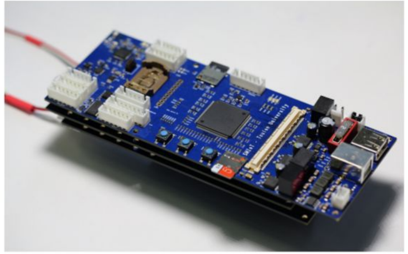


Figure 1. QHB plugged to 2 daughter-boards.

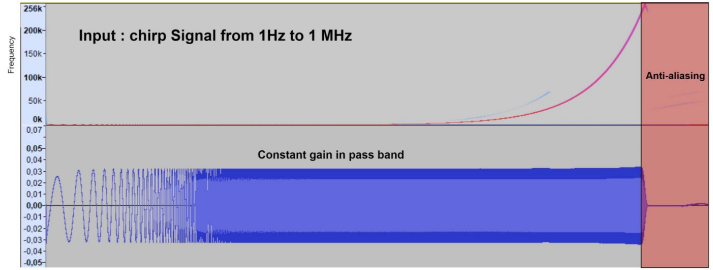
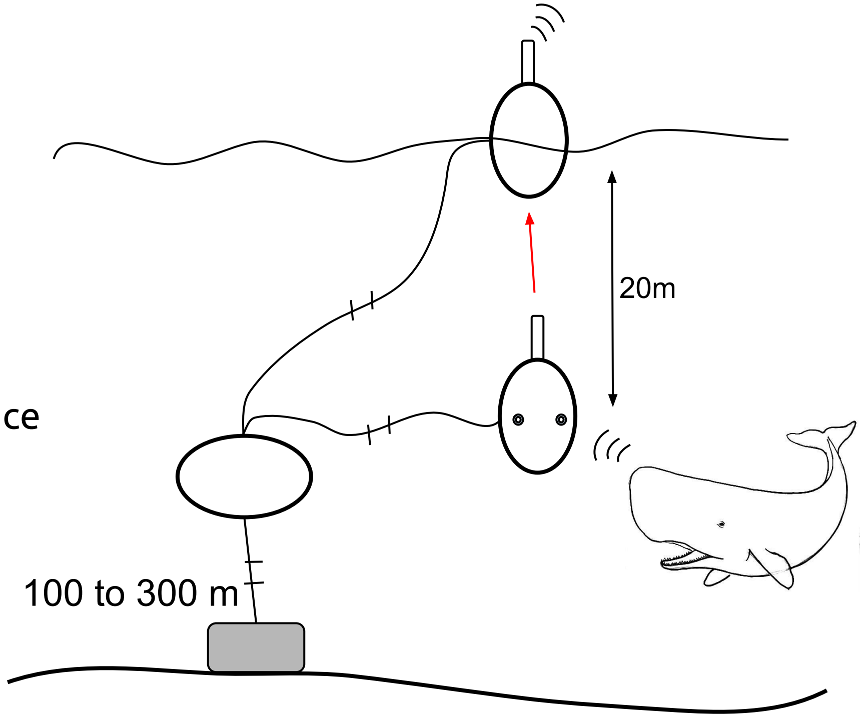


Figure 5. Spectrogram and signal of a chirp test from 1 Hz to 1 MHz recorded on QHB.

Online AI
Bombyx 2 - Material

- To be placed in 2021
  - South of Port-Cros Island and Cape Corsica
- Floatability variation system
  - 20m deep recording and surface 4G communications
- Alert system for sperm whale and fin whale presence
  - Mitigate ship strikes risk
- 5 hydrophones
  - Azimuth and distance estimation
- Battery powered (approx. 6 month)
- PIC32-Mz microprocessor



Embeded AI
Bombyx 2 - Analog wake-up

- Background noise estimation
- >8kHz Energy thresholding
- State Machine consistency validation
- 75% AUC on Bombyx 1
- Ultra low power **12.5µA**

