# Lie symmetries applied to guaranteed integration: application to mobile robotics localisation

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#### Hanover, 20th July 2022





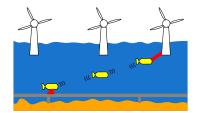
### Section 1

# Introduction

# Context of this research

#### Applications:

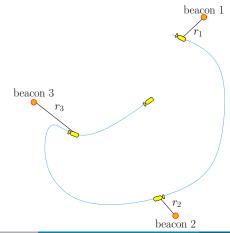
- Offshore wind farms
- Underwater mining
- Underwater sensor fields
- Constraint:
  - No possibility to return to the surface before the end of the mission
  - Cheaper sensors (swarms)
- $\longrightarrow$  Problem to localise our robot



Autonomous Underwater Vehicles (AUV) used as data mules and for monitoring

# The localisation problem

- Aim:
  - Locate the robot offline to replace data on map
- Data available
  - Behaviour of the robot (evolution function)
  - Range-only measurements
  - Completely unknown initial condition



# Outline



- 2 Modelling a robot
- Towards a new guaranteed integration method
- 4 Solving the localisation problem for an unknown initial condition
- 5 Conclusion

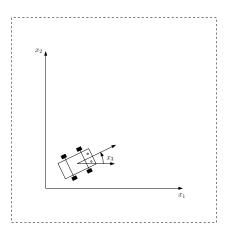
#### Section 2

# Modelling a robot

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The robot state is represented by a vector. For instance:

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$



# Differential equation

Behaviour modeled by the evolution function

 $\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)).$ 

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ln the examples we will consider in this presentation,  $\mathbf{u}(t)$  is known.

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Finding solution of an Initial Value Problem (IVP)

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t)), t \in T \\ \mathbf{x}(t=0) = \mathbf{x}_0 \in \mathbb{R}^n \end{cases}$$

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- 4. For any  $\mathbf{x} \in S$ , and  $t, \tau \in T$ ,  $\Phi(t, \Phi(\tau, \mathbf{x})) = \Phi(t + \tau, \mathbf{x})$ .

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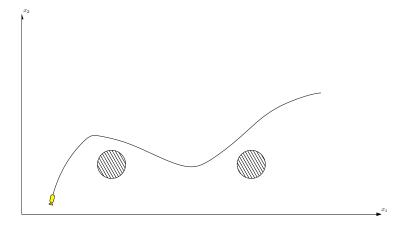
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- We will focus on continuous time systems where  $T = \mathbb{R}$ .
- An analytic expression of the flow function is rarely available

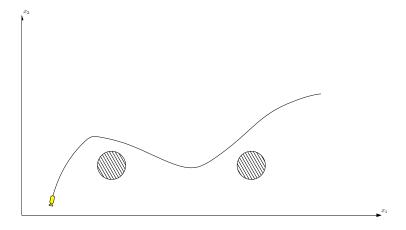
#### Section 3

# Towards a new guaranteed integration method

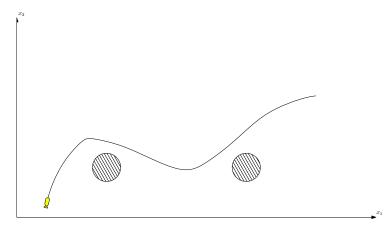
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- ▶ Need for guarantee as we are working with complex systems
- Conventional tools can be quite slow when performing numerous integrations
- Conventional tools cannot deal with large initial conditions

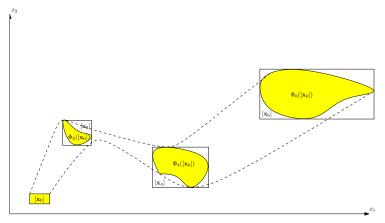


2 main methods:

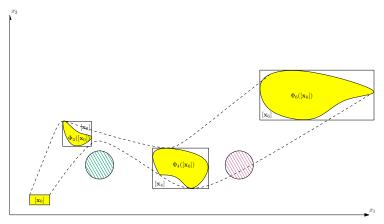
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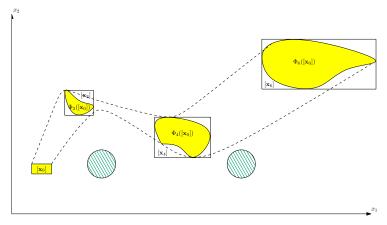
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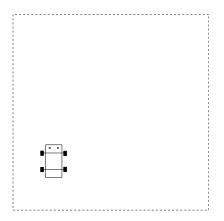


