The Robotics Research Lab

A Study of Image Processing Applications in Autonomous Marine Vehicles using Forward-Looking Sonar

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Motivation

- Growing need of underwater exploration using Autonomous vehicles

Problem Statement

- Critical ability required:
  - Autonomous long-term, safe and reliable traversal in underwater environments
  - Comprising data collection, physical & semantic understanding of environment, safe navigation, etc.

State-of-the-Art Solutions

- Uses of acoustic imaging sensors *(to overcome limitations of underwater optical imaging)*

- Tasks undertaken:
  - Object detection, recognition, tracking
  - Obstacle detection and avoidance

- Techniques used in the tasks:
  - Image Processing
  - Machine Learning
  - Deep Learning

Methodology

- Typically, in the studies, a workflow similar to the following are evaluated to cater to the proposed problem:
  - **Sonar Imaging**
  - **Object Detection**
  - **Object Classification**
  - **Object Association and Tracking**
  - **Obstacle Detection and Avoidance**

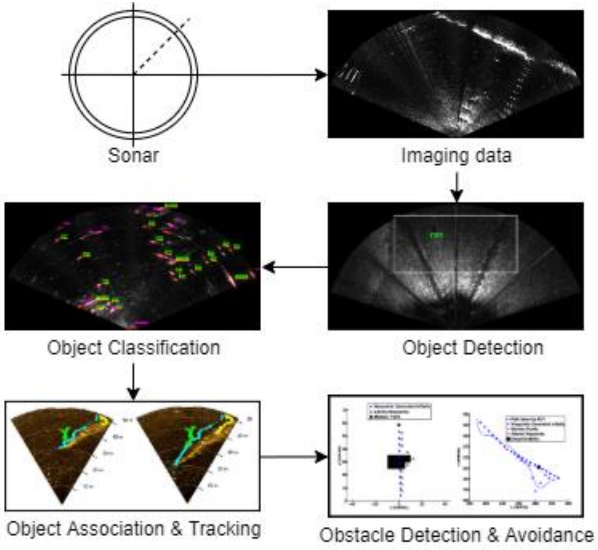

*Fig: Methodical workflow **

* Galceran, Enric. (2012). A real-time underwater object detection algorithm for multi-beam forward looking sonar. 306-311. 10.3182/20120410-3-PT-4028.00051.

* dos Santos, Matheus & Ribeiro, Pedro Otávio & Núñez, Pedro & Drews-Jr, Paulo & Botelho, Silvia. (2017). Object Classification in Semi Structured Enviroment Using Forward-Looking Sonar. Sensors. 17. 2235. 10.3390/s17102235.

* Karoui, Imen & Quidu, Isabelle & Legris, Michel. (2015). Automatic Sea-Surface Obstacle Detection and Tracking in Forward-Looking Sonar Image Sequences. IEEE Transactions on Geoscience and Remote Sensing. 53. 1-10. 10.1109/TGRS.2015.2405672.

* Ganesan, Varadarajan & Chitre, Mandar & Brekke, Edmund. (2016). Robust Underwater Obstacle Detection for Collision Avoidance. Autonomous Robots. 39. 10.1007/s10514-015-9532-2.

Sonar Imaging

- ***Sonars*** (specifically, active Sonars):
  - Insonify the environment
  - Spans the adjustable field-of-view
  - Reflected waves captured for imaging
- ***Why Sonar?***
  - Constraints of Optical waves underwater
  - Overcome by Acoustic waves
- ***Types of Sonars*** (majorly used in studies):
  - Side Scan Sonar (SSS), Synthetic Aperture Sonar (SAS)
  - **Forward Looking Sonar** (FLS)

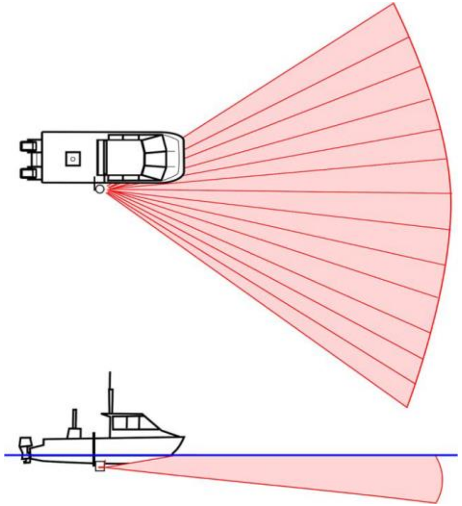

Fig: Sonar configuration *

* Karoui, Imen & Quidu, Isabelle & Legris, Michel. (2015). Automatic Sea-Surface Obstacle Detection and Tracking in Forward-Looking Sonar Image Sequences. IEEE Transactions on Geoscience and Remote Sensing. 53. 1-10. 10.1109/TGRS.2015.2405672.

Sonar Imaging

- ***Imaging*** **(for FLS):**
  - A horizontal array of transducers captures acoustic returns
  - **Beamforming** process generates imaging data
  - The imaging is represented in *Polar coordinates*
  - It is transformed into *Cartesian coordinates*
  - Information pertaining to elevation is usually indistinguishable

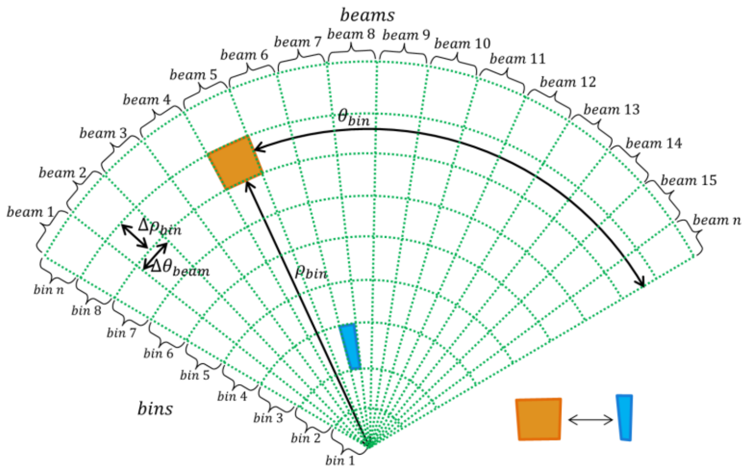

*Fig: A representative FLS image **

* dos Santos, Matheus & Ribeiro, Pedro Otávio & Núñez, Pedro & Drews-Jr, Paulo & Botelho, Silvia. (2017). Object Classification in Semi Structured Enviroment Using Forward-Looking Sonar. Sensors. 17. 2235. 10.3390/s17102235.