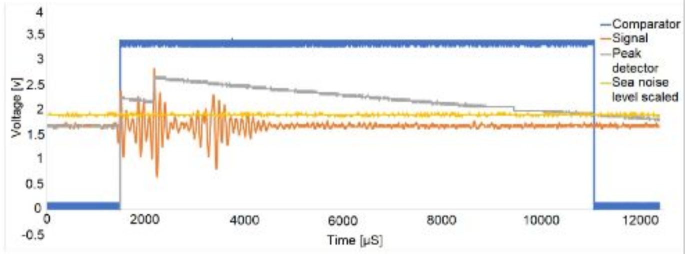


Fig. 7. Clicks of cetacean (Pm) with ULP processing, acquired on real signals (High-pass filtered input signal (orange), V_{Ref} (yellow), click envelope (grey), output of the comparator (blue)).

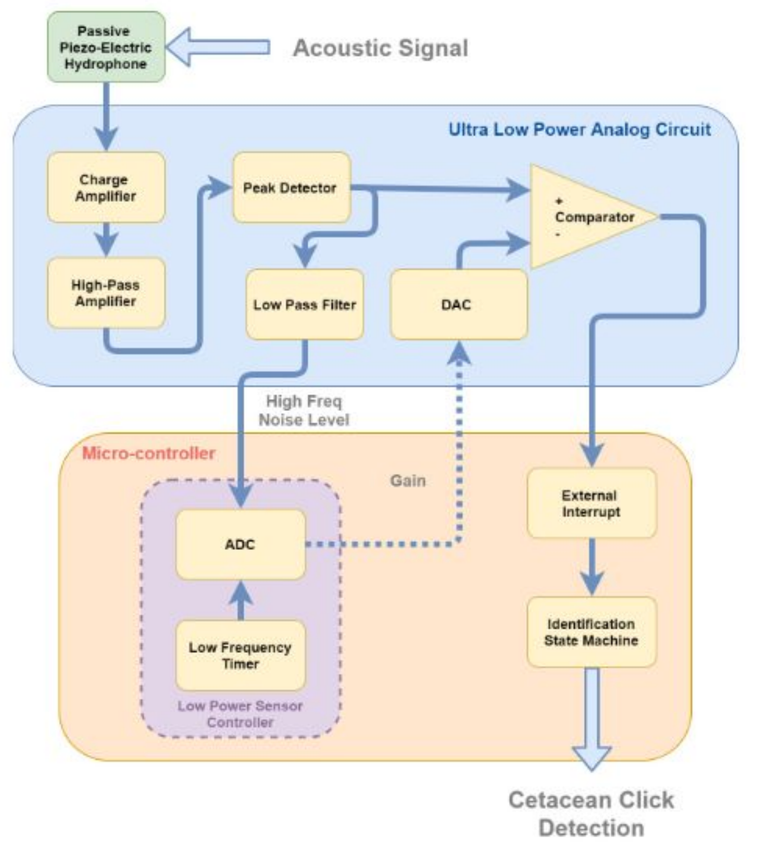
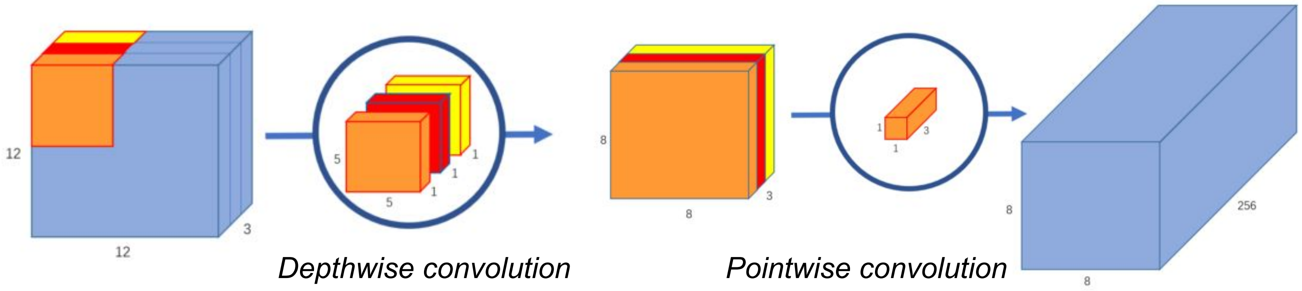


Fig. 4. Block diagram of the detector of a train of pulses of a Sperm Whale.

