

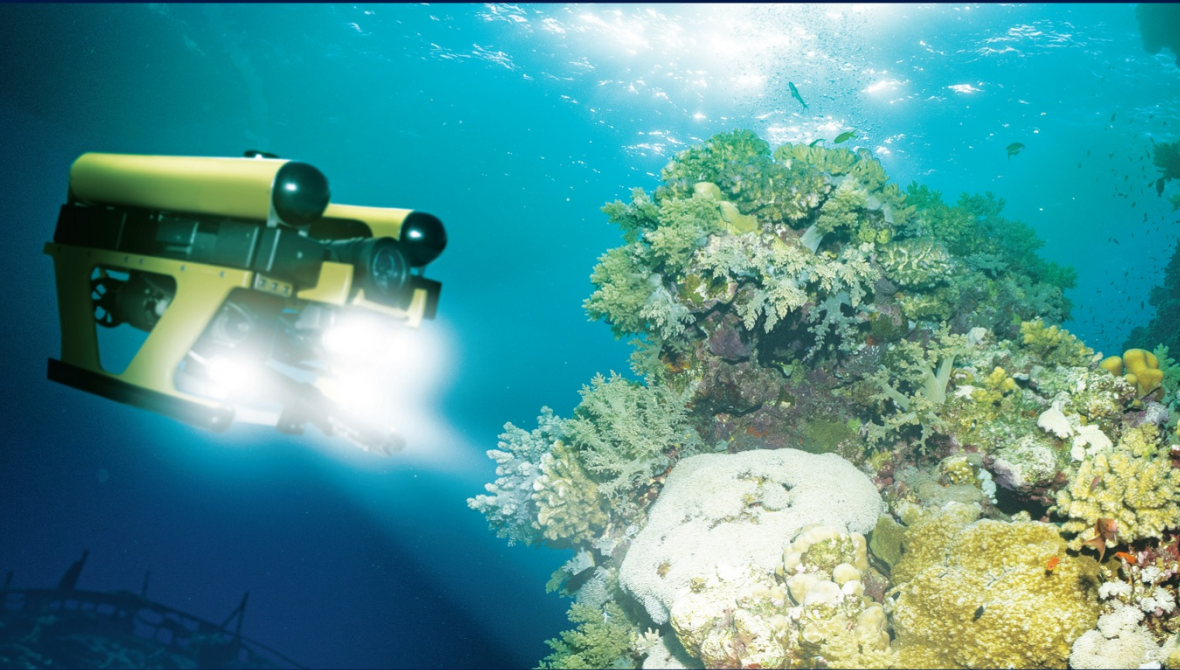
ROBOTICS SERIES

Reliable Robot Localization



*A Constraint-Programming Approach
Over Dynamical Systems*

**Simon Rohou, Luc Jaulin
Lyudmila Mihaylova, Fabrice Le Bars
and Sandor M. Veres**



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Reliable Robot Localization

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Hisham Abou-Kandil

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Preface

In the field of mobile robotics, *navigation* is the building block of any autonomous mission. It involves several competencies, which are *perception* of the environment, *localization* of the robot with respect to a given reference frame, the *cognition* leading to a set of trajectory decisions and *control* of the actuators to achieve these decisions. The *localization* problem has given a tremendous impetus to the development of new technologies and algorithms, such as global navigation satellite systems (GNSSs) or a variety of Kalman filters. The challenges raised by this localization imply a wide variety of contexts, sensors and uncertainties that still gather a large part of the robotic community today.

This book focuses on a new approach to deal with the localization problem. It finds its inspiration in the challenges raised by strong uncertainties and perception difficulties present in underwater robotics. Furthermore, for safety reasons related to surface navigation or risks of collision with the seabed, it is crucial to consider the quality of position estimates. Emergent set-membership methods allow us to define reliable bounds on uncertainties in computations; this book explains how to apply these tools to mobile robots. The illustrations are related to underwater robotics, but the concepts remain fully valid for other applications involving dynamical systems.