Sonar Imaging

- ***Challenges of Imaging*** (for FLS)**:**
  - Sonars have ***low resolution***, although still considered high-definition
  - The number of pixels representing a bin decreases with range in the Cartesian space, causing ***inhomogeneous resolution***
  - Presence of speckle noise, other natural source of noise, causes ***low Signal-to-Noise Ratio***
  - Multiple acoustic returns from the same object causes ***acoustic reverberation***
  - ***Acoustic shadow effect*** occurs when paths of waves are blocked by obstacles
  - ***Inhomogeneous intensity*** patterns caused by differing sensitivity of transducers and lenses
  - ***Changes in viewpoint*** of the same region can cause enormous changes in the visual appearance

Object Detection

- ***Detection of submerged objects using Integral Image*:**
  - Analyzes local regions to find echo-highlights that are higher than the local background
- **Approach**:
  - Rectangular ***Regions of Interest*** are extracted for analysis
  - The **Integral Image** representation of the image is computed

$$I(x,y) = \sum_{x' \le x, y' \le y} A(x', y')$$

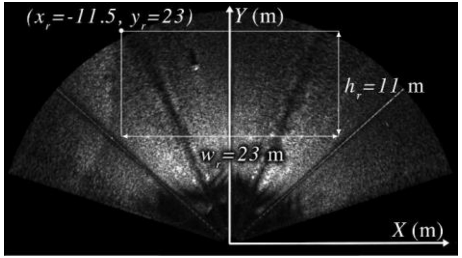

Fig: Region of Interest

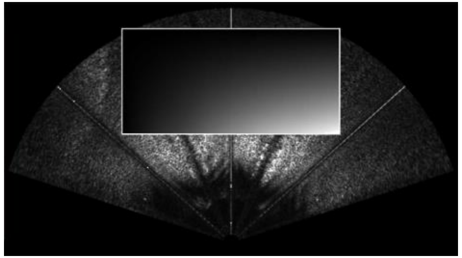

*Fig: Integral Image **

* Galceran, Enric. (2012). A real-time underwater object detection algorithm for multi-beam forward looking sonar. 306-311. 10.3182/20120410-3-PT-4028.00051.

Object Detection

- **Background map** establishes the seabed reverberation level using two concentric windows around each point

$$\boldsymbol{B}(\boldsymbol{x},\boldsymbol{y}) = \frac{1}{no-ni}\left[I\left(x+\frac{ox}{2},y+\frac{oy}{2}\right)+I\left(x-\frac{ox}{2},y-\frac{oy}{2}\right)-I\left(x-\frac{ox}{2},y+\frac{oy}{2}\right)-I\left(x+\frac{ox}{2},y-\frac{oy}{2}\right) - I\left(x+\frac{ix}{2},y+\frac{iy}{2}\right)-I\left(x-\frac{ix}{2},y-\frac{iy}{2}\right)+I\left(x-\frac{ix}{2},y+\frac{iy}{2}\right)+I\left(x+\frac{ix}{2},y-\frac{iy}{2}\right)\right]$$

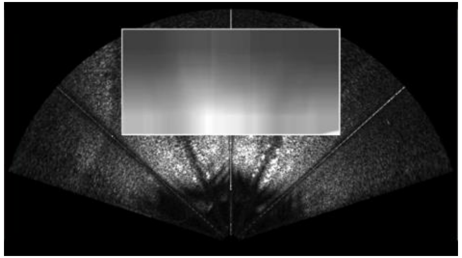

Fig: Background Map

- **Echo map** locates high intensity echo returns of objects using a single sliding window around each point

$$\boldsymbol{E}(\boldsymbol{x},\boldsymbol{y}) = \frac{1}{nw}\left[I\left(x+\frac{wx}{2},y+\frac{wy}{2}\right)+I\left(x-\frac{wx}{2},y-\frac{wy}{2}\right)-I\left(x-\frac{wx}{2},y+\frac{wy}{2}\right)-I\left(x+\frac{wx}{2},y-\frac{wy}{2}\right)\right]$$

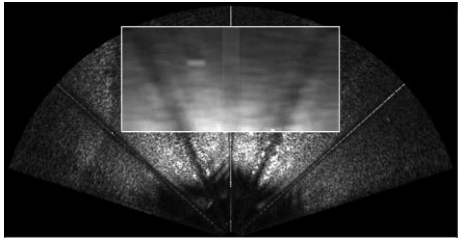

*Fig: Echo Map **

* Galceran, Enric. (2012). A real-time underwater object detection algorithm for multi-beam forward looking sonar. 306-311. 10.3182/20120410-3-PT-4028.00051.