S. Marzetti, V. Gies, V Barchasz, P. Best, S. Paris, H. Barthelemy, H. Glotin (2020), Ultra-Low Power Wake-Up for Long-Term Biodiversity Monitoring, in proc. IEEE IoTAIS

Embeded AI
Depthwise separable convolution



Conv : 5 x 5 x 3 x 256
DW Conv : 5 x 5 x 3 + 3 x 256

	# parameters	# mutliplications
Traditionnal	272×10^3	309×10^6
Depthwise	11×10^3	13×10^6

- Conv 64 - 512
- Conv 512 - 512
- Conv 512 - 1

L. Bai, Y. Zhao and X. Huang, "A CNN Accelerator on FPGA Using Depthwise Separable Convolution," in *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 65, no. 10, pp. 1415-1419, Oct. 2018, doi: 10.1109/TCSII.2018.2865896.

Embeded AI
Low power micro-processor

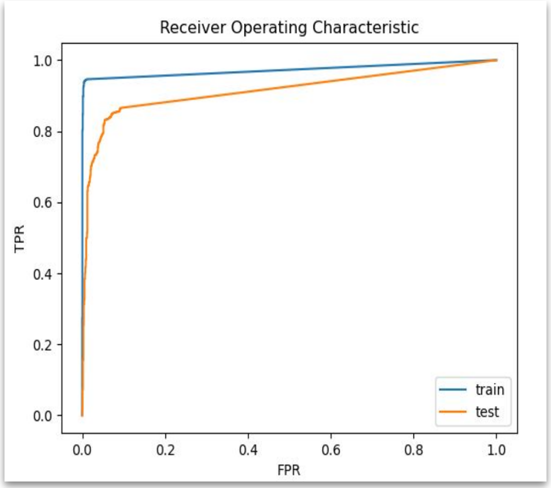
Analyse pour 5 secondes de signal

	Fin Whale	Sperm Whale
Sampling rate	200 Hz	50 kHz
Spectrogram size	128 x 46	64 x 974
Spectrogram computation time	0.2 sec	4.5 sec
Forward pass time	0.5 sec	2.1 sec

PIC 32MZ by Microchip

Embeded AI
Bombyx 2 - CNN validation / Localization

- **Convolutionnal neural network validation**
  - Relatively low compleity (~10k parameters)
  - Input : Mel-scaled spectrum between 2kHz and 25kHz
  - 98% AUC train, 93% AUC test
- **Azimuth and distance estimation**
  - Click onset recording using the analog detector
  - 50ns time resolution
  - All hydrophones pointing downwards
  - Integration of the triangulation of multiple pulses