This book is expected to be useful for students and researchers in the areas of mobile robotics, nonlinear control systems, underwater robotics, interval analysis and constraint programming.

It originates from a PhD thesis that was prepared by Simon Rohou during a Franco-British PhD program at ENSTA Bretagne/Lab-STICC (Brest, France) and at the University of Sheffield (Sheffield, UK). This work was supervised by the other authors: Luc Jaulin, Lyudmila Mihaylova, Fabrice Le Bars and Sandor M. Veres. It was awarded as the best PhD thesis by the French research community in robotics in 2018.

This book would not have been possible without the precious help and the contributions of the following people who are gratefully acknowledged here:

– we thank Peter Franek (from the Institute of Science and Technology of Austria) for his fruitful collaboration in the field of topological degree theory. He contributed to the material presented in Chapter 5;

– we are grateful to Philippe Bonnifait, Gilles Trombettoni, Hisham Abou-Kandil, Gilles Chabert and Benoit Zerr for their feedback, remarks and suggestions provided during and after the thesis defense;

– we thank Michel Legris for his knowledge and extensive discussions related to the applications of this work;

– we also thank Alain Bertholom and the crew of the ship *Aventurière II* (DGA-TN Brest). The experimental results of this book, involving the *Daurade* robot, would not have been possible without their help;

– we also thank the French *Direction Générale de l'Armement* (DGA) and its UK-France PhD program for funding this work.

– we finally thank the French *Agence Nationale de la Recherche* (ANR) for their financial support during the Contredo project (ANR-16-CE33-0024).

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Sandor M. VERES
August 2019

Notations

To facilitate the reader's understanding of this book, the mathematical notations that will be used are listed here in Notations. All of these will be introduced within the chapters. Vectors, matrices and vectorial functions will be represented in bold while intervals will be indicated by brackets $[]$. The blackboard bold convention is used to represent other classical sets, for example \mathbb{X} , \mathbb{Y} .

Modelization

x	: state vector, $\mathbf{x} \in \mathbb{R}^n$: (or an arbitrary variable)
p	: 2D position vector, $\mathbf{p} = (x_1, x_2)^\top$
u	: input vector, $\mathbf{u} \in \mathbb{R}^m$
f	: evolution function, $\mathbf{f} : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n$: (or an arbitrary function)
z	: vector of observations, $\mathbf{z} \in \mathbb{R}^p$
g	: observation function, $\mathbf{g} : \mathbb{R}^n \rightarrow \mathbb{R}^p$
h	: drifting function (clock problem, Chapter 4) : configuration function (SLAM method, Chapter 6)
τ	: drifting time reference
ϕ, θ, ψ	: roll, pitch, yaw (heading)

Intervals and sets

\emptyset	: empty set
\mathbb{IR}	: set of all intervals of \mathbb{R}
\mathbb{IR}^n	: set of all boxes of \mathbb{R}^n
$[x]$: interval $[x^-, x^+]$, $[x] \in \mathbb{IR}$
x^-	: lower bound of the interval $[x]$
x^+	: upper bound of the interval $[x]$
x^*	: actual (unknown) value enclosed by $[x]$
$[\mathbf{x}]$: box or interval vector, $[\mathbf{x}] \in \mathbb{IR}^n$
$[f]$: inclusion function of f
$[f]^*$: minimal inclusion function of f
\sqcup	: squared union, envelope of the following terms
\mathcal{L}_f	: constraint related to a function f
\mathcal{C}_f	: contractor related to \mathcal{L}_f
$[\mathbb{X}]$: box enclosing the set \mathbb{X}
$\partial\mathbb{X}$: boundary of the set \mathbb{X}
$\#\mathbb{E}$: cardinality (number of items) of the set \mathbb{E}