Object Detection

- **Potential Alarms** are detected by distinguishing Echo from Background, using:

$$E(x,y) > \boldsymbol{\beta} B(x,y)$$

- The alarms are filtered using **Geometrical** and **Morphological** properties like *Major and Minor Axis Lengths*, *Circularity Coefficient*, *Area*, etc.
- The mean pixel value of all pixels of the blob is the **Echo Score**, for each remaining alarm, are **Thresholded** for further filtering**:**

$$\boldsymbol{S_i} = \sum_{\forall(\boldsymbol{x},\boldsymbol{y})\in \boldsymbol{A_i}} (\boldsymbol{x},\boldsymbol{y})$$

Table: Tracking results *

Mission pattern	Target type	Target depth	Distance error
Circle	Trunc. cone	6 m	3.8 m
Circle	Trunc. cone	10 m	1.6 m
Circle	Cylinder	5 m	1.1 m
Circle	Cylinder	12 m	3 m
Cross	Trunc. cone	6 m	2.6 m
Cross	Trunc. cone	10 m	1.4 m
Cross	Cylinder	5 m	0.6 m
Cross	Cylinder	12 m	1.6 m

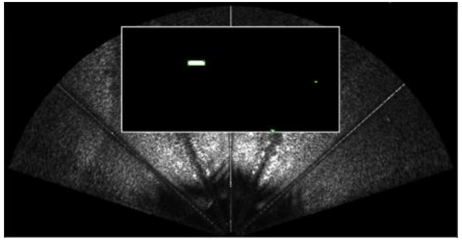

Fig: Potential Alarms

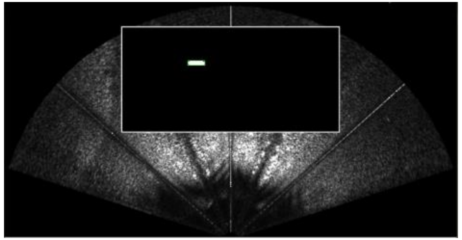

Fig: Geometrical & Morphological filter

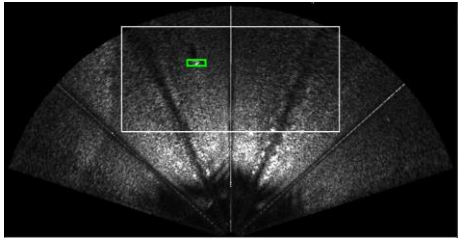

*Fig: Echo scored and thresholded **

* Galceran, Enric. (2012). A real-time underwater object detection algorithm for multi-beam forward looking sonar. 306-311. 10.3182/20120410-3-PT-4028.00051.

Object Detection

- ***Detection of Sea-surface objects*:**
  - Hierarchical detection workflow that simultaneously detects and tracks

- **Approach:**
  - **Stationary ship's self-noise** is detected first, as highly energetic beams compared to their neighbors

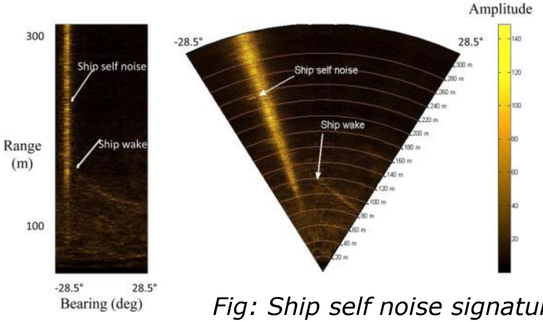

Fig: Ship self noise signature

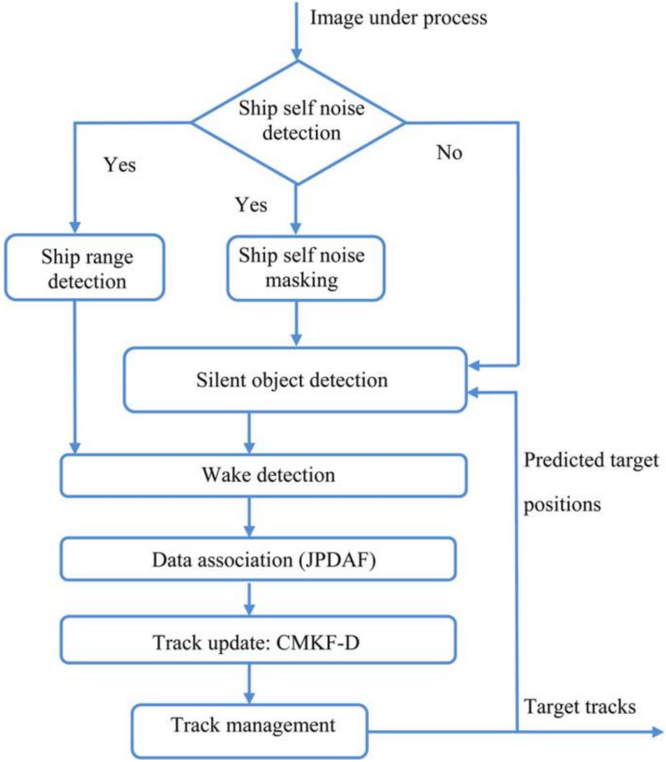

*Fig: Flow chart of overall method **

* Karoui, Imen & Quidu, Isabelle & Legris, Michel. (2015). Automatic Sea-Surface Obstacle Detection and Tracking in Forward-Looking Sonar Image Sequences. IEEE Transactions on Geoscience and Remote Sensing. 53. 1-10. 10.1109/TGRS.2015.2405672.

Object Detection

- Next, **static noise-free targets** are detected using the Constant False-Alarm Rate (CFAR) algorithm with an adaptive threshold

- Finally, the CFAR detector is used for identifying **wakes of moving ships**, and oriented strips to find the wake-ends

