# A short introduction to Codac

 $\mathsf{SWIM}$  30  $^{\mathrm{th}}$  June 2025, Rennes, France

Tutorial proposed by Fabrice Le Bars, Maël Godard, Damien Massé, Simon Rohou ENSTA, Lab-STICC, Brest, France

https://codac.io/v2/tuto/cp\_robotics











# Codac in a nutshell



- for reals  $x \in \mathbb{R}$ ,  $\mathbf{x} \in \mathbb{R}^n$ : intervals [x] and boxes [x]
- for trajectories  $x(\cdot) : \mathbb{R} \to \mathbb{R}$ : tubes  $[x](\cdot)$



- for reals  $x \in \mathbb{R}$ ,  $\mathbf{x} \in \mathbb{R}^n$ : intervals [x] and boxes [x]
- for trajectories  $x(\cdot) : \mathbb{R} \to \mathbb{R}$ : tubes  $[x](\cdot)$
- for subsets  $\mathbb{X} \subset \mathbb{R}^n$ : thicksets  $\mathbb{X} \in [\mathbb{X}] = [\mathbb{X}^-, \mathbb{X}^+]$



Illustration of a thickset (right-hand side) for enclosing and uncertain red set (left-hand side)

Thick set inversion Desrochers, Jaulin. Artificial Intelligence. Volume 249, Issue C, Pages 1-18, 2017



- for reals  $x \in \mathbb{R}$ ,  $\mathbf{x} \in \mathbb{R}^n$ : intervals [x] and boxes [x]
- for trajectories  $x(\cdot) : \mathbb{R} \to \mathbb{R}$ : tubes  $[x](\cdot)$
- for subsets  $\mathbb{X} \subset \mathbb{R}^n$ : thicksets  $\mathbb{X} \in [\mathbb{X}] = [\mathbb{X}^-, \mathbb{X}^+]$
- etc.



Illustration of a thickset (right-hand side) for enclosing and uncertain red set (left-hand side)

Thick set inversion Desrochers, Jaulin. Artificial Intelligence. Volume 249, Issue C, Pages 1-18, 2017



Example of mixing tubes and thicksets



Computing a Guaranteed Approximation of the Zone Explored by a Robot. Desrochers, Jaulin. *IEEE Trans. on Automatic Control. Volume 62, Issue 1.*, 2017



Catalog Of Domains And Contractors

Several types of **domains**:

- Interval (mainly from the GAOL library)
- IntervalVector, IntervalMatrix (using Eigen templates)
- SlicedTube<T>..., Slice<T>...
- Ellipsoid, Paving, Thickset, ...



Catalog Of Domains And Contractors

Several types of **domains**:

- Interval (mainly from the GAOL library)
- IntervalVector, IntervalMatrix (using Eigen templates)
- SlicedTube<T>..., Slice<T>...
- Ellipsoid, Paving, Thickset, ...

Contractors for various constraints:

- non-linear constraints f(x) = 0 (involving centered form)
- geometric constraints: distance, polar equation, no-cross, ...
- differential equations:  $\dot{x}=f(x),\,\dot{x}=Ax+Bu,\,\iint$
- time uncertainties:  $\mathbf{y} = \mathbf{x}(t)$ , with  $t \in [t]$
- delays:  $x(t) = y(t \tau)$





Example of scalar tube: interval of two trajectories





Computer implementation



The library is open source and available:

- in Python, C++, Matlab
- on Linux, Windows, MacOS systems
- from official packages:

Python package: pip install codac Debian in progress..: sudo apt install libcodac

http://www.codac.io



- Auguste Bourgois
- Cyril Bouvier
- Quentin Brateau
- Gilles Chabert
- Julien Damers
- Benoît Desrochers
- Peter Franek
- Maël Godard
- Nuwan Herath M.
- Luc Jaulin
- Fabrice Le Bars

- Morgan Louédec
- Damien Massé
- Bertrand Neveu
- Verlein Radwan
- Andreas Rauh
- Simon Rohou
- Joris Tillet
- Gilles Trombettoni
- Christophe Viel
- Raphael Voges

# **Constraint programming**

#### **COORD** Contract of the Contractors Contract of the Contractors Contractors And Contractors





# **SLAM**: Simultaneous Localization And Mapping. Classically, we have:

$$\begin{cases} \mathbf{x}(0) = \mathbf{0} & \text{(initial state)} \\ \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)) & \text{(evolution)} \end{cases}$$

With:

- $\boldsymbol{x}:$  state vector (position, heading,  $\dots)$
- u: input vector (command)
- f: evolution function



# **SLAM**: Simultaneous Localization And Mapping. Classically, we have:

$$\begin{cases} \mathbf{x}(0) = \mathbf{0} & \text{(initial state)} \\ \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)) & \text{(evolution)} \\ y_i = \mathbf{g}(\mathbf{x}(t_i), \mathbf{b}_j) & \text{(observations)} \end{cases}$$