Trajectories and tubes

t	: time variable
(\cdot)	: (dot) system independent variable
$a(\cdot)$: trajectory, $\mathbb{R} \rightarrow \mathbb{R}$
$a(t)$: evaluation of $a(\cdot)$ at t
$\dot{a}(\cdot)$: derivative of $a(\cdot)$
$[a](\cdot)$: tube of trajectories, $\mathbb{R} \rightarrow \mathbb{IR}$
$[a](t)$: interval value of $[a](\cdot)$ at t
$\emptyset(\cdot)$: empty tube
$\mathbf{p}(\cdot)$: horizontal robot trajectory, $\mathbb{R} \rightarrow \mathbb{R}^2$
$\mathcal{C}_{\frac{d}{dt}}$: differential tube contractor

$\mathcal{C}_{\text{eval}}$: evaluation tube contractor
\mathcal{C}_{t_1, t_2}	: inter-temporal evaluation tube contractor
$\mathcal{C}_{\mathbf{p} \Rightarrow \mathbf{z}}$: inter-temporal implication tube contractor
d	: thickness function, diagonal of a slice, $d : \mathbb{I}\mathbb{R}^2 \rightarrow \mathbb{R}$
δ	: time discretization of a tube

Loops

\mathbf{t}	: t -pair defining a loop, also denoted by (t_1, t_2)
\mathbb{T}^*	: set of all \mathbf{t}
\mathbb{T}	: set of feasible \mathbf{t} in a bounded-error context
\mathbb{T}_i	: compact and connected subset of \mathbb{T}
Ω	: outer approximation of \mathbb{T} made of subpavings
Ω_i	: compact and connected subset of Ω
\mathcal{N}	: Newton test
\mathcal{T}	: topological degree test
λ	: number of loops along a trajectory $\mathbf{p}(\cdot)$

Other notations

ε	: precision of a SIVIA algorithm
$\text{deg}(\mathbf{f}, \Omega)$: topological degree of \mathbf{f} over Ω
$\mathbf{J}_{\mathbf{f}}$: Jacobian matrix of \mathbf{f}
$\det([\mathbf{J}])$: enclosure of interval matrix's determinant

Abbreviations

AUV	Autonomous Underwater Vehicle
BPF	Box Particle Filter
CN	Constraint Network
CSP	Constraint Satisfaction Problem
DEM	Digital Elevation Model
DVL	Doppler Velocity Log
GNSS	Global Navigation Satellite System
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
IVP	Initial Value Problem
LBL	Long BaseLine
ODE	Ordinary Differential Equation
PF	Particle Filter
SIVIA	Set-Inversion via Interval Analysis
SLAM	Simultaneous Localization and Mapping
USBL	Ultra-Short BaseLine

Introduction

I.1. Underwater challenges

“On peut braver les lois humaines, mais non résister aux lois naturelles.”

We may brave human laws, but we cannot resist natural ones.

Twenty Thousand Leagues Under the Sea, Jules Verne

I.1.1. *In the vastness of the unknown*

95%. This striking figure, stated¹ by the American National Oceanic and Atmospheric Administration (NOAA), tells us how little we know about oceans: about 95% of this underwater realm remains unseen by human eyes. Yet, it covers two-thirds of the Earth’s surface. It is even said that we know the Moon’s surface better than our oceans’ depths. Nevertheless, marine technologies have changed dramatically over the last 100 years, discovering ways to explore bodies of water that previously would have been unimaginable.

We could say that the underwater exploration started with the *Challenger Expedition* (1872, Figure I.1) by probing the depths from the surface with lead lines. The *Challenger Deep*, which is the deepest known point on Earth²,

¹ <http://www.noaa.gov/oceans-coasts>.

² *Challenger Deep*: the depth was estimated at 10916m *in situ* by submersibles.

was discovered during this expedition. Yet, it was not until the start of the 1960s that this spot was visited by humans, during the dive of the manned submersible *Trieste* (Figure I.2). Ever since, the place has been reached by very few expeditions, mainly unmanned descents.