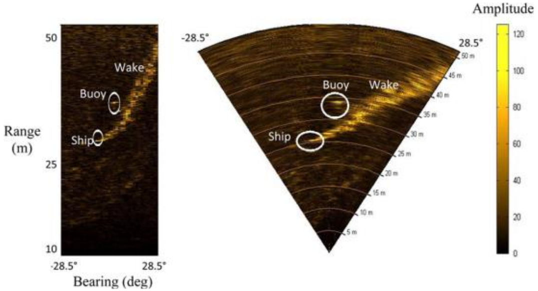

Fig: Ship wake and Static object's signatures

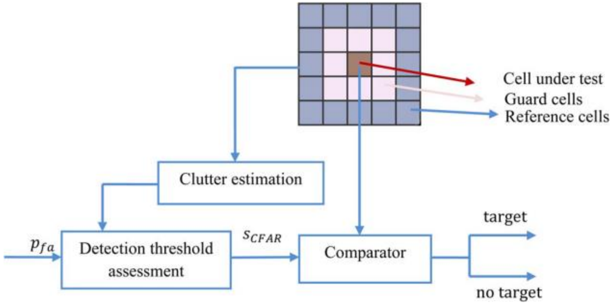

Fig: CFAR detector

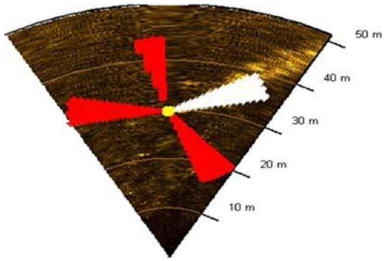

*Fig: Oriented strips for wake ends **

* Karoui, Imen & Quidu, Isabelle & Legris, Michel. (2015). Automatic Sea-Surface Obstacle Detection and Tracking in Forward-Looking Sonar Image Sequences. IEEE Transactions on Geoscience and Remote Sensing. 53. 1-10. 10.1109/TGRS.2015.2405672.

Object Detection

- ***Detection of submerged objects using Convolutional Neural Network*:**
  - Class-independent object detection that scores the Objectness of image windows based on:

$$IoU(A,B) = \frac{(A \cap B)}{(A \cup B)}$$

  - **Network:**

$\mathrm{Conv}(32,\ 5 \times 5) \rightarrow \mathrm{MP}(2,\ 2) \rightarrow \mathrm{Conv}(32,\ 5 \times 5) \rightarrow \mathrm{MP}(2,\ 2) \rightarrow \mathrm{FC}(96) \rightarrow \mathrm{FC}(1)$

  - **Training:**
    - Mean Squared Error (MSE) loss
    - Mini-batch gradient descent
    - ADAM optimizer

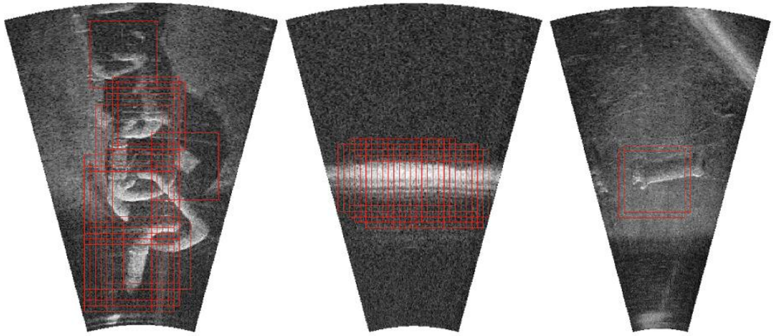

Fig: Windows detected as objects

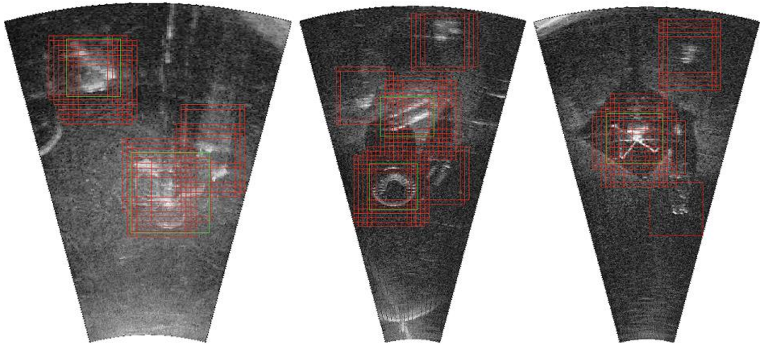

*Fig: Windows detected as objects **

* Valdenegro, Matias. (2016). Objectness Scoring and Detection Proposals in Forward-Looking Sonar Images with Convolutional Neural Networks. 9896. 209-219. 10.1007/978-3-319-46182-3_18.

Object Classification

- Machine Learning approach based on segmentation of images

- **Approach**
  - First, **Image Enhancement** is performed by estimating and correcting the inhomogeneous insonification.
  - Next, **Segmentation** of Images is performed by detecting peaks of intensity, and searching for connected pixels

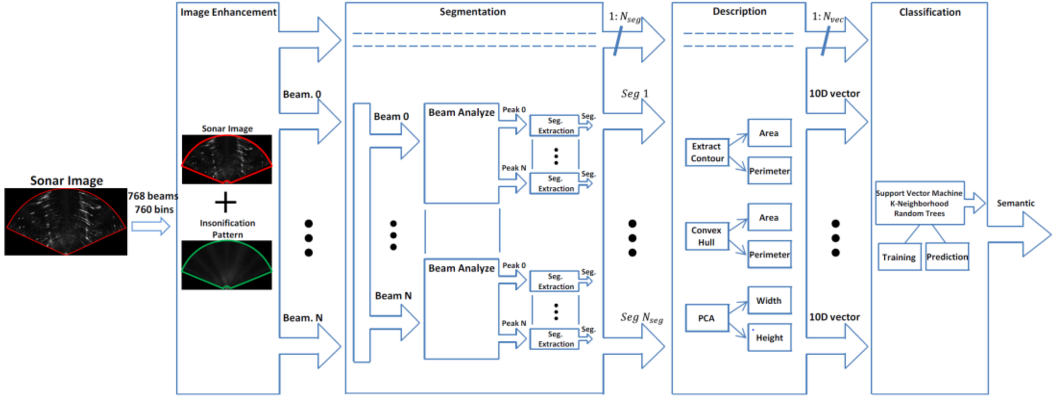

Fig: Classification workflow

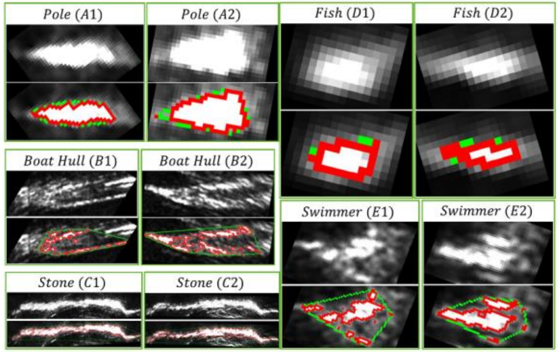

Fig: Image segmentation *

* dos Santos, Matheus & Ribeiro, Pedro Otávio & Núñez, Pedro & Drews-Jr, Paulo & Botelho, Silvia. (2017). Object Classification in Semi Structured Enviroment Using Forward-Looking Sonar. Sensors. 17. 2235. 10.3390/s17102235.