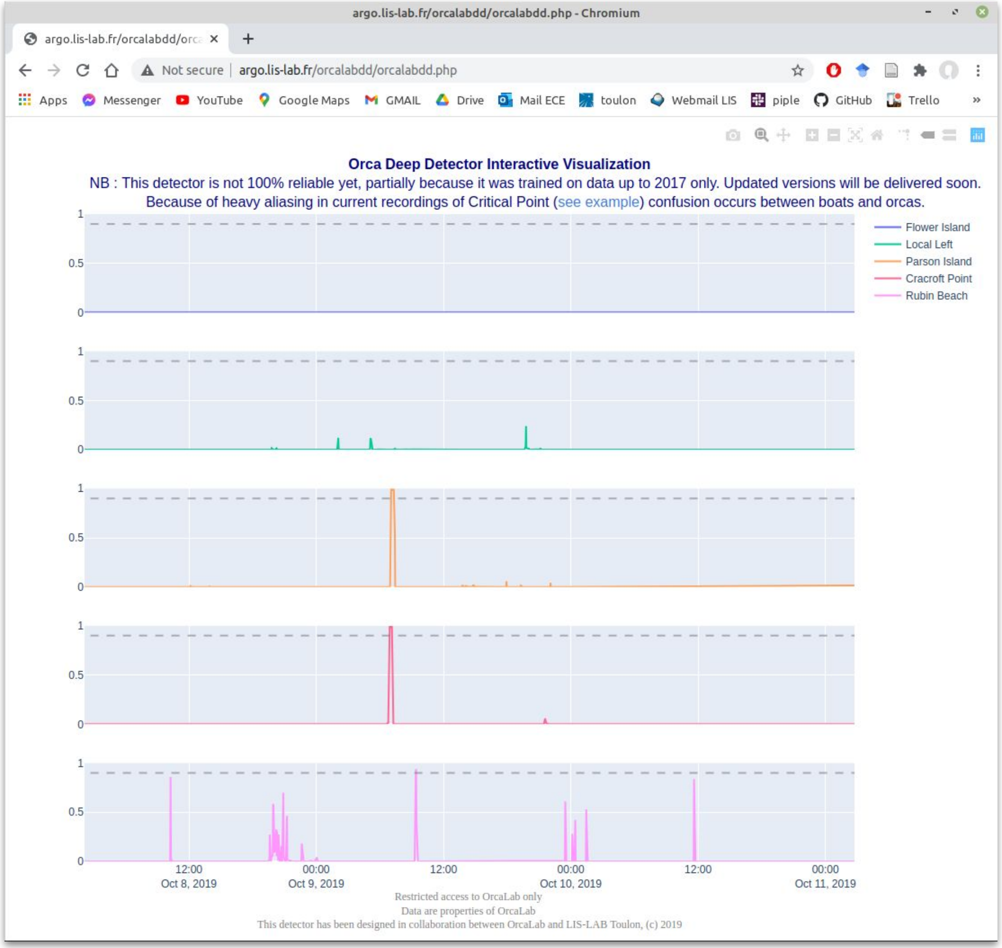
- Sampling frequency = 50kHz
- STFT (winsize=512, hopsize=256)
- Mel (64 features from 2 to 25kHz)
- Log
- Conv 64 - 64
- Conv 64 - 64
- Conv 64 - 1
- MaxPool

Conv = batch norm, depthwise conv, dropout, Relu
Valid AUC = 0,93

Online AI

KM3Net - OrcaLab

- Close to real-time data transfer
- Distributed computation power
- Scheduled detection systems
- Automatic reporting
- Online report visualisation