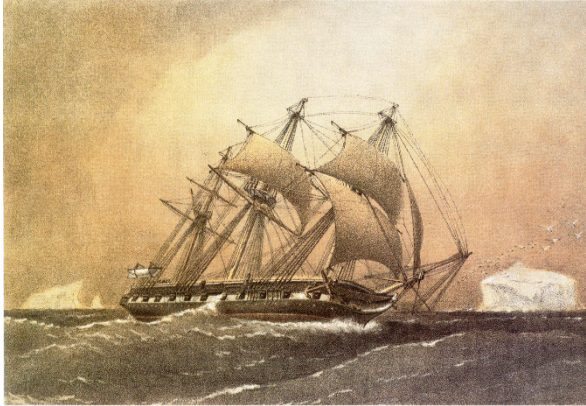


Figure I.1. *The HMS Challenger, a British corvette that took part in the first global marine research expedition: the Challenger Expedition, 1872–1876. Painting by William Frederick Mitchell. For a color version of the figures in this chapter see www.iste.co.uk/rohou/robot.zip*

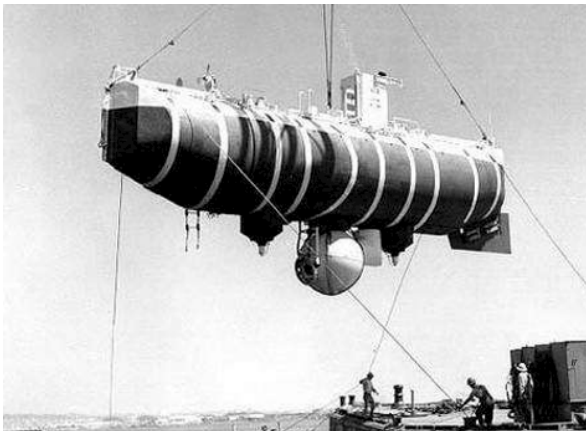


Figure I.2. *Trieste is a Swiss-designed and Italian-built deep-diving research bathyscaphe. It was able to reach any point of the Earth's abysses, such as the Mariana Trench in 1960. Photo: U.S. Naval Historical Center*

The dive of the *Trieste* revealed the capacity to build vehicles that are able to resist colossal pressures. However, the cost of this endeavor is huge when compared to the range of the explored area: only a few square meters around the submersible. If exploration techniques have evolved considerably over the years, the ratio of exploration/cost or exploration/time remains a major impediment to the discovery of our oceans.

I.1.2. Hostile environments

Withstanding the high pressures of the column water, corrosive salinity, unpredictable currents, etc. is one thing; perceiving the environment is another. Figure I.3 provides an example of poor visibility that can be encountered under the surface. Strong opacities in shallow waters, or lack of light in the deepest ones, make it difficult to gather information from cameras. Other conventional means of exploration or communication suffer from strong attenuations of their electromagnetic waves through the water column.

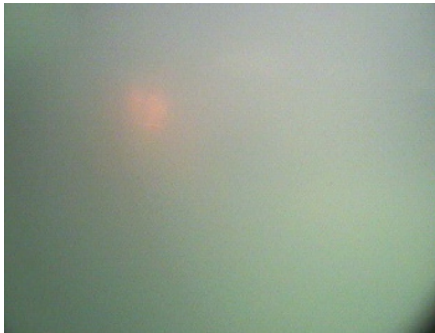
Underwater acoustics

Underwater acoustics is the only technology left with sufficient performances to increase the range of visibility. A telling experiment is the *Heard Island* test performed in 1991 (Munk *et al.* 1994), which was planned in order to test the emission of an artificial acoustic signal in the world's oceans. A special phase-modulated signal of 57 Hz, emitted from an island located in the southern Indian Ocean, was received by 16 sites around the world, some of them were based on the two coasts of North America. This experiment demonstrated that great distances can be reached by acoustics.