Object Classification

- Then, the Image **Segments** are **described** by a 10-dimensional vector, using a gaussian probabilistic function

- Finally, the dataset is balanced, and segments are classified using the following supervised ML algorithms:

    - ***Support Vector Machine*** (~89.90% with RBF kernel)
    - ***Random Trees*** (~78.89%)
    - ***K-Nearest Neighbors*** (~93.57% with K=1)

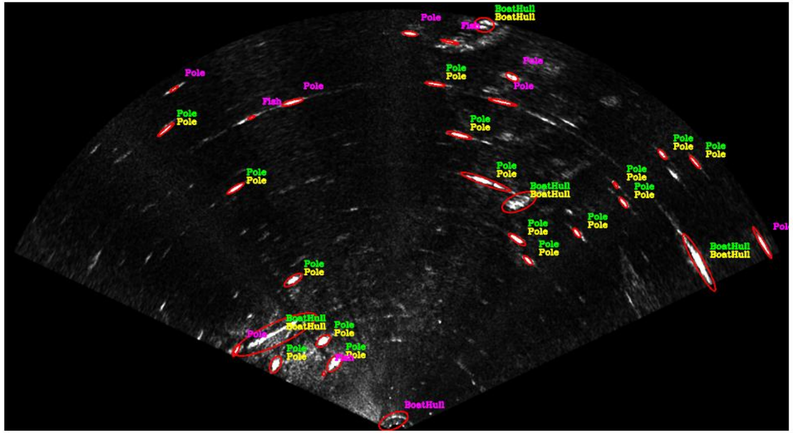

Fig: Object classification result *

* dos Santos, Matheus & Ribeiro, Pedro Otávio & Núñez, Pedro & Drews-Jr, Paulo & Botelho, Silvia. (2017). Object Classification in Semi Structured Enviroment Using Forward-Looking Sonar. Sensors. 17. 2235. 10.3390/s17102235.

Object Association and Tracking

- ***Sea-surface object tracking*:**

  - **Target Tracking** is performed using the *Converted Measurement Kalman Filter with Debiased conversion* (CMKF-D)
    - Performed in the Cartesian frame according to the classic *near-constant velocity dynamical model*

$$\boldsymbol{x}_k^t = \boldsymbol{F}\boldsymbol{x}_{k-1}^t + \boldsymbol{G}\boldsymbol{v}_{k-1}$$

$$\boldsymbol{y}_k = \boldsymbol{H}\boldsymbol{x}_k^t + \boldsymbol{w}_k$$

  - **Association** is performed using the *Joint Probabilistic Data Association Filter* (JPDAF)
    - The innovation vector, used in the tracking update step, is calculated by combining valid measurements

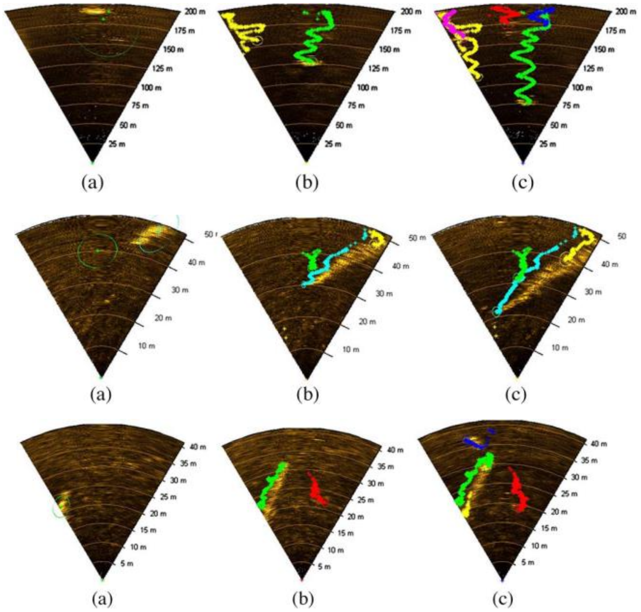

*Fig: Tracking results, over time (a → b → c) **

* Karoui, Imen & Quidu, Isabelle & Legris, Michel. (2015). Automatic Sea-Surface Obstacle Detection and Tracking in Forward-Looking Sonar Image Sequences. IEEE Transactions on Geoscience and Remote Sensing. 53. 1-10. 10.1109/TGRS.2015.2405672.

Object Association and Tracking

- ***Occupancy Grid based association and tracking*:**
  - Bayesian Filtering-based tracking approach that uses Local Occupancy Grids to represent belief
  - **Local Occupancy Grid:**
    - Attached to the AUV's frame of reference
    - Associates a probability of occupancy to every cell on the grid