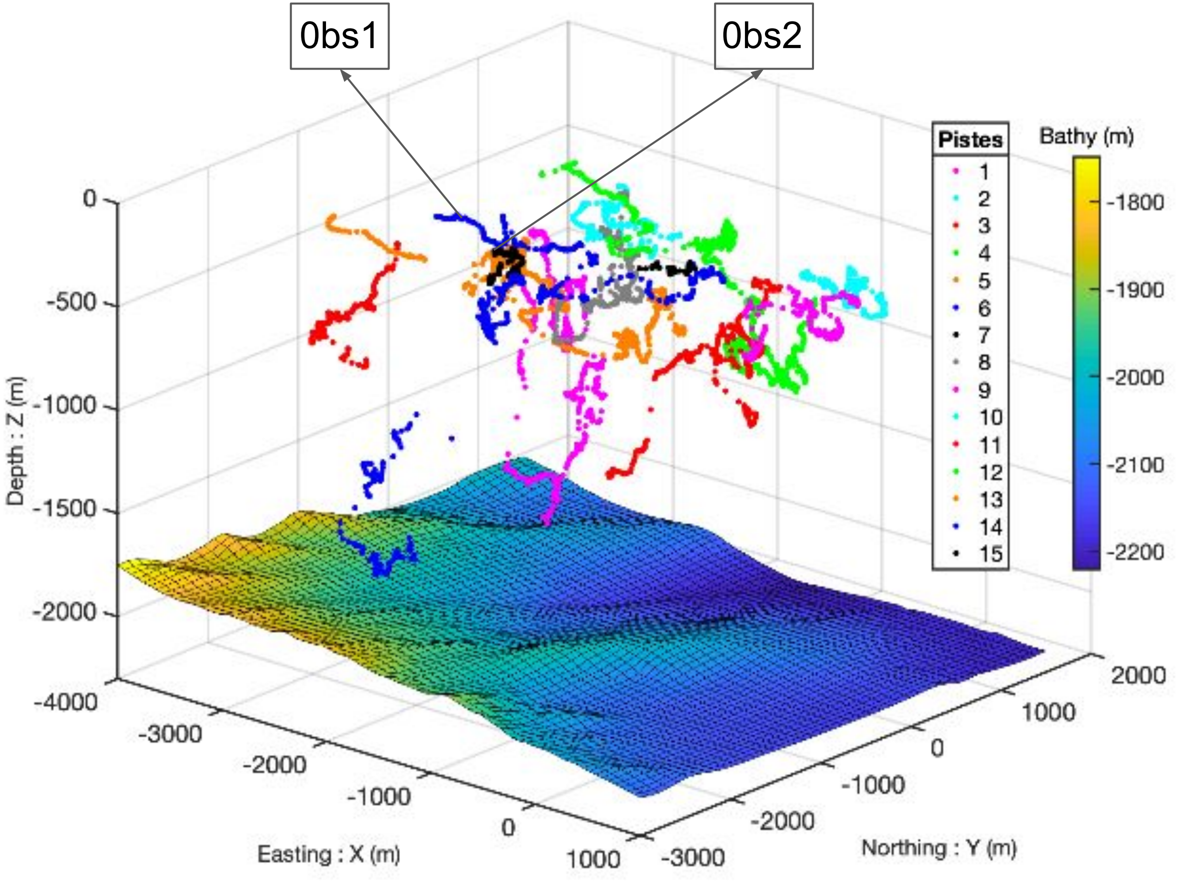


E) Maximisation of observation & Detection for Classification & Localisation (T1 +T2 + T3)

- **Corpus Sphyrna Missions**

  2018, 2020, 2021…

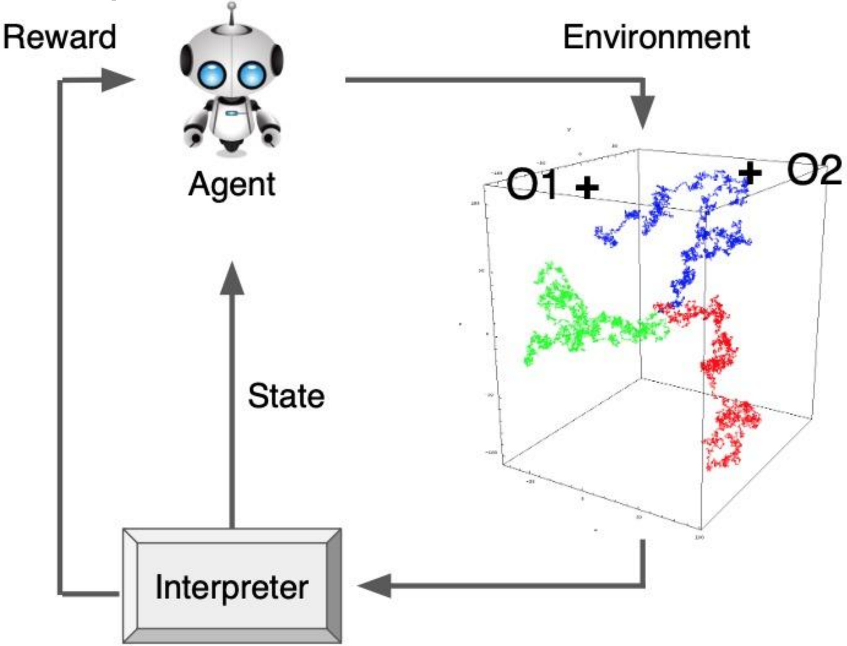
- **Bombyx + KM3ENV**



AI to learn how to track targets

Obs 1, Obs 2 : fixed (GIAS) or mobile (Sphyrna)