Considering an estimation of the sound celerity profile along the propagation, an acoustic wave is even well suited to perceive distances between the emitter and any obstacle in the environment. In practice, ranges of a few dozen meters are affordable to maintain precision at a reasonable energy cost. However, we should note that an acoustic signal rarely propagates in a straight line. This has an impact on estimation of distances and may even generate blind zones³. Underwater acoustics nonetheless

³ In the Atlantic Ocean, for example, due to the physical properties of the environment, two vehicles on the same layer of water, which are separated by 60 meters, may not be able to perceive each other.

remains the most suited approach for wide explorations, but the related solutions are far from being straightforward.



(a) An orange buoy dimly visible at 3m.



(b) Unstructured environments.



(c) A lost wireless router.



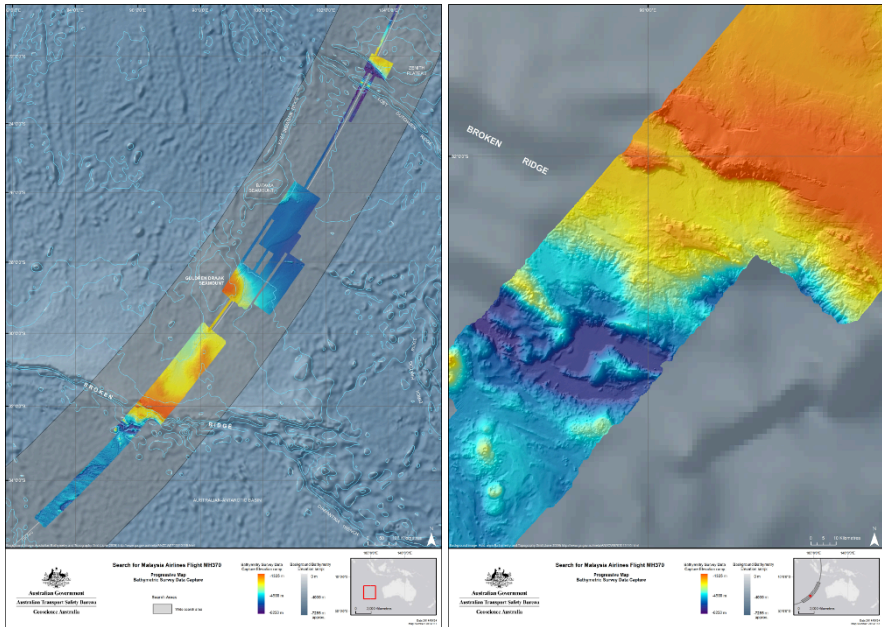
(d) Sea life, leading to outliers.

Figure 1.3. *In the shallow waters of La Spezia (Italy) during the SAUC-E competitions in the NATO Centre for Maritime Research and Experimentation (CMRE, formerly NURC), 2013–2014. These images were taken by the ENSTA Bretagne’s autonomous robot Vici. Designing algorithms to automatically analyze these observations remains a challenging task*

A needle in a haystack

The work presented in this book started on the very same day that the underwater search began for the lost MH370 aircraft operated by Malaysia Airlines, which presumably disappeared in the southern Indian Ocean in 2014. Despite a tremendous deployment of maritime means, making this multinational search effort the largest and most expensive in aviation history,

the aircraft remains unfound. From October 2014 to January 2017, an overall survey of 120,000 km² of the seafloor was performed with unsuccessful results. Given the vast areas involved, this search sadly reveals the difficulty we still have in exploring the extent of the seabed.



(a) Overview of the survey.

(b) Zoomed area.

