

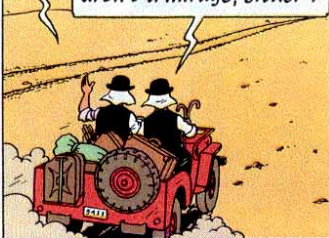
*Meanwhile ...*

I don't like it, Thomson ...  
... If we don't get  
somewhere soon ...



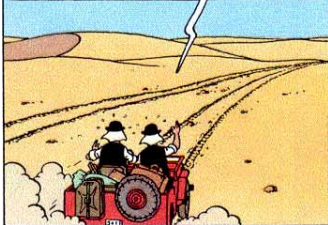
It's all right! ... Look! ... There!  
... Tracks of a car!

Quite correct! And they  
aren't a mirage, either!



*An hour later ...*

Hooray! ... More tracks! ... A  
second car joined the first one ...



A real stroke of luck  
hitting this road.

To be precise:  
we've really had  
a stroke!



# Reliable underwater SLAM using seabed roughness

Simon Rohou, Michel Legris

15<sup>th</sup> December 2023, Paris

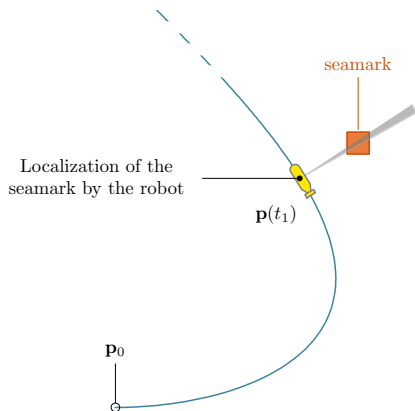
## Section 2

# Motivations

## Motivations

## Simultaneous Localization and Mapping

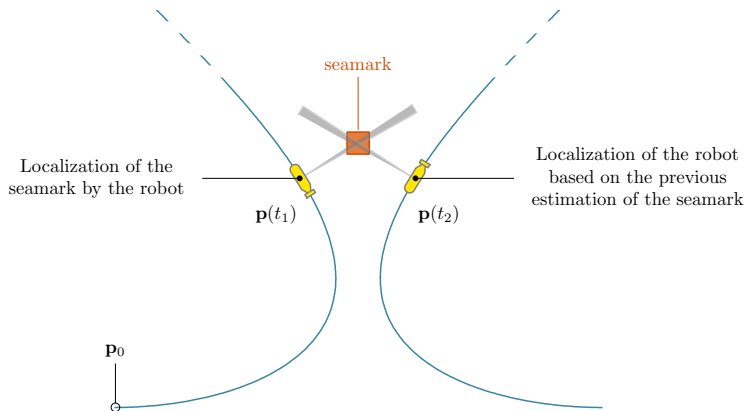
- ▶ **come back** to a previous pose and **recognize** the environment
- ▶ problem: loop closure detection



## Motivations

## Simultaneous Localization and Mapping

- ▶ **come back** to a previous pose and **recognize** the environment
- ▶ problem: loop closure detection



Motivations

## Simultaneous Localization and Mapping

The problem of **false loop detections** in similar environments.

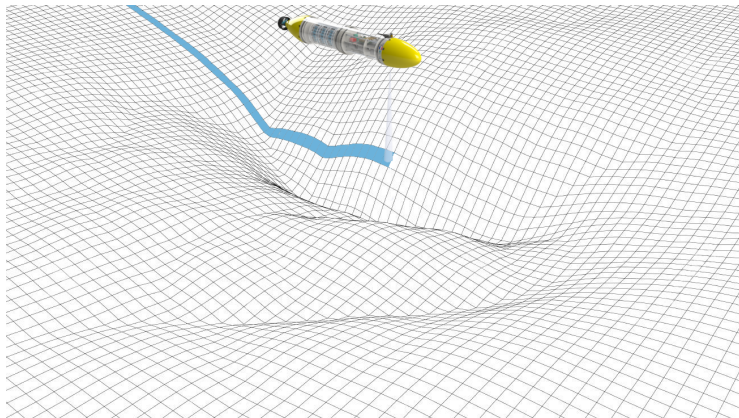


In Versailles' gardens: similar places. *Did we really come back to a previous place?*

Motivations

## Underwater robot localization

An underwater robot performing a loop during an exploration:



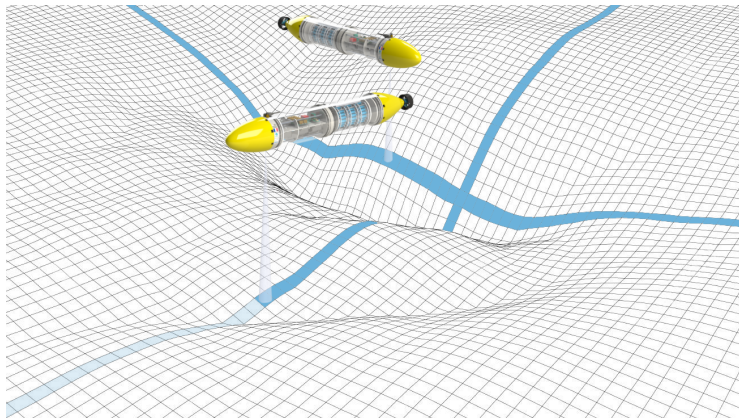
Robot's trajectory is projected in blue on the seabed.



Motivations

## Underwater robot localization

An underwater robot performing a loop during an exploration:

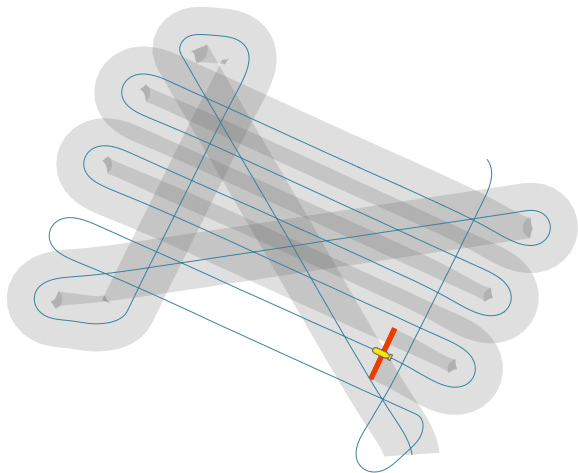


Robot's trajectory is projected in blue on the seabed.

Motivations

## Underwater robot localization

Typical path involving numerous loops:

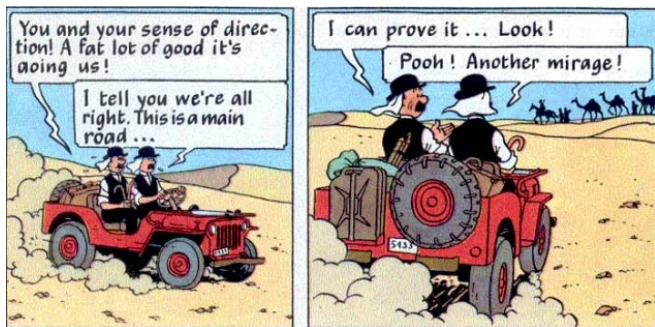


Underwater robot performing a survey with a multibeam sonar.

## Motivations

## Reliability of loops

Can we prove that we revisited the same place only from observations?

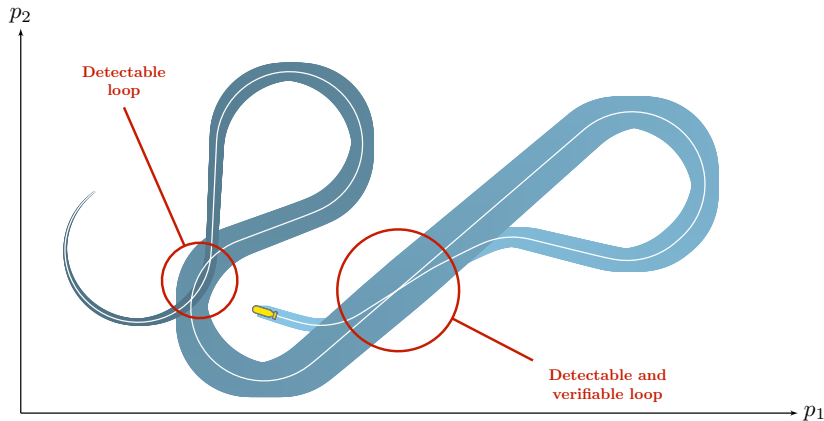


..they are wrong!

## Motivations

## Uncertainties: detection vs verification

Uncertain trajectories enclosed by **tubes**.