Simple model to start : Reinforcement Learning



INPUT : millions of trajectories generated (based on Markov Model)

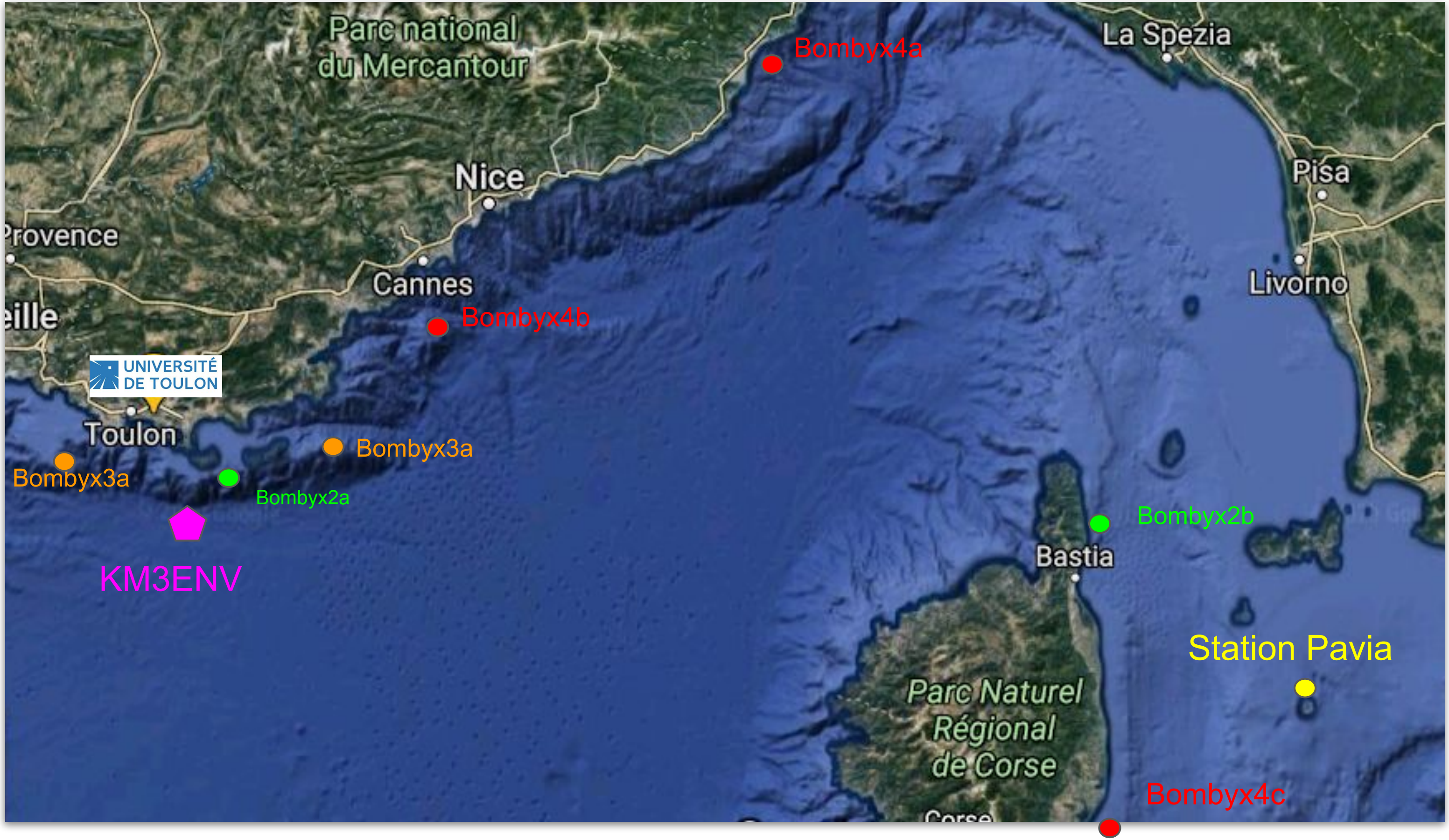
The goal(s) :