Figure I.4. Extract from the bathymetric survey conducted during the search for MH370 aircraft off the west coast of Australia. Gray areas represent the bathymetry that was indirectly estimated using satellite-derived gravity data. In contrast, colored data were acquired by marine means, highlighting the need to undertake surveys in situ for higher precisions. ©Copyright 2014, Commonwealth of Australia

The unfruitful research nonetheless improved the knowledge we had on this part of the oceans, providing a level of details that had rarely been reached in the deep environment (Picard *et al.* 2017). Figure I.4 shows a comparison between the previous mapping of the seabed, which had an average spatial resolution of about 5 km², and the new digital elevation model (DEM) obtained with a resolution of less than 0.01 km². During the search, the vessels equipped with acoustic means, such as side-scan sonars or multibeam echosounders, were not able to scan the entire extent of the search

area. Indeed, the seabed parts with the most complex and challenging topography could only be reached by autonomous underwater vehicles (AUVs), equipped with similar technology and specifically designed for high-resolution survey operations in remote deep water locations. These vehicles lend a helping robotic hand in such exploration efforts.

I.1.3. Autonomous underwater vehicles

Owing to the difficulties posed by complex environments and vast areas that are still uncovered, the use of autonomous vehicles appears to be a durable solution to face these challenges and push the boundaries of the knowledge of the oceans. Indeed, even with efficient methods such as underwater acoustics, the footprint of marine sensors is still modest in view of the extent of what has to be explored. Multiplying the number of vessels equipped with sensors is expensive due to the involvement of crew. In addition, surface vehicles are not sufficient to provide the details of deep waters. Marine robots (Creuze 2014) are an attractive alternative to increase the exploration means at a reasonable cost.

Furthermore, global supervision of an underwater robot performing an exploration task is rarely affordable due to the opacities of the environment mentioned previously. The low rate of underwater communications and the latency during the propagation of messages require the robot to possess a full degree of autonomy. For these reasons, new marine robots are designed to make unsupervised decisions in order to achieve a given task. They can be involved in several marine applications such as hydrography, oceanography, climate change monitoring, military operations in mine hunting (Toumelin and Lemaire 2001), wreck searches (L'Hour and Creuze 2016), etc.

Because they sail underwater without receiving orders from the surface, AUVs need to sense their environment and act accordingly; thus, they are equipped with sensors such as sonars or cameras. In addition, they estimate their own position by themselves (Leonard *et al.* 1998), which is always a complicated task in the underwater world. The localization problem will be presented in section I.2, which is the main motivation of this book. The

contributions of this work will be presented through actual experiments involving two AUVs⁴, *Redermor* and *Daurade*, which are introduced below.

The Redermor AUV

The *Redermor*⁵ AUV, shown in Figure I.5, was an experimental robot designed during the Franco-British collaborative project *Remote Mine Hunting System*. Built during the 1990s at DGA Techniques Navales Brest (formerly GESMA), it served as a platform for several studies (Quidu *et al.* 2007). The main characteristics of the vehicle are summarized in Table I.1, (Toumelin and Lemaire 2001).

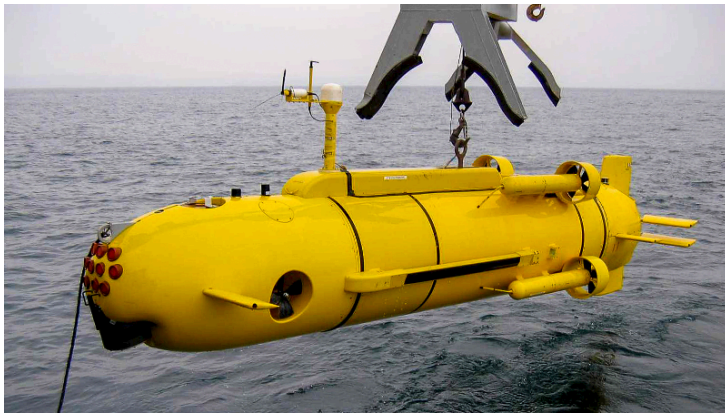



Figure I.5. The Redermor AUV before a sea trial. The thrusters' layout allows it to circumnavigate a point such as a mine to be identified, its front-looking sonar providing different viewing angles of the target. Photo: DGA-TN Brest

During a mission, the position of the robot is provided by an inertial navigation system (INS) coupled with a Doppler Velocity Log (DVL) sensing the robot's speed. The positioning error is estimated at some meters per hour.