Only one loop can be verified – at least two feasible loops are detected

## Section 3

# Looped trajectories

## Looped trajectories

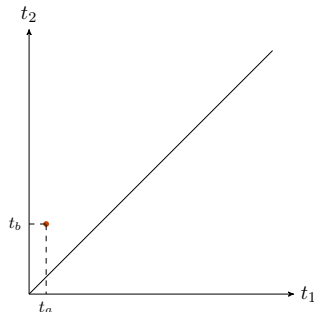
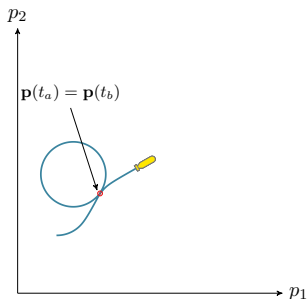
## Definitions (Aubry, 2013)

- ▶ robot position:  $\mathbf{p} = (x, y)^T \in \mathbb{R}^2$
- ▶ 2D robot trajectory:  $\mathbf{p}(t) : \mathbb{R} \rightarrow \mathbb{R}^2, t \in [t_0, t_f]$
- ▶ looped trajectory  $\Leftrightarrow$  trajectory that crosses itself
  - ▶  $\mathbf{p}(t_1) = \mathbf{p}(t_2), t_1 \neq t_2$
  - ▶ 1 loop  $\Leftrightarrow$  1  $t$ -pair  $(t_1, t_2)$

## Looped trajectories

## Definitions (Aubry, 2013)

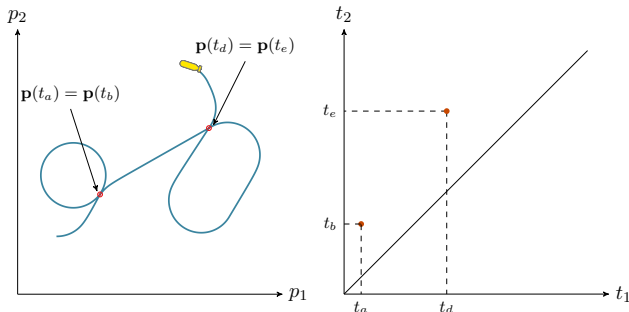
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## Looped trajectories

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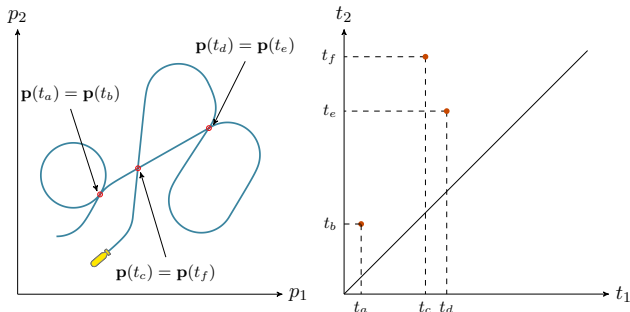




## Looped trajectories

## Definitions (Aubry, 2013)

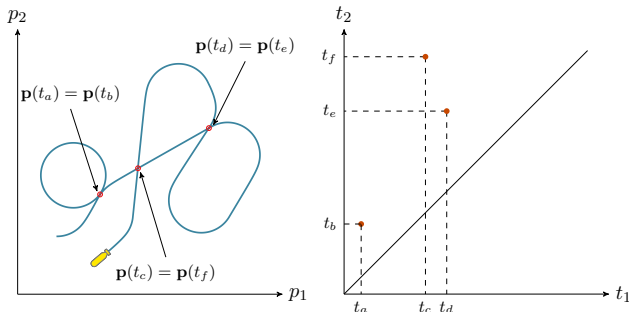
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  - ▶ 1 loop  $\Leftrightarrow$  1  $t$ -pair  $(t_1, t_2)$



## Looped trajectories

## Definitions (Aubry, 2013)

- ▶  $t$ -plane  $\Leftrightarrow$  all feasible  $t$ -pairs =  $[t_0, t_f]^2$
- ▶ loop set  $\mathbb{T}^*$ :
  - ▶  $\mathbb{T}^* = \{(t_1, t_2) \in [t_0, t_f]^2 \mid \mathbf{p}(t_1) = \mathbf{p}(t_2), t_1 < t_2\}$
- ▶ loop set of below example:
  - ▶  $\mathbb{T}^* = \{(t_a, t_b), (t_c, t_f), (t_d, t_e)\}$



Looped trajectories

## Computing loops from robot sensors

**Context:** robot trajectory  $\mathbf{p}(t)$  cannot be directly sensed.

Computation from speed measurements:

$$\mathbf{p}(t) = \int_{t_0}^t \mathbf{v}(\tau) d\tau + \mathbf{p}_0, \quad (1)$$

with  $\mathbf{v}(t) \in \mathbb{R}^2$ : robot velocity vector at time  $t \in [t_0, t_f]$ .

Looped trajectories

## Computing loops from robot sensors

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with  $\mathbf{v}(t) \in \mathbb{R}^2$ : robot velocity vector at time  $t \in [t_0, t_f]$ .

**Loop-set from velocity:**

$$\mathbb{T}^* = \{(t_1, t_2) \in [t_0, t_f]^2 \mid \mathbf{p}(t_1) = \mathbf{p}(t_2), t_1 < t_2\} \quad (2)$$

$$= \left\{ (t_1, t_2) \in [t_0, t_f]^2 \mid \int_{t_1}^{t_2} \mathbf{v}(\tau) d\tau = \mathbf{0}, t_1 < t_2 \right\} \quad (3)$$

## Section 4

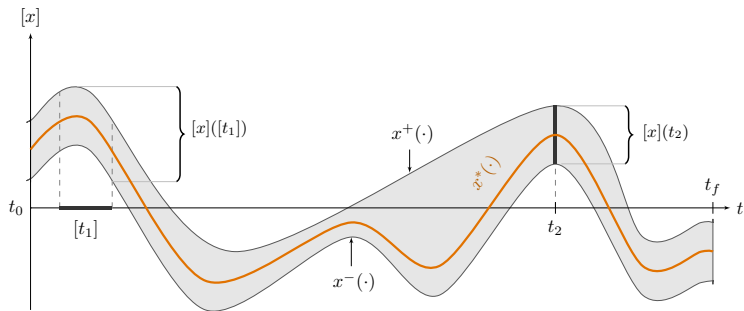
# Loop detection

Loop detection

Bounded-error context

**Tubes: sets of trajectories**

$[x](\cdot)$ , interval of trajectories  $[x^-(\cdot), x^+(\cdot)]$   
 such that  $\forall t \in \mathbb{R}, x^-(t) \leq x^+(t)$



Tube  $[x](\cdot)$  enclosing an uncertain trajectory  $x^*(\cdot)$

Loop detection

Bounded-error context

Actual loop-set  $\mathbb{T}^*$  (error free):

$$\mathbb{T}^* = \left\{ (t_1, t_2) \mid \int_{t_1}^{t_2} \mathbf{v}^*(\tau) d\tau = \mathbf{0} \right\} \quad (4)$$

Loop detection

## Bounded-error context

Actual loop-set  $\mathbb{T}^*$  (error free):

$$\mathbb{T}^* = \left\{ (t_1, t_2) \mid \int_{t_1}^{t_2} \mathbf{v}^*(\tau) d\tau = \mathbf{0} \right\} \quad (4)$$

Bounded-error context, assuming  $\mathbf{v}^*(\cdot) \in [\mathbf{v}](\cdot)$ :

$$\mathbb{T} = \left\{ (t_1, t_2) \mid \exists \mathbf{v}(\cdot) \in [\mathbf{v}](\cdot), \int_{t_1}^{t_2} \mathbf{v}(\tau) d\tau = \mathbf{0} \right\} \quad (5)$$



Loop detection

## Bounded-error context

Actual loop-set  $\mathbb{T}^*$  (error free):

$$\mathbb{T}^* = \left\{ (t_1, t_2) \mid \int_{t_1}^{t_2} \mathbf{v}^*(\tau) d\tau = \mathbf{0} \right\} \quad (4)$$

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Set-membership approach:

$$\mathbb{T}^* \subset \mathbb{T} \subset [t_0, t_f]^2 \quad (6)$$

Loop detection

Inclusion function

**Simplification:**

defining the actual but unknown function  $\mathbf{f}^* : \mathbb{R}^2 \rightarrow \mathbb{R}^2$

$$\mathbf{f}^*(t_1, t_2) = \int_{t_1}^{t_2} \mathbf{v}^*(\tau) d\tau \quad (7)$$

Loop detection

## Inclusion function

### Simplification:

defining the actual but unknown function  $\mathbf{f}^* : \mathbb{R}^2 \rightarrow \mathbb{R}^2$

$$\mathbf{f}^*(t_1, t_2) = \int_{t_1}^{t_2} \mathbf{v}^*(\tau) d\tau \quad (7)$$

### Assessed knowledge:

$[\mathbf{f}] : \mathbb{R}^2 \rightarrow \mathbb{I}\mathbb{R}^2$  is an *interval function* of  $\mathbf{f}^*$ :

$$\mathbf{f}^*(t_1, t_2) \in [\mathbf{f}](t_1, t_2) = \int_{t_1}^{t_2} [\mathbf{v}](\tau) d\tau \quad (8)$$

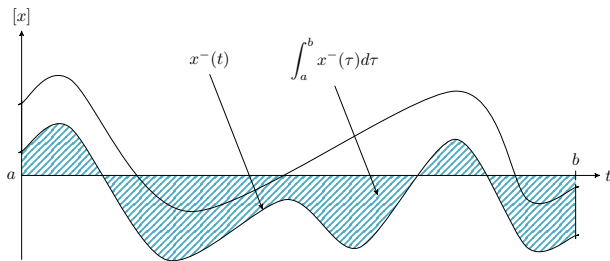
## Loop detection

## Integral of tubes

**Definition:** the integral of a tube  $[x](\cdot) = [x^-, x^+]$  is an interval:

$$\int_a^b [x](\tau) d\tau = \left\{ \int_a^b x(\tau) d\tau \mid x(\cdot) \in [x](\cdot) \right\} = \left[ \int_a^b x^-(\tau) d\tau, \int_a^b x^+(\tau) d\tau \right]$$