With:

- **x**: state vector (position, heading, ...)
- u: input vector (command)
- **f**: evolution function
- g: observation function (scalar, distance equation)
- $y_i$ : scalar measurements (at  $t_i$ ) (distance values)
- **b**<sub>j</sub>: unknown position of a landmark



# **SLAM**: Simultaneous Localization And Mapping. Classically, we have:

$$\begin{cases} \mathbf{x}(0) = \mathbf{0} & \text{(initial state)} \\ \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)) & \text{(evolution)} \\ y_i = \mathbf{g}(\mathbf{x}(t_i), \mathbf{b}_j) & \text{(observations)} \end{cases}$$

With:

- **x**: state vector (position, heading, ...)
- u: input vector (command)
- **f**: evolution function
- g: observation function (scalar, distance equation)
- $y_i$ : scalar measurements (at  $t_i$ ) (distance values)
- **b**<sub>j</sub>: unknown position of a landmark



## Variables:

- reals:  $y_i \in \mathbb{R}$
- vectors:  $\mathbf{b}_j \in \mathbb{R}^2$
- trajectories:  $\mathbf{x}(\cdot): \mathbb{R} \to \mathbb{R}^n$



## Variables:

- reals:  $y_i \in \mathbb{R}$
- vectors:  $\mathbf{b}_j \in \mathbb{R}^2$
- trajectories:  $\mathbf{x}(\cdot): \mathbb{R} \to \mathbb{R}^n$

# Domains (envelopes) of the variables:

- intervals:  $[y_i] \in \mathbb{IR}$
- boxes:  $[\mathbf{b}_j] \in \mathbb{IR}^2$
- tubes:  $[\mathbf{x}](\cdot): \mathbb{R} \to \mathbb{IR}^n$



**Tube**  $[x](\cdot)$ : 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  $x(\cdot)$ 



$$\begin{cases} \dot{\mathbf{x}}(\cdot) = \mathbf{f}(\mathbf{x}(\cdot)) \\ y_i = g(\mathbf{x}_{1,2}(t_i), \mathbf{b}_j) \end{cases}$$



$$\begin{cases} \dot{\mathbf{x}}(\cdot) = \mathbf{f}(\mathbf{x}(\cdot)) \\ y_i = g(\mathbf{x}_{1,2}(t_i), \mathbf{b}_j) \end{cases}$$

$$- \ \mathbf{v}(\cdot) = \mathbf{f}\big(\mathbf{x}(\cdot)\big) \rightarrow \text{algebraic constraint} \rightarrow \mathcal{C}_{\mathbf{f}}\big([\mathbf{x}](\cdot), [\mathbf{v}](\cdot)\big)$$



$$\begin{cases} \dot{\mathbf{x}}(\cdot) = \mathbf{f}(\mathbf{x}(\cdot)) \\ y_i = g(\mathbf{x}_{1,2}(t_i), \mathbf{b}_j) \end{cases}$$

$$\begin{split} & - \ \textbf{v}(\cdot) = \textbf{f}\big(\textbf{x}(\cdot)\big) \rightarrow \text{algebraic constraint} \rightarrow \mathcal{C}_{\textbf{f}}\big([\textbf{x}](\cdot), [\textbf{v}](\cdot)\big) \\ & - \ \dot{\textbf{x}}(\cdot) = \textbf{v}(\cdot) \rightarrow \text{derivative constraint} \rightarrow \mathcal{C}_{\mathrm{deriv}}\big([\textbf{x}](\cdot), [\textbf{v}](\cdot)\big) \end{split}$$



$$\begin{cases} \dot{\mathbf{x}}(\cdot) = \mathbf{f}(\mathbf{x}(\cdot)) \\ y_i = g(\mathbf{x}_{1,2}(t_i), \mathbf{b}_j) \end{cases}$$

$$- \mathbf{v}(\cdot) = \mathbf{f}(\mathbf{x}(\cdot)) \rightarrow \text{algebraic constraint} \rightarrow \mathcal{C}_{\mathbf{f}}([\mathbf{x}](\cdot), [\mathbf{v}](\cdot))$$