- Not losing track of target
- Optimise criterias such as :
  - SNR
  - error on position of sources (range estimation)

Kaelbling, Leslie P.; Littman, Michael L.; Moore, Andrew W.(1996). "Reinforcement Learning: A Survey". *Journal of Artificial Intelligence Research*. **4**: 237–285. arXiv:cs/9605103. doi:10.1613/jair.301. S2CID 1708582. Archived from the original on 2001-11-20.

Perspective à 2 ans : Institut / Fondation ABYSSE

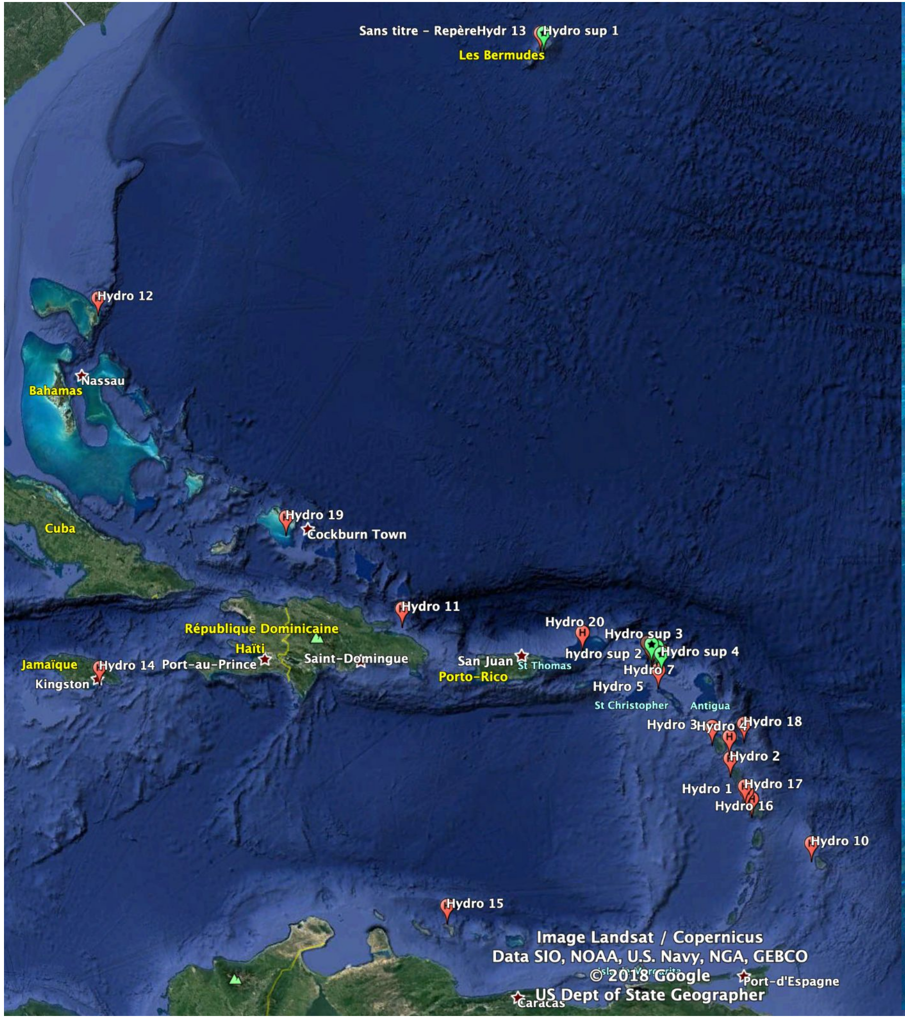
observer les Canyons profonds de 2500m et leurs habitants en 3D