[Aubry2013]



blue area: lower bound of the tube's integral

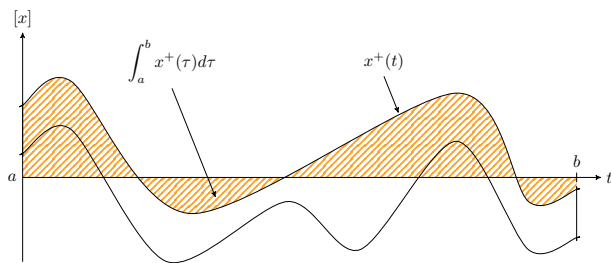
Loop detection

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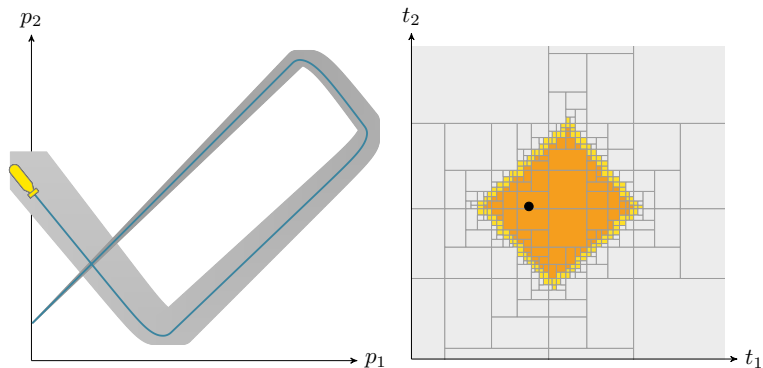
[Aubry2013]



orange area: upper bound of the tube's integral

Loop detection

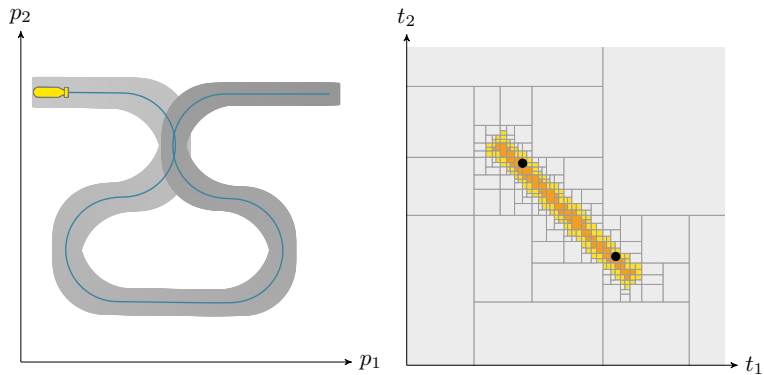
Reliable approximation of a loop set



Undeniable looped trajectory

Loop detection

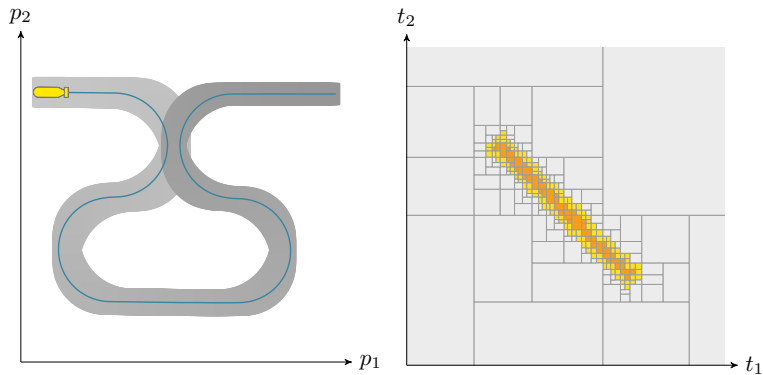
Reliable approximation of a loop set



Doubtful looped trajectory

Loop detection

Reliable approximation of a loop set

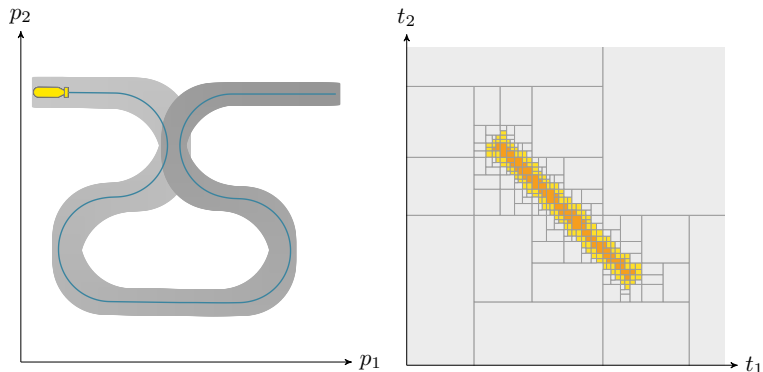


Doubtful looped trajectory



Loop detection

Reliable approximation of a loop set

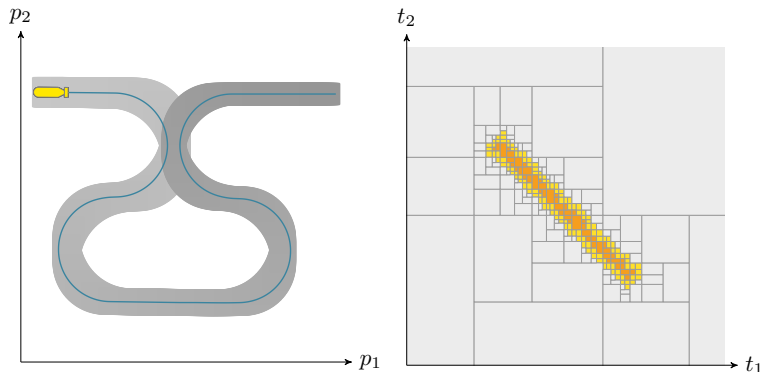


Doubtful looped trajectory

$$\forall \mathbf{f} \in [\mathbf{f}], \exists \mathbf{t} \in \mathbb{T}_i \mid \mathbf{f}(\mathbf{t}) = \mathbf{0} \implies \underbrace{\exists \mathbf{t} \in \mathbb{T}_i \mid \mathbf{f}^*(\mathbf{t}) = \mathbf{0}}_{\text{loop existence proof}} \quad (9)$$

## Loop detection

## Reliable approximation of a loop set



Doubtful looped trajectory

Proving the existence of loops in robot trajectories  
Simon Rohou, Peter Franek, Clément Aubry, Luc Jaulin  
The International Journal of Robotics Research, 2018

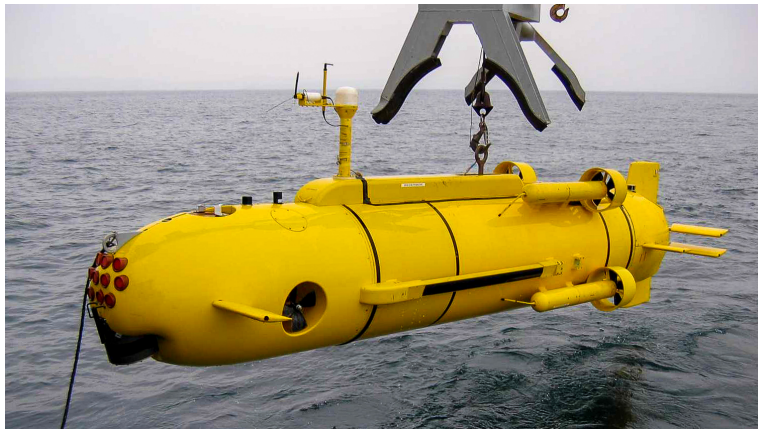
## Section 5

# Application (loops detections/proofs)

Application (loops detections/proofs)

## Redermor mission

2 hours experimental mission in Brittany (France)

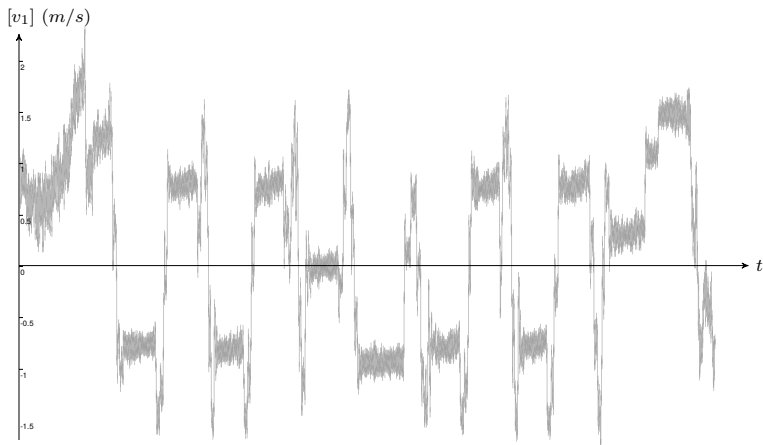


The *Redermor* Autonomous Underwater Vehicle (AUV)

Application (loops detections/proofs)

Redermor mission

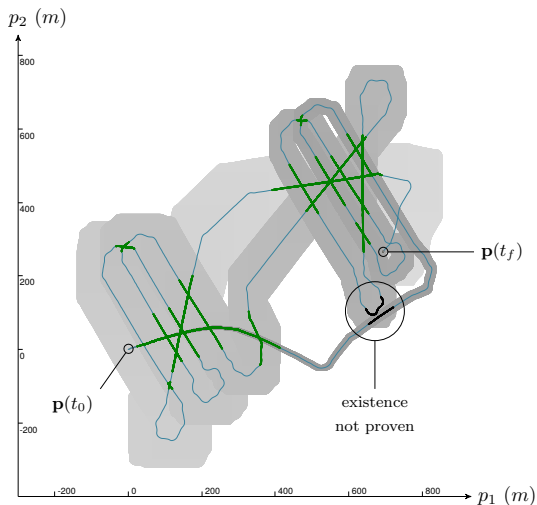
Tube of proprioceptive measurements  $[\mathbf{v}](\cdot)$ :