⁴ The main characters of this book will be drawn by the following  as a reference to the MOOS-IvP middleware (Benjamin *et al.* 2010) from which this symbol comes. MOOS-IvP is a set of open source modules for providing autonomy on robotic platforms, particularly autonomous marine vehicles. This framework was used during this work as the basis of actual experiments.

⁵ *Redermor* means *rider of the seas* in the Breton language.

It is difficult to provide the reader with accurate figures about this error as it is related to the pattern followed by the vehicle, its altitude or its speed⁶.

Weight : 3400 kg
Length : 6.40 m
Speed : up to 10 knots (5.14 m/s)
Max depth : 200 m

Table I.1. Redermor's main characteristics

The Daurade AUV

Today, *Redermor* is retired and has left its place to the new *Daurade* AUV (see Figure I.6). This vehicle was built by the ECA group, which has been performing many experiments on the shores of France since 2005. It is still used by DGA-TN Brest, in collaboration with the Service Hydrographique et Océanographique de la Marine (SHOM) for survey purposes or mine hunting applications. Its main characteristics are given in Table I.2.



Figure I.6. Daurade AUV managed by the crew of the *Aventurière II*, during an experiment in the Rade de Brest, October 2015.

Photo: S. Rohou

⁶ The DVL accuracy depends among other things on its distance from the seabed and the sensed velocity. For a 1200 kHz Teledyne DVL, the errors are given as follows: ± 0.3 cm/s at 1 m/s, ± 0.4 cm/s at 3 m/s, ± 0.5 cm/s at 5 m/s.

Weight : 1010 kg
Length : 5 m
Speed : up to 8 knots (4.11 m/s)
Max depth : 300 m
Autonomy : 10 h at 4 knots, 2 h at 8 knots
Sonar coverage range : 150 m

Table I.2. *Daurade's main characteristics*

It is equipped with an INS Phins from iXblue, which is connected to a DVL⁷ in the same way as for the *Redermor*. Its positioning accuracy is 3 m/h at 2 knots, or 0.1% of the traveled distance, based on a hybridization INS/DVL. In contrast, 20 meters of positioning error are obtained after 5 minutes of navigation in pure inertial mode.

Redermor and *Daurade* are heavy vehicles with high costs of handling and maintenance. Furthermore, the embedded navigation systems cannot be easily changed, which is a limitation when it comes to try new algorithms for autonomous navigation. This motivated the design of smaller and cheaper units.

The Toutatis AUVs project

A new class of autonomous underwater vehicles was designed during this work. The term *class* refers to a group of several units of the same type. The aim of the *Toutatis*⁸ (Team Of Underwater robots for Autonomous Tasks of Inspection and Survey) project was to apply the tools presented in this book in realistic scenarios. The project has been paused and will resume later.

Figure I.7 presents some modeling views of the vehicles. The units are modular in order to be fit with the mission requirements. The aluminum cage protects the tube, sensors and thrusters. It is also convenient to arrange the devices everywhere on the frame without difficulty. In addition, the cage is used to carry, transport and store the vehicles; then, all AUVs can be stowed on top of each other in a reduced place. Finally, landing on the seabed will not present any risk.

⁷ The vehicle can be configured with either a 300 or 1200 kHz Workhorse Teledyne RDI DVL.

⁸ *Toutatis* is a Celtic god in ancient Gaul and Brittany. It was seen as the tribe's leader: this name illustrates the future behavior of these robots which will act as members of a team based on communication and collaboration.