Bombyx2 = GIAS 2018-26 ; Bombyx3 = APOG 2021-26 ; Bombyx4 = GIAS2 2021-2026 ; stations UTLN / Pavia

Carimam 2019-21+

- 20 stations SMIoT UTLN / IM2NP / LIS
- 256 Fe * 3 weeks
- 500 Go x 10 sessions x 20 stations
- Data analysis DYNI
  20 espèces



Teaching

Ferrari M2 PSI
Poupard M1 Biomar
Glotin M1 M2 ROC, M1 M2 DID, M1 M2 Biomar
Paiement M1 ROC, M2 DID
Marxer M1 DID
Paris M1 ROC
Best L3 info TI & bioacoustics
Gies Seatech, DUT, M1 M2 ROC
Giraudet M1 Biomar
Patris L Physic

Publication of the team since june 2020

Ferrari, Glotin, Marxer, Asch (2021) Classification of Marine Mammal Clicks by Raw Audio Multiscale Hierarchical Convolutional Neural Network and a Study of Learned Representation, submitted to JASA

Poupard, Symonds, Spong, Glotin (Submitted to Scientific Report Nature 2021) Evidences of Intra-Group Orca Call Rate Modulation Using A Small-Aperture Four Hydrophone Array.
https://assets.researchsquare.com/files/rs-116685/v1_stamped.pdf

Barchasz, Gies, Marzetti, Glotin (2020) A novel low-power high speed accurate and precise DAQ with embedded artificial intelligence for long term biodiversity survey, Eu. Forum Acusticum
http://sabiod.univ-tln.fr/pub/QualiHighBlue_DAQ_FA2020.pdf

Best, Ferrari, Poupard, Paris, Marxer, Symonds, Glotin (2020) Deep Learning and Domain Transfer for Orca Vocalization Detection. In International joint conference on neural networks. IEEE IJCNN,
https://hal.archives-ouvertes.fr/hal-02865300/document

Ferrari, Glotin, Marxer, Asch (2020) End to end raw audio deep learning of transients, application to bioacoustics, Eu. Forum Acusticum https://hal.archives-ouvertes.fr/hal-03078665/document

Ferrari et al. (2020) 3D diarization of a sperm whale click cocktail party by an ultra high sampling rate portable hydrophone array for assessing individual cetacean growth curves, Eu. Forum Acusticum
https://hal.archives-ouvertes.fr/hal-03078655/document

Ferrari et al. (2020) DOCC10: Open access dataset of marine mammal transient studies and end-to-end CNN classification, in 2020 International Joint Conference on Neural Networks (IJCNN). IEEE
https://hal.archives-ouvertes.fr/hal-02866091/document

Marzetti, Gies, Barchasz, Best, Paris, Barthelemy, Glotin (2020) Ultra-Low Power Wake-Up for Long-Term Biodiversity Monitoring, in proc. IEEE IoTAIS

Poupard, Best, Ferrari, Spong, Symonds, Prevot, Soriano, Glotin (2020) From massive detections and localisations of orca at orcalab over three years to real-time survey joint to environmental conditions in Eu. Forum Acusticum

Ferrari (2020) Study of a Biosonar Based on the Modeling of a Complete Chain of Emission-Propagation-Reception with Validation on Sperm Whales, Phd Thesis, Université Picardie Jules Verne, (dir Glotin & Asch)
https://hal.archives-ouvertes.fr/tel-03078625/document

Poupard (2020) Contributions en Méthodes Bioacoustiques Multiéchelles: Spécifiques, populationnelles, individuelles et comportementale, Phd Thesis, Université de Toulon (dir Glotin Soriano Lengagne)
http://sabiod.univ-tln.fr/pub/poupard/cv/m_poupard_phd_08012021.pdf

Glotin, Thellier, Best, Poupard, Ferrari, et al. (2020) Rapport Mission Sphyrna Odyssey : Découvertes Ethoacoustiques de Chasses Collaboratives de Cachalots en Abysse & Impacts en Mer du Confinement COVID19
,http://sabiod.univ-tln.fr/pub/SO1.pdf