East speed velocity tube  $[v_1](\cdot)$

Application (loops detections/proofs)

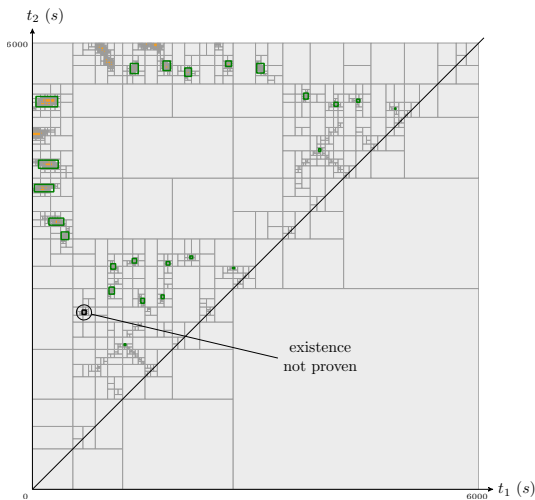
Guaranteed computation of the trajectory



2d trace of Redermor AUV

Application (loops detections/proofs)

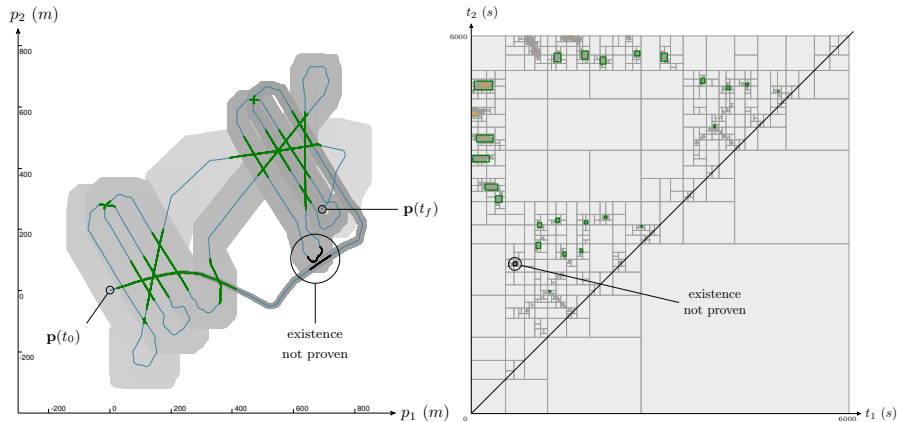
$t$ -plane of the mission:  $\mathbb{T} = \{(t_1, t_2) \mid \mathbf{0} \in [\mathbf{f}](t_1, t_2), t_1 < t_2\}$



$t$ -plane corresponding to *Redermor's* mission

Application (loops detections/proofs)

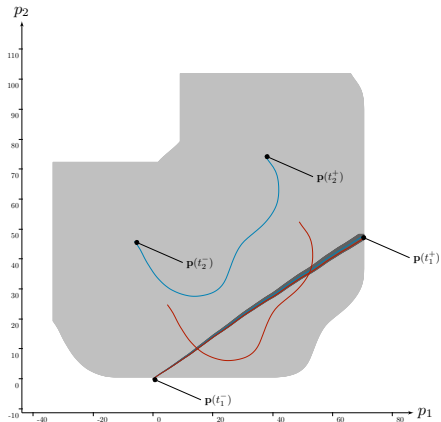
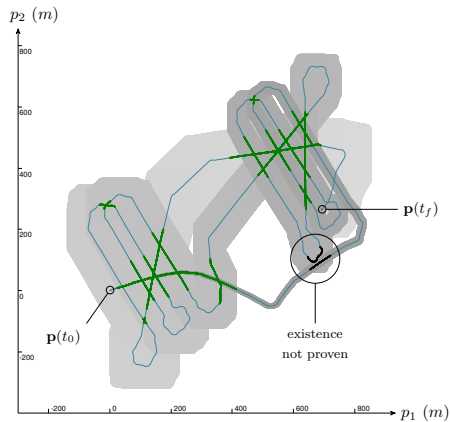
## Overview and results





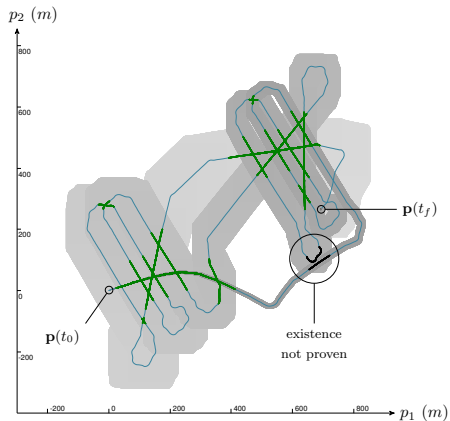
Application (loops detections/proofs)

## Overview and results



Application (loops detections/proofs)

## Overview and results



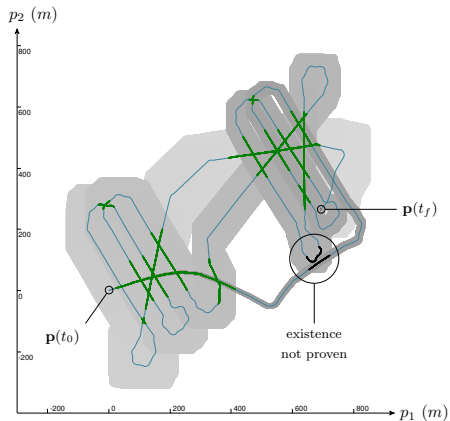
### Loop proof number

Without uncertainties:

$$\lambda^* = \#\{\mathbf{t} \mid \mathbf{f}^*(\mathbf{t}) = \mathbf{0}, t_1 < t_2\}$$

Application (loops detections/proofs)

## Overview and results



### Loop proof number

Without uncertainties:

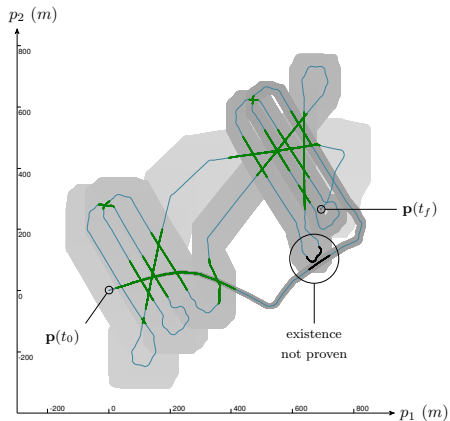
$$\lambda^* = \#\{\mathbf{t} \mid \mathbf{f}^*(\mathbf{t}) = \mathbf{0}, t_1 < t_2\}$$

### Results:

Newton operator test:  $\lambda_{\mathcal{N}} = 14$

Application (loops detections/proofs)

## Overview and results



### Loop proof number

Without uncertainties:

$$\lambda^* = \#\{\mathbf{t} \mid \mathbf{f}^*(\mathbf{t}) = \mathbf{0}, t_1 < t_2\}$$

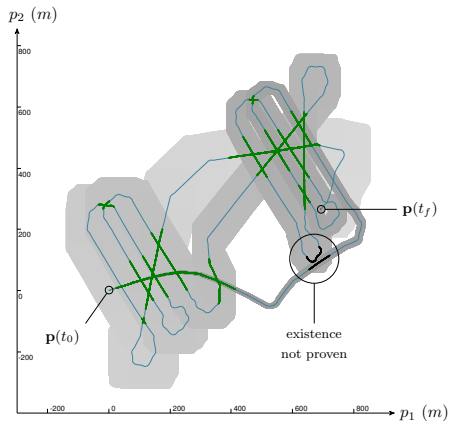
### Results:

Newton operator test:  $\lambda_{\mathcal{N}} = 14$

Topological degree test:  $\lambda_{\mathcal{T}} = 24$

Application (loops detections/proofs)

## Overview and results

**Loop proof number**

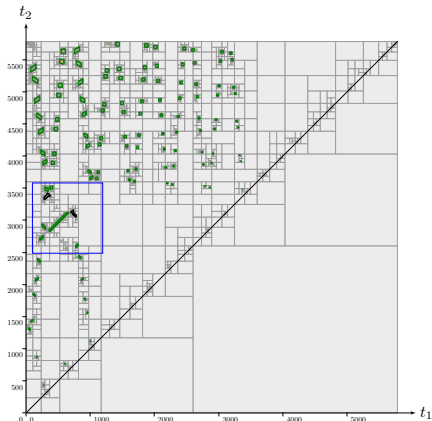
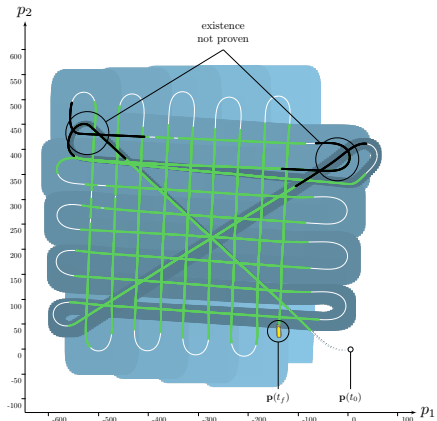
Without uncertainties:

$$\lambda^* = \#\{\mathbf{t} \mid \mathbf{f}^*(\mathbf{t}) = \mathbf{0}, t_1 < t_2\}$$