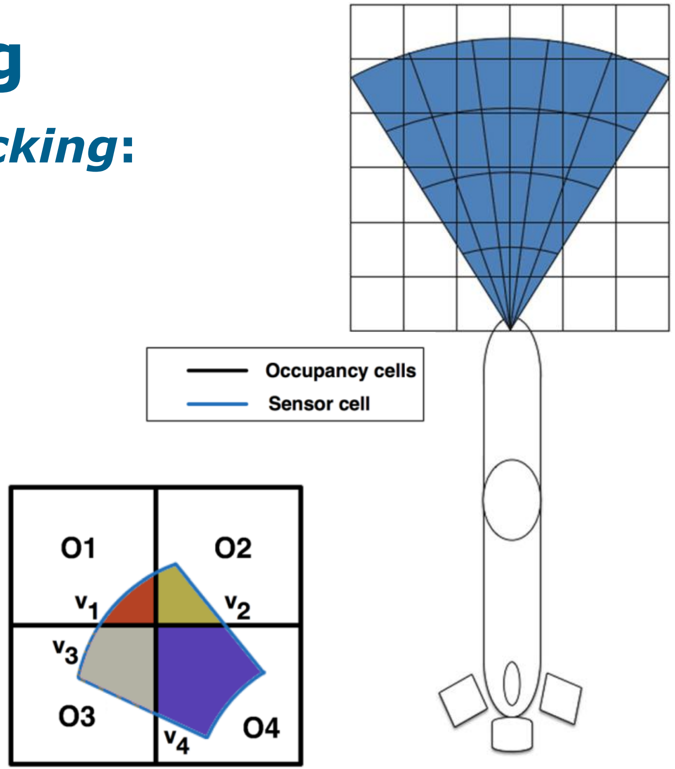

Fig: Local occupancy grid *

* Ganesan, Varadarajan & Chitre, Mandar & Brekke, Edmund. (2016). Robust Underwater Obstacle Detection for Collision Avoidance. Autonomous Robots. 39. 10.1007/s10514-015-9532-2.

Object Association and Tracking

- The **Motion Model** accounts for the translational and the rotational motion of the AUV
  - Updates the probabilities of the occupancy cells accordingly.
  - It is modelled as a *convolution* operation:

$$\boldsymbol{P_t = P_{t-1} \otimes K}$$

- The **Measurement Model** updates the occupancy grid probabilities, based on Bayes' rule, when new measurement is available.

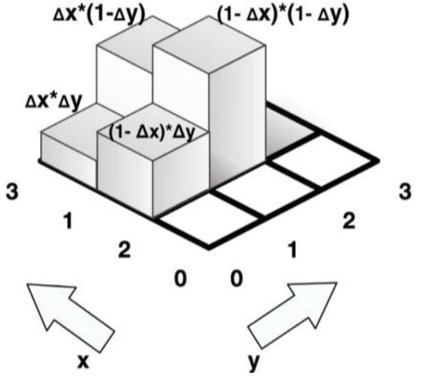

Fig: Deterministic kernel

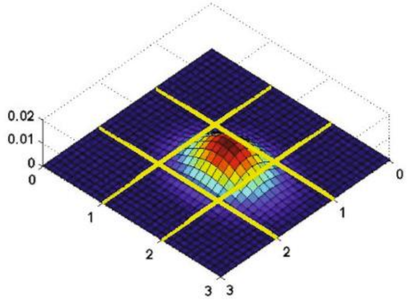

Fig: Probabilistic kernel *

* Ganesan, Varadarajan & Chitre, Mandar & Brekke, Edmund. (2016). Robust Underwater Obstacle Detection for Collision Avoidance. Autonomous Robots. 39. 10.1007/s10514-015-9532-2.

Object Association and Tracking

- ***Adaptive Particle Swarm Optimization*:**

  - An **Adaptive Inertia Weight** is defined which is iteratively reduced throughout the process
    - Controls the *exploration vs. exploitation* capability of particles.

$$w = ((1 + cos(\frac{t \cdot \pi}{t_{max}})) \cdot (1 - \frac{f}{f_{max}}) \cdot w_{init})/(2 + w_{min})$$

  - A new **Update** strategy for particles is proposed that handles occluded target tracking using randomly generated particles.

$$v_{ij}^{t} = w \cdot v_{ij}^{t-1} + \sum_{k \in \{particle, global, random\}} c_k \cdot r_k \cdot (best_{kij}^{t-1} - x_{ij}^{t-1})$$

$$x_{ij}^{t} = \begin{cases} x_{ij}^{t-1} + v_{ij}^{t}, & non - occluded\ target \\ X, & occluded\ target \end{cases}$$

* Wang, Xingmei & Wang, Guoqiang & Wu, Yanxia. (2018). An Adaptive Particle Swarm Optimization for Underwater Target Tracking in Forward Looking Sonar Image Sequences. IEEE Access. PP. 1-1. 10.1109/ACCESS.2018.2866381.

Object Association and Tracking

- The **target tracking** using APSO is performed on *rectangular regions* of the image
  - In each iteration, features are extracted using the ***Hu moment invariant*** *feature*
  - Similarity with the target is the fitness of particles

Average position error per frame (pixel)	APSO	ADSO	PSO-PF	PF	PSO
The normal target	2.3006	3.9508	5.0428	7.2699	3.1073
The occluded target	2.8669	7.8950	49.1230	69.1575	31.2800
The target with large contrast changes	7.0550	9.8185	10.7207	51.8278	34.3121
The weak and small target	3.7316	4.5126	3.6576	74.2948	44.9809
The target affected by noise	4.9227	5.6187	8.9512	77.5817	6.3828
Average	4.1754	6.3591	15.4991	56.0263	24.0126

*Table: Error position (pixel) per frame **

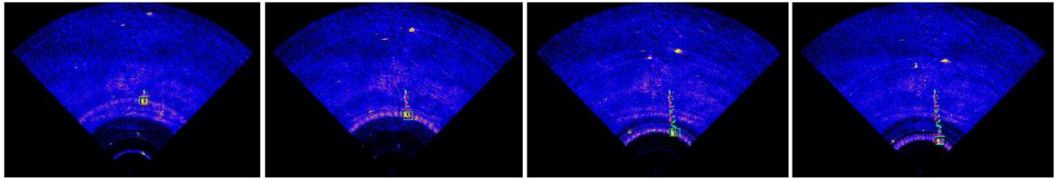

Fig: Tracking result of normal target (temporally →)