- $\ \dot{\textbf{x}}(\cdot) = \textbf{v}(\cdot) \rightarrow \text{derivative constraint} \rightarrow \mathcal{C}_{\mathrm{deriv}}\big([\textbf{x}](\cdot), [\textbf{v}](\cdot)\big)$
- $\mathbf{p}_i = \mathbf{x}_{1,2}(t_i) \rightarrow \text{evaluation constraint} \rightarrow \mathcal{C}_{\text{eval}}\big([t_i], [\mathbf{p}_i], [\mathbf{x}_{1,2}](\cdot)\big)$



$$\begin{cases} \dot{\mathbf{x}}(\cdot) = \mathbf{f}(\mathbf{x}(\cdot)) \\ y_i = g(\mathbf{x}_{1,2}(t_i), \mathbf{b}_j) \end{cases}$$

$$\begin{aligned} - \mathbf{v}(\cdot) &= \mathbf{f}(\mathbf{x}(\cdot)) \rightarrow \text{algebraic constraint} \rightarrow \mathcal{C}_{\mathbf{f}}([\mathbf{x}](\cdot), [\mathbf{v}](\cdot)) \\ - \dot{\mathbf{x}}(\cdot) &= \mathbf{v}(\cdot) \rightarrow \text{derivative constraint} \rightarrow \mathcal{C}_{\text{deriv}}([\mathbf{x}](\cdot), [\mathbf{v}](\cdot)) \\ - \mathbf{p}_{i} &= \mathbf{x}_{1,2}(t_{i}) \rightarrow \text{evaluation constraint} \rightarrow \mathcal{C}_{\text{eval}}([t_{i}], [\mathbf{p}_{i}], [\mathbf{x}_{1,2}](\cdot)) \\ - y_{i} &= g(\mathbf{p}_{i}, \mathbf{b}_{j}) \rightarrow \text{distance constraint} \rightarrow \mathcal{C}_{\text{dist}}([\mathbf{p}_{i}], [\mathbf{b}_{j}], [y_{i}]) \end{aligned}$$



 $\mathbf{v}(\cdot)$  and  $\mathbf{p}_i$  are intermediate variables

 $\begin{cases} \dot{\mathbf{x}}(\cdot) = \mathbf{f}(\mathbf{x}(\cdot)) \\ y_i = g(\mathbf{x}_{1,2}(t_i), \mathbf{b}_j) \end{cases}$ 

$$- \mathbf{v}(\cdot) = \mathbf{f}(\mathbf{x}(\cdot)) \rightarrow \text{algebraic constraint} \rightarrow \mathcal{C}_{\mathbf{f}}([\mathbf{x}](\cdot), [\mathbf{v}](\cdot))$$

- $\ \dot{\textbf{x}}(\cdot) = \textbf{v}(\cdot) \rightarrow \text{derivative constraint} \rightarrow \mathcal{C}_{\mathrm{deriv}}\big([\textbf{x}](\cdot), [\textbf{v}](\cdot)\big)$
- $\mathbf{p}_i = \mathbf{x}_{1,2}(t_i) \rightarrow \text{evaluation constraint} \rightarrow \mathcal{C}_{\text{eval}}([t_i], [\mathbf{p}_i], [\mathbf{x}_{1,2}](\cdot))$

$$- y_i = g(\mathbf{p}_i, \mathbf{b}_j) \rightarrow \text{distance constraint} \rightarrow \mathcal{C}_{\text{dist}}([\mathbf{p}_i], [\mathbf{b}_j], [y_i])$$



 $\begin{cases} \dot{\mathbf{x}}(\cdot) = \mathbf{f}(\mathbf{x}(\cdot)) \\ y_i = g(\mathbf{x}_{1,2}(t_i), \mathbf{b}_j) \end{cases}$ 

# $\mathbf{v}(\cdot)$ and $\mathbf{p}_i$ are intermediate variables

Note: some symbolic solver could break down such problem automatically.

$$- \mathbf{v}(\cdot) = \mathbf{f}(\mathbf{x}(\cdot)) \rightarrow \text{algebraic constraint} \rightarrow \mathcal{C}_{\mathbf{f}}([\mathbf{x}](\cdot), [\mathbf{v}](\cdot))$$

- $\ \dot{\textbf{x}}(\cdot) = \textbf{v}(\cdot) \rightarrow \text{derivative constraint} \rightarrow \mathcal{C}_{\mathrm{deriv}}\big([\textbf{x}](\cdot), [\textbf{v}](\cdot)\big)$
- $\mathbf{p}_i = \mathbf{x}_{1,2}(t_i) \rightarrow \text{evaluation constraint} \rightarrow \mathcal{C}_{\text{eval}}([t_i], [\mathbf{p}_i], [\mathbf{x}_{1,2}](\cdot))$

$$- y_i = g(\mathbf{p}_i, \mathbf{b}_j) \rightarrow \text{distance constraint} \rightarrow \mathcal{C}_{\text{dist}}([\mathbf{p}_i], [\mathbf{b}_j], [y_i])$$



#### Differential constraint:

- $\ \dot{x}(\cdot) = v(\cdot)$
- one trajectory and its derivative





#### Differential constraint:

- $\ \dot{x}(\cdot) = v(\cdot)$
- one trajectory and its derivative
- Contractor programming:
  - $\ \mathcal{C}_{\mathrm{deriv}}\big([\boldsymbol{x}](\cdot), [\boldsymbol{v}](\cdot)\big)$