**Results:**Newton operator test:  $\lambda_{\mathcal{N}} = 14$ Topological degree test:  $\lambda_{\mathcal{T}} = 24$ Truth:  $\lambda^* = 24$

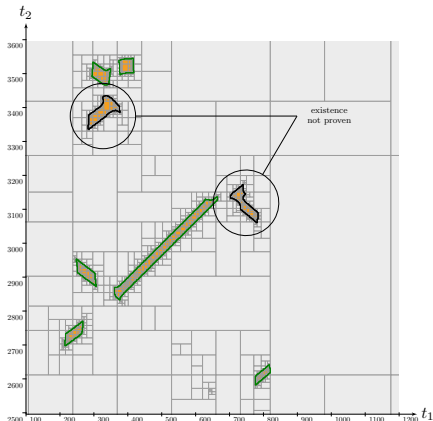
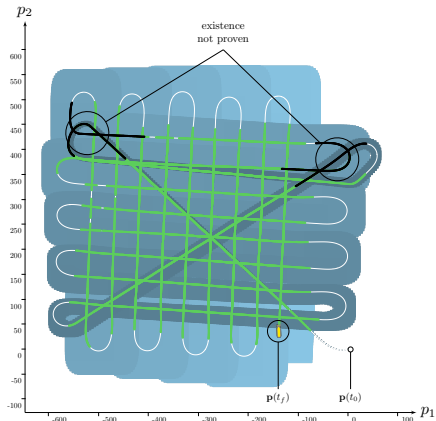
Application (loops detections/proofs)

Another experiment (*Daurade* AUV)



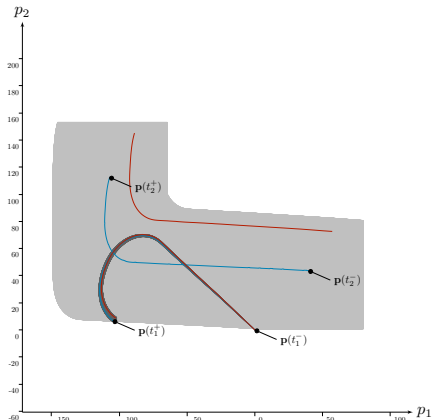
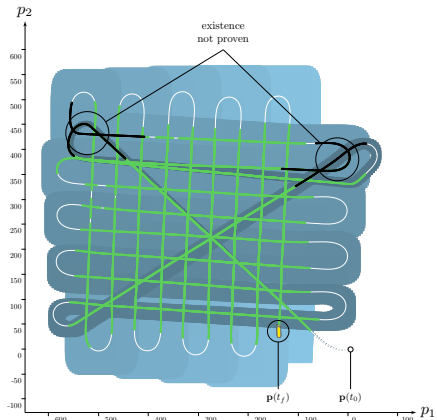
Application (loops detections/proofs)

Another experiment (*Daurade* AUV)



Application (loops detections/proofs)

Another experiment (*Daurade* AUV)





Now that loops are proved with proprioceptive measurements...



...it remains to perform localization by adding environment perceptions.

## Section 8

# Towards SLAM

Towards SLAM

## Experiment (3<sup>rd</sup> December, 2014)

- ▶ Daurade: Autonomous Underwater Vehicle (AUV)
- ▶ weight: 1010kg – length: 5m – max depth: 300m

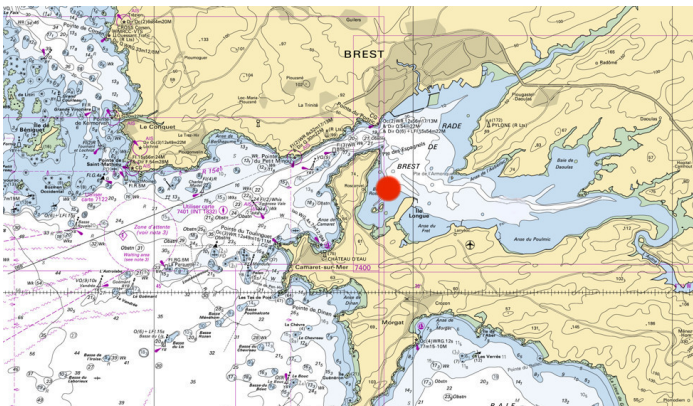


Special thanks to DGA-TN Brest (formerly GESMA)

## Towards SLAM

# Experiment (3<sup>rd</sup> December, 2014)

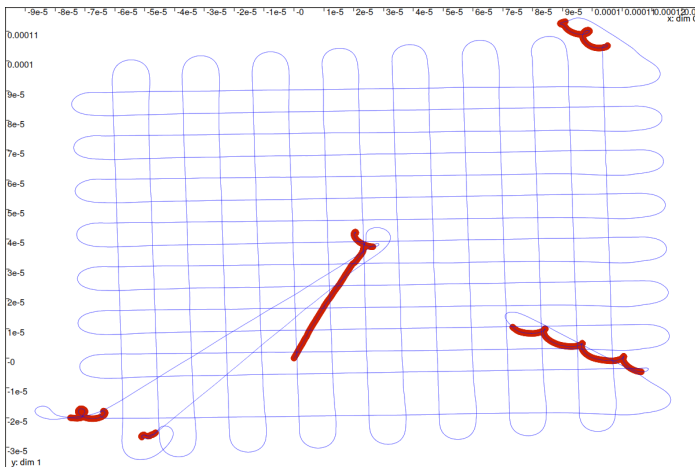
- ▶ 3.5 hours experimental mission
- ▶ *Rade de Brest*, Brittany



Location: *Baie de Roscanvel* – Credits: Shom

Towards SLAM

## Experiment (Boustrophédon)



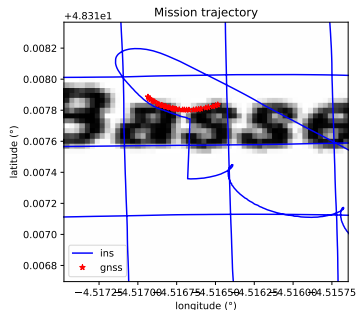
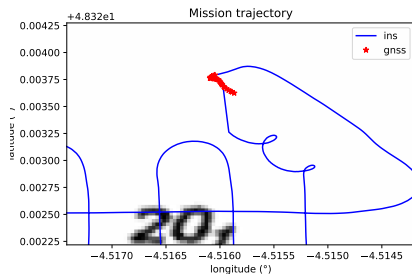
Multi-boustrophedon pattern  
(actual trajectory followed by Daurade)

## Towards SLAM

## Actual positioning drift (40m)

Current Kalman algorithms, from the constructor, are able to filter the trajectory with GNSS fixes (when surfacing).

→ up to 40m of positioning drift after  $\sim 1$ h of deadreckoning



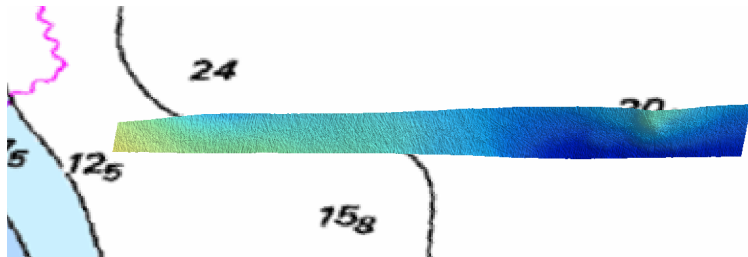
Blue: actual trajectory corrected in forward filtering.  
Red: GNSS positions.

Towards SLAM

## SLAM approach: observations of the seabed

Use of a Multi-Beam Echo-Sounder (MBES)

- ▶ accurate sensing of the seabed
- ▶ main usage: building maps (Digital Elevation Models)

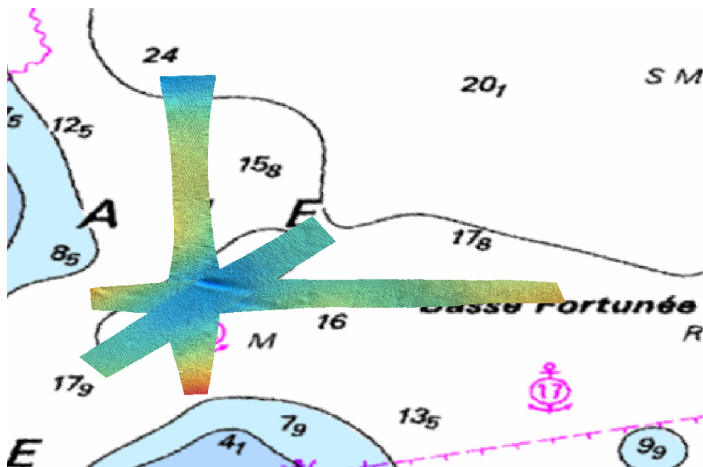


Example of one acquisition track, during the Daurade mission.