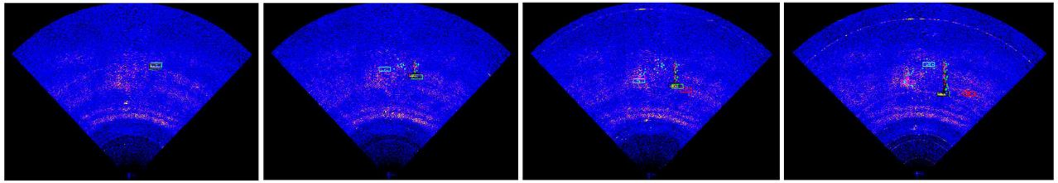

Fig: Tracking result of occluded target (temporally →)

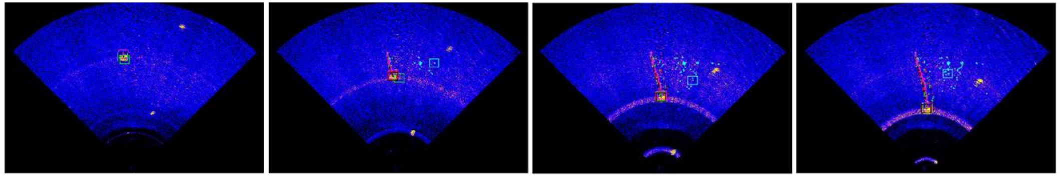

*Fig: Tracking result of noisy target (temporally →) **

* Wang, Xingmei & Wang, Guoqiang & Wu, Yanxia. (2018). An Adaptive Particle Swarm Optimization for Underwater Target Tracking in Forward Looking Sonar Image Sequences. IEEE Access. PP. 1-1. 10.1109/ACCESS.2018.2866381.

Object Association and Tracking

- ***Fourier Based Registration and Mosaicing*:**
  - Renders 2D acoustic mosaics of high detail, and extracts the AUV's 2D motion estimates
  - The **Pairwise registration** of FLS images is done using ***Phase Correlation***
    - Smoothing filter is applied in the spatial domain to reduce noise
    - **Motion** is modelled using Fourier shift property

$$f(x,y) = g(x - t_x, y - t_y)$$
$$F(u,v) = G(u,v) \cdot e^{-i(ut_x + vt_y)}$$

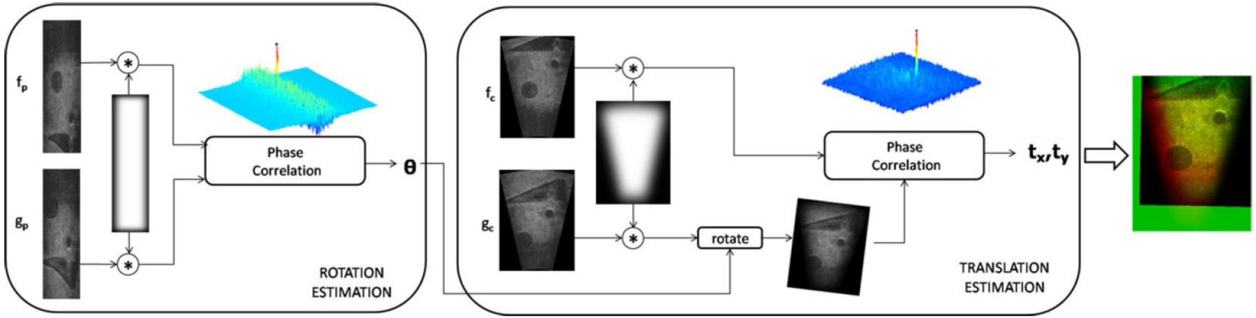

*Fig: Registration pipeline **

* Hurtós, Natàlia & Romagós, David & Cufi, Xavier & Petillot, Yvan & Salvi, Joaquim. (2015). Fourier-based Registration for Robust Forward-looking Sonar Mosaicing in Low-visibility Underwater Environments. Journal of Field Robotics. 32. 10.1002/rob.21516.

Object Association and Tracking

- The **Global Alignment** of the images is formulated as a *Pose-based Graph Optimization* problem using least-squares minimization.
  - Estimates the maximum-likelihood configuration of the images

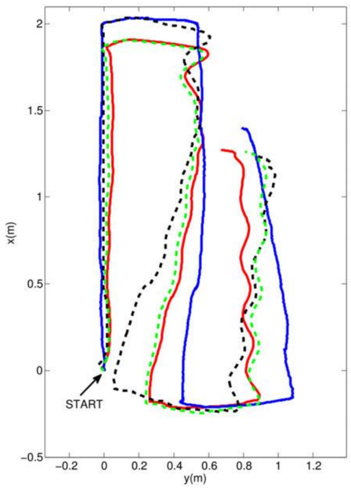

Fig: Trajectory of AUV

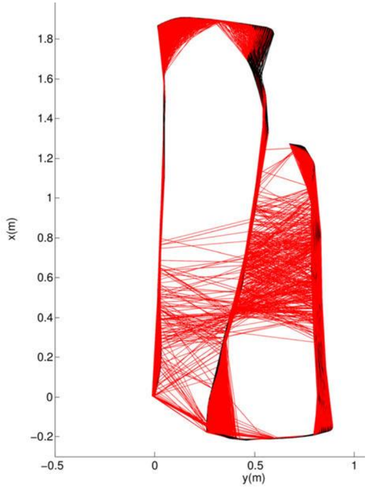

Fig: Graph constraints

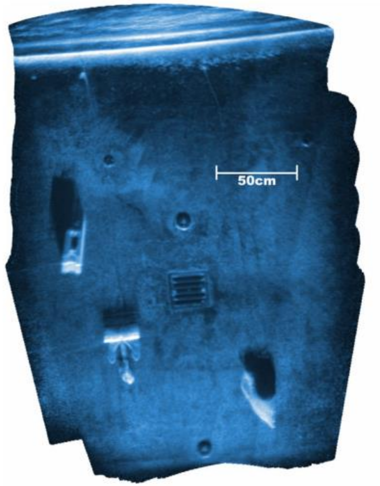

Fig: Mosaic composition *

* Hurtós, Natàlia & Romagós, David & Cufi, Xavier & Petillot, Yvan & Salvi, Joaquim. (2015). Fourier-based Registration for Robust Forward-looking Sonar Mosaicing in Low-visibility Underwater Environments. Journal of Field Robotics. 32. 10.1002/rob.21516.