Towards SLAM

SLAM approach: observations of the seabed

**Goal:** use bathymetric information for localization purposes



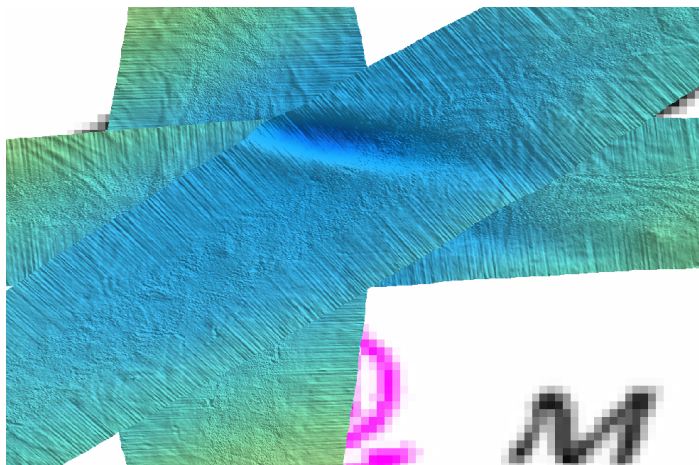
Crossed acquisition tracks (looped trajectories), in case of positioning drift.



Towards SLAM

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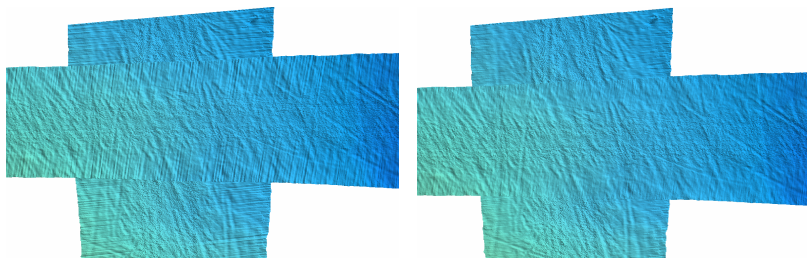
Towards SLAM

## SLAM on seabed roughness (micro-relief)

### Which information?

- ▶ low frequencies: sensitive to tide effects, or flat environments
- ▶ high frequencies: artefacts related to electronic noise (borders of the tracks)

→ **approach based on seafloor roughness**, such as ripples, grooves, small rocks...



Left: no correction. Right: the two racks match.

## Towards SLAM

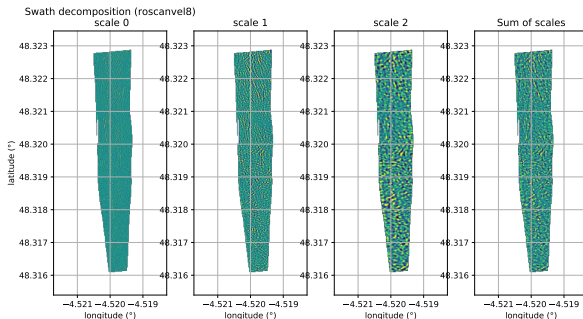
## Bathymetric decomposition

- ▶ separate resolution scales
- ▶ keep only those that are reliable and descriptive

→ **use of multilevel B-Splines**

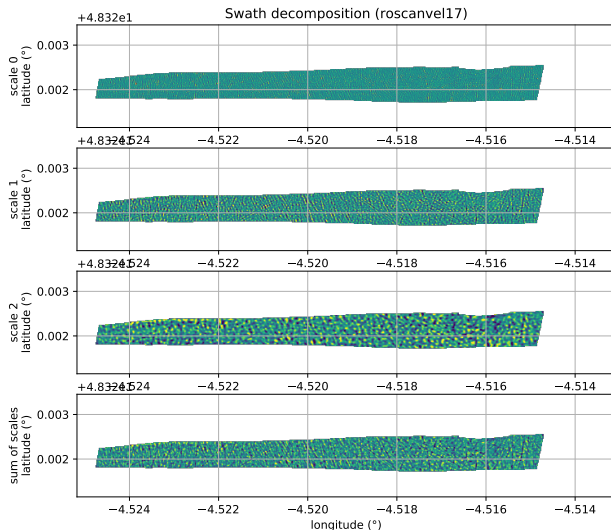
Seungyong Lee, George Wolberg, and Sung Yong Shin,  
IEEE Transactions On Visualization And Computer Graphics, Vol. 3, No. 3, July-Sept 1997

Application to bathymetry:



## Towards SLAM

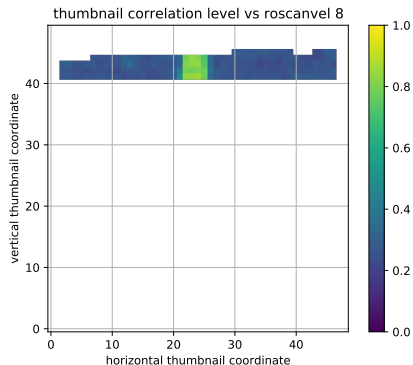
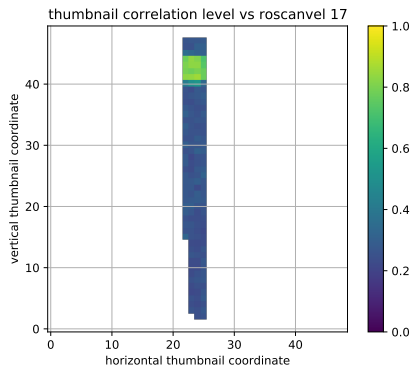
## Multilevel B-Splines on bathymetric data



## Towards SLAM

## Global correlation between two racks (ex: n17 and n8)

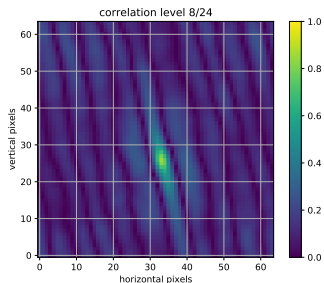
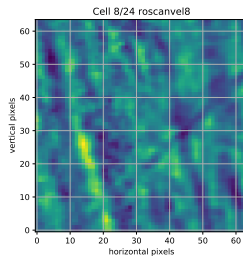
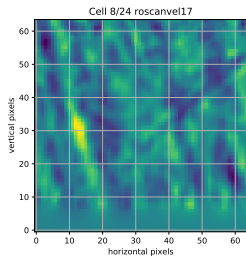
Each rack is broken down into cells of  $64 \times 64$  pixels (32m by 32m)



These figures are obtained by correlation of the cells.

## Towards SLAM

## Correlation of a couple of cells of two racks



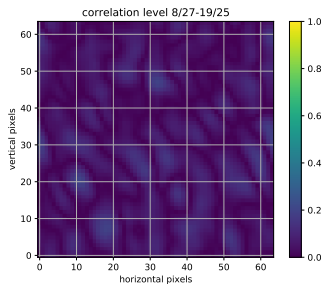
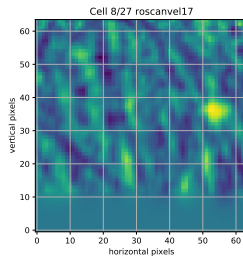
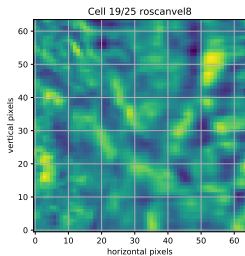
► Correlation: 0.84

$dx = 0.58\text{m}$

$dy = -2.53\text{m}$

## Towards SLAM

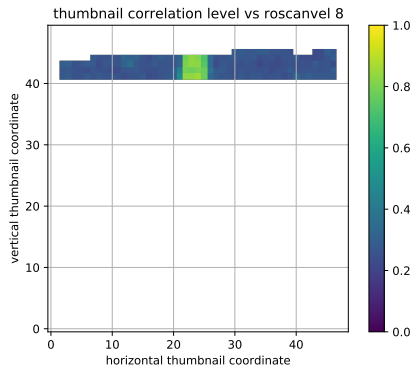
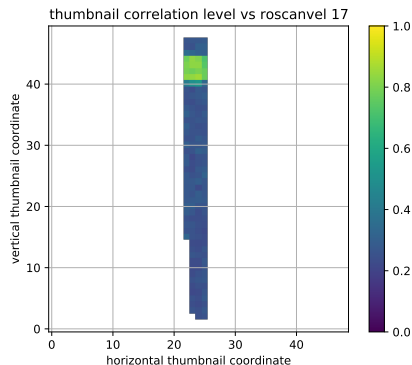
## Non-correlation of a couple of cells of two racks



► Correlation: 0.17

## Towards SLAM

## Global correlation between two racks (ex: n17 and n8)



These figures are obtained by correlation of the cells.



# Towards SLAM Formalism

## Inter-temporal measurement in SLAM:

$$\mathbf{x}(t_1) + \mathbf{d}_{1,2} = \mathbf{x}(t_2)$$

$$\dot{\mathbf{x}}(t) = \mathbf{v}(t)$$

## Set-membership approach:

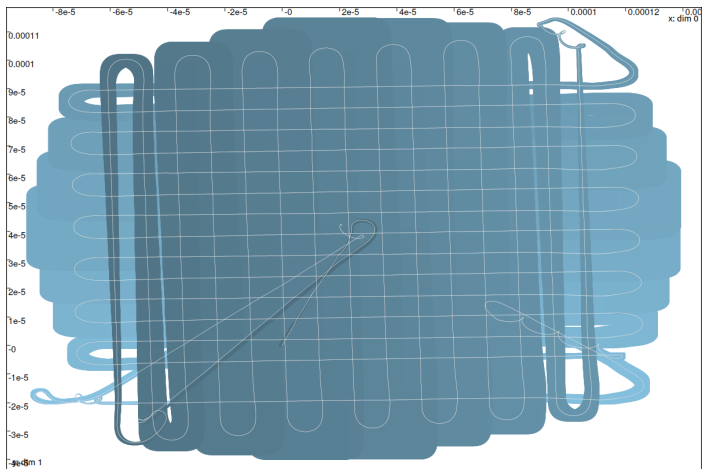
$$\mathbf{x}(\cdot) \in [\mathbf{x}](\cdot), \mathbf{v}(\cdot) \in [\mathbf{v}](\cdot)$$

$$t_1 \in [t_1], t_2 \in [t_2]$$

$$\mathbf{d}_{1,2} \in [\mathbf{d}_{1,2}]$$

# Towards SLAM

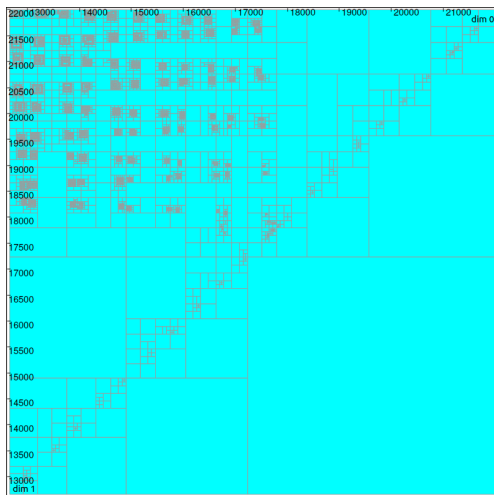
## Deadreckoning



Initial tube before SLAM (inertial/DVL odometry + GNSS fixes).

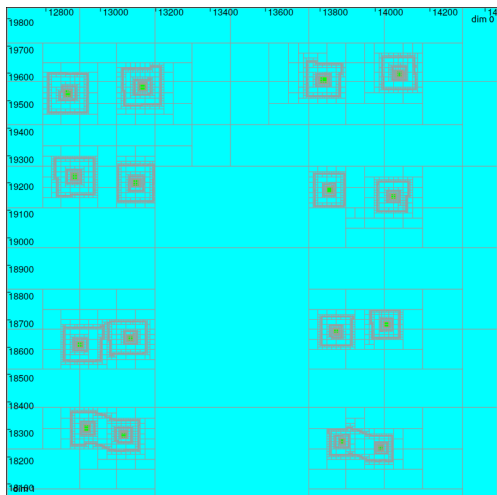
Towards SLAM

$t$ -plane of the mission (loops summary)

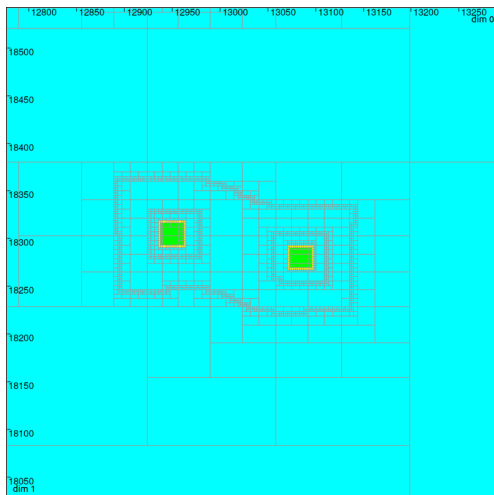


$t$ -plane  $[0, t_{\max}]^2$

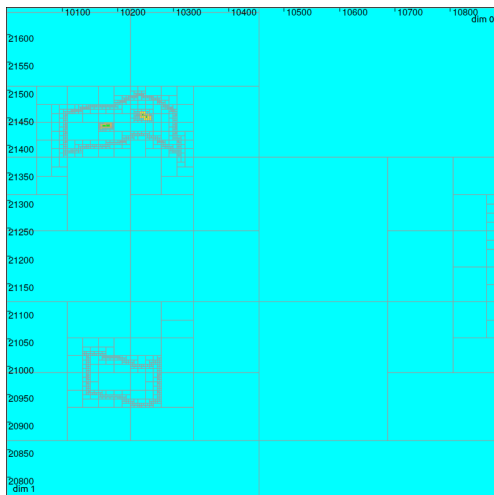
Towards SLAM

 $t$ -plane of the mission (loops summary) $t$ -plane  $[0, t_{\max}]^2$

## Towards SLAM

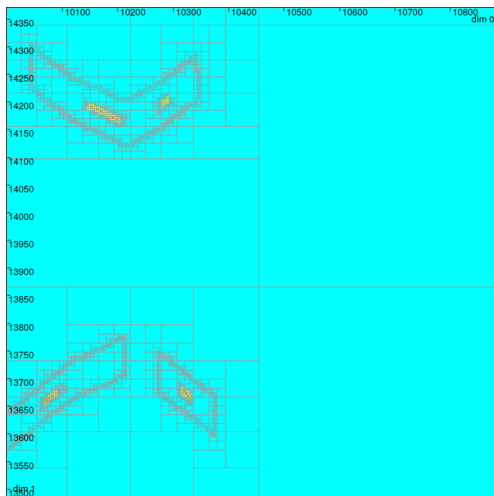
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## Towards SLAM

 $t$ -plane of the mission (loops summary) $t$ -plane  $[0, t_{\max}]^2$

Towards SLAM

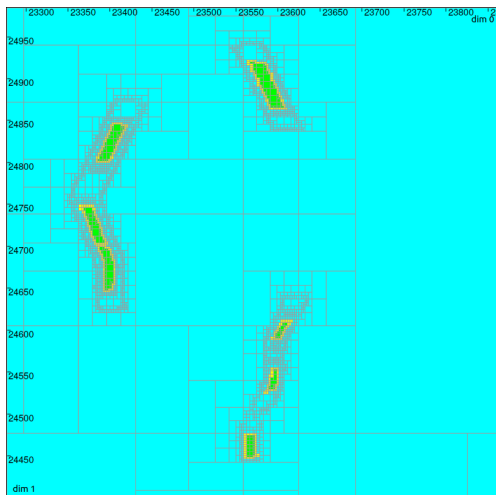
$t$ -plane of the mission (loops summary)



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Towards SLAM

$t$ -plane of the mission (loops summary)