Obstacle Detection and Avoidance

- ***Detection & Local avoidance approach*:**
  - Extends the **Occupancy Grid** approach
  - **Command and Control (C2) system:**
    - *Hybrid Hierarchical Control* architecture
    - Adapts an agent-based deliberate-reactive system
  - **Proposed updates to C2 system:**
    - Adds a FLS detector agent, which generates the local occupancy grid, and a ***detection map***
    - Updates the Navigator agent to create an ***obstacle map*** from the detection map, detect collision, and replan waypoints

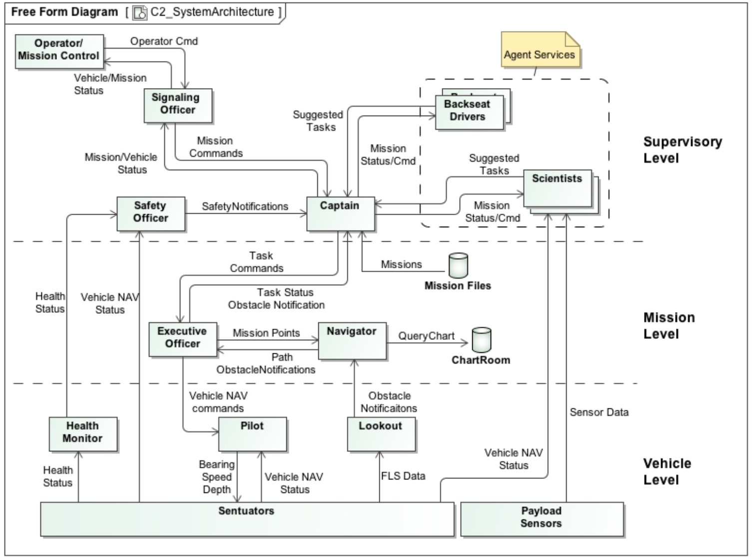

*Fig: C2 Architecture **

* Teck TY, ChitreM(2012) Hierarchical multi-agent command and control system for autonomous underwarter vehicles. In Autonomous Underwater Vehicles (AUV), 2012 IEEE/OES (pp. 1–6).

Obstacle Detection & Avoidance

- ***Detection & Local avoidance approach*:**
  - Successful empirical results at a reservoir

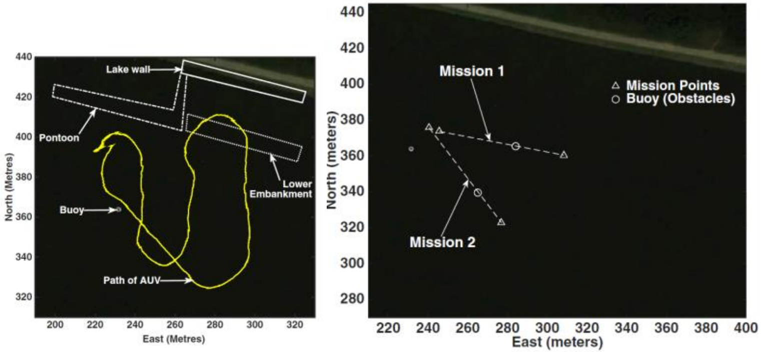

Fig: Planned Missions

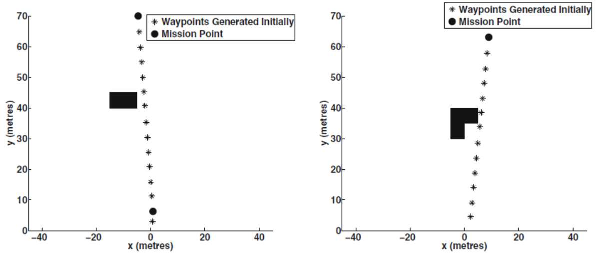

Fig: Collision checking, Mission 1 & 2

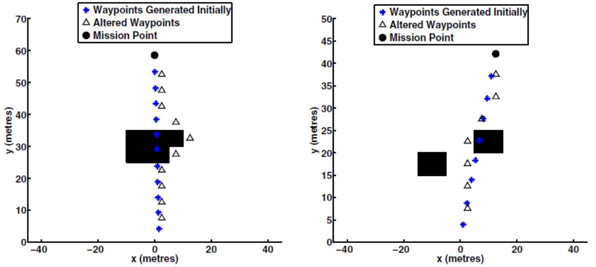

Fig: Waypoint replanning, Mission 1 & 2

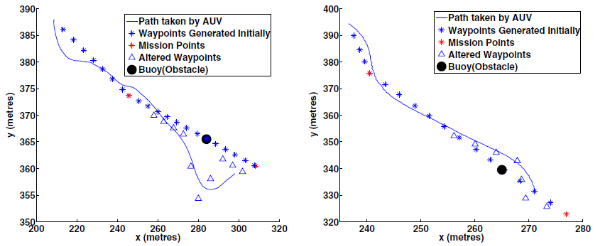

*Fig: Mission paths, Mission 1 & 2 **

* Ganesan, Varadarajan & Chitre, Mandar & Brekke, Edmund. (2016). Robust Underwater Obstacle Detection for Collision Avoidance. Autonomous Robots. 39. 10.1007/s10514-015-9532-2.

Conclusion

- Various proposed techniques, and empirical evidences explored:
  - **Acoustic image-based** object detection, classification, registration, and tracking, avoidance
  - Existing **pipelining capability** of various related tasks applied to sonar imagery
  - **Caveats** still exist to these various approaches
    - Some techniques do not explicitly **pre-process images** to remove noise
  - Application of advanced techniques from **Machine Learning** and **Deep Learning** needs further **exploration**
  - **Sensor fusion** techniques also needs to be studied