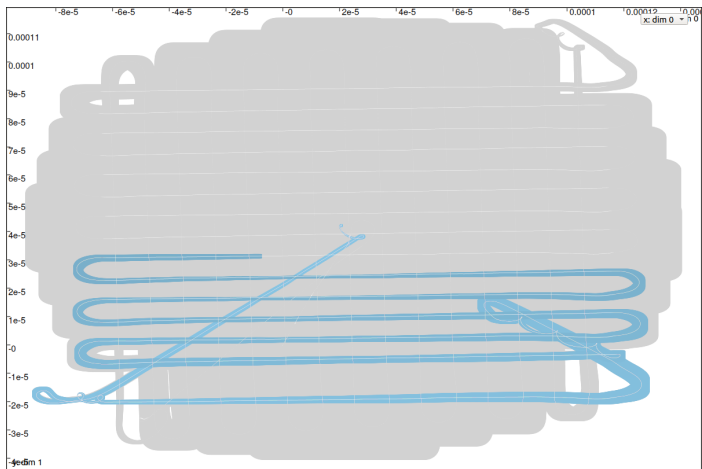


$t$ -plane  $[0, t_{\max}]^2$



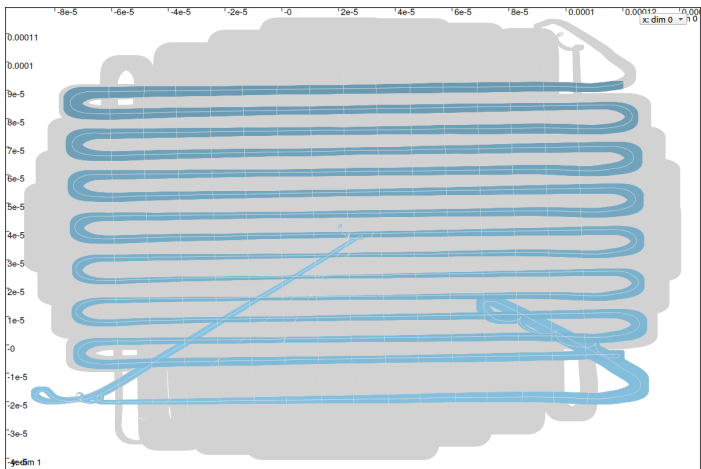
Towards SLAM

# SLAM results



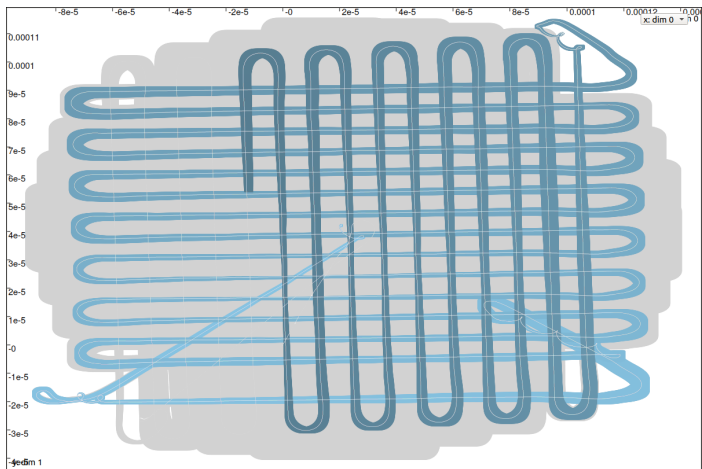
Towards SLAM

# SLAM results



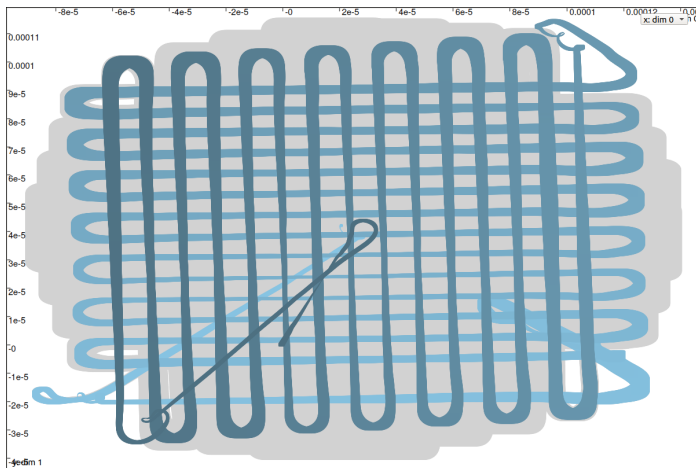
Towards SLAM

# SLAM results



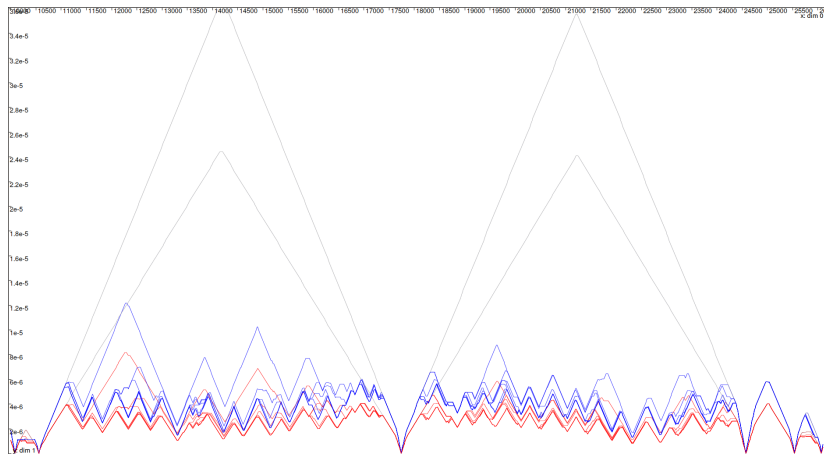
Towards SLAM

# SLAM results



## Towards SLAM

## SLAM results



Tubes thickness along time:  $\text{width}(\mathbf{x}(t))$ .

In gray: tubes without SLAM (deadreckoning only). In blue/red: with SLAM in x/y.

Towards SLAM

## Conclusion

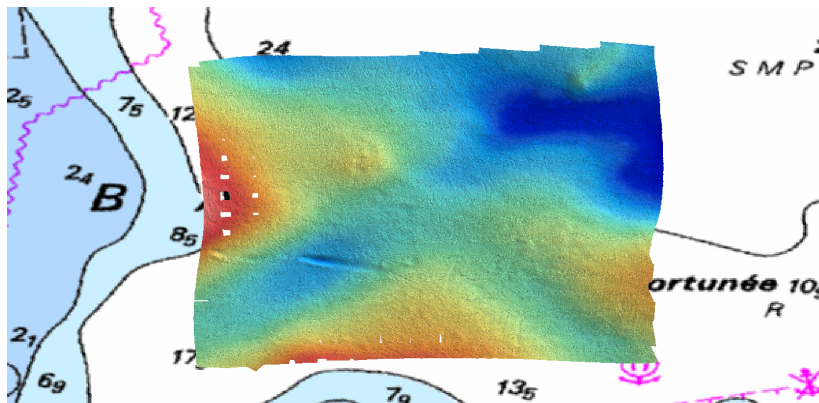
### Assets of this approach:

- ▶ reliable localization, whatever the roughness/similarities of the seabed
- ▶ localization method efficient even over flat seabeds

### Remaining points to investigate:

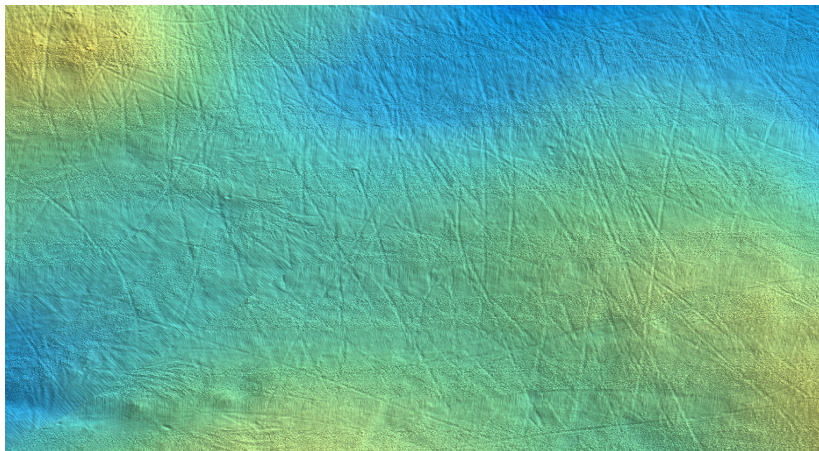
- ▶ need to automatically "clean" the MBES data before the correlation step
- ▶ online SLAM?

# Towards SLAM Conclusion



todo: Build the final DEM of the Roscanvel Baie.

# Towards SLAM Conclusion



todo: Build the final DEM of the Roscanvel Baie.



## Section 9

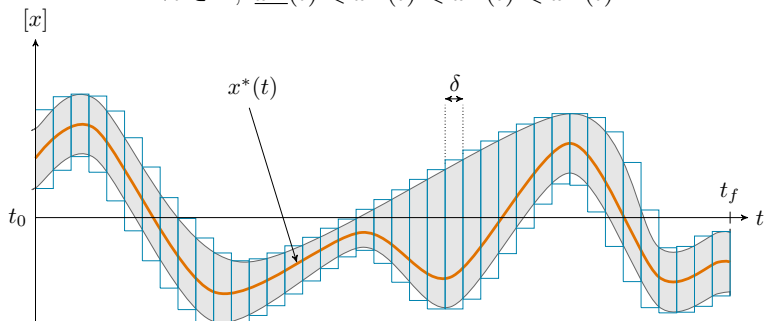
# Appendix

## Appendix

## Tubes: computer representation

Implementation **enclosing**  $[x^-(\cdot), x^+(\cdot)]$  inside an interval of step functions  $[\underline{x}(\cdot), \overline{x}(\cdot)]$  such that:

$$\forall t \in \mathbb{R}, \underline{x}(t) \leq x^-(t) \leq x^+(t) \leq \overline{x}(t)$$



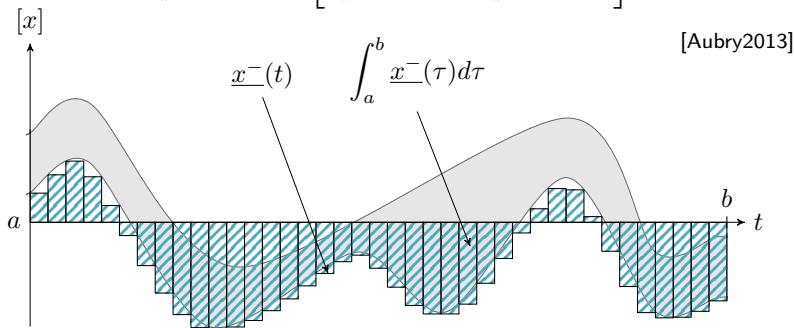
tube implementation with a set of boxes – this outer representation adds pessimism but enables guaranteed and simple computations

## Appendix

## Tubes integral: implementation

Outer approximation of the integral computed by:

$$\int_a^b [x](\tau) d\tau \subset \left[ \int_a^b \underline{x}^-(\tau) d\tau, \int_a^b \overline{x}^+(\tau) d\tau \right]$$



blue area: outer approximation of the lower bound of the tube's integral

## Appendix

Reliable approximation of absolute speed  $\mathbf{v}^*(\cdot)$ 

Robot sensors for **absolute speed computation**:

- ▶ velocity sensor (DVL)
- ▶ inertial measurement unit

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**Uncertainties:**

- ▶ datasheets  $\implies$  standard deviation  $\sigma$  for each sensor

## Appendix

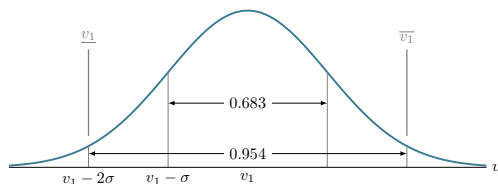
Reliable approximation of absolute speed  $\mathbf{v}^*(\cdot)$ 

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**Uncertainties:**

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- ▶ 95% confidence rate:  $v_1^* \in [v_1] = [v_1 - 2\sigma, v_1 + 2\sigma]$



## Appendix

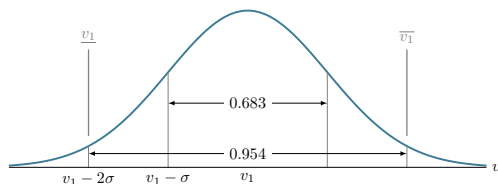
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- ▶ uncertainties propagated thanks to interval arithmetic