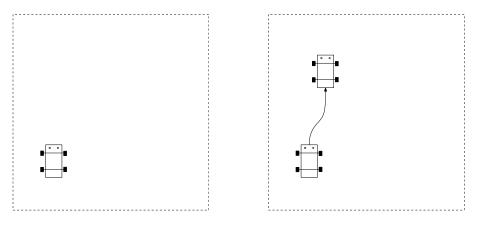
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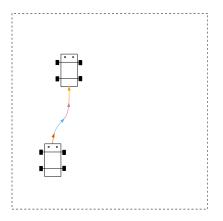


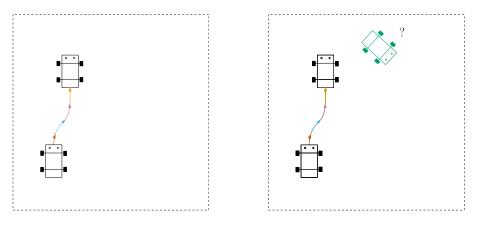
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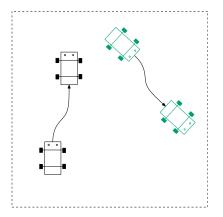


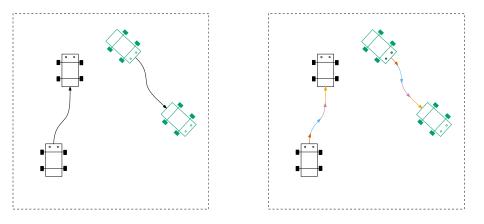


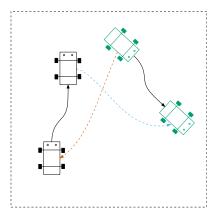


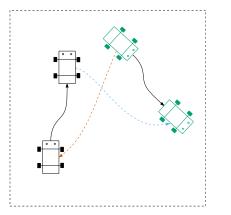


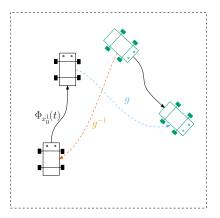








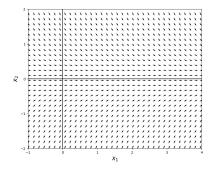




# Hints from the vector field

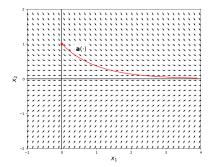
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$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) = \begin{pmatrix} 1 \\ -x_2 \end{pmatrix}$$



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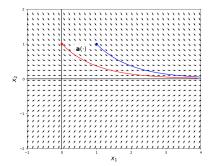
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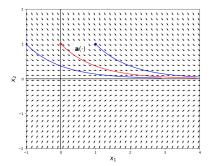
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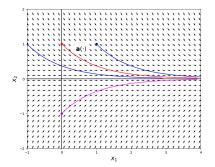
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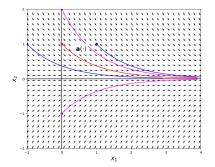
- A translation symmetry along  $Ox_1$
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# Action of a diffeomorphisms

#### Definition (Action of diffeomorphisms)

Consider a state equation  $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$ ,  $\mathbf{x} \in \mathbb{R}^n$  and  $\mathbf{g} \in \text{diff}(\mathbb{R}^n)$ . We define the action  $\bullet$  of  $\mathbf{g}$  on  $\mathbf{f}$  as

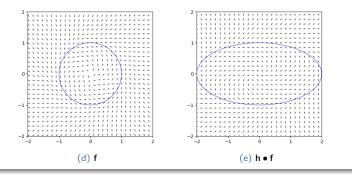
$$\mathbf{g} \bullet \mathbf{f} = \left(\frac{d\mathbf{g}}{d\mathbf{x}} \circ \mathbf{g}^{-1}\right) \cdot \left(\mathbf{f} \circ \mathbf{g}^{-1}\right)$$

# Action of a diffeomophisms

#### Example

Consider:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) = \begin{pmatrix} -x_1^3 - x_1x_2^2 + x_1 - x_2 \\ -x_2^3 - x_1^2x_2 + x_1 + x_2 \end{pmatrix} \text{ and } \mathbf{h}(\mathbf{x}) = \begin{pmatrix} 2x_1 \\ x_2 \end{pmatrix}$$

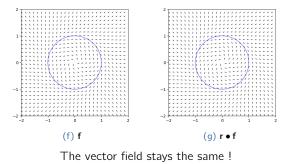


# Action of a diffeomophisms

#### Example

Consider the previous system and the following function:

$$\mathbf{r}(\mathbf{x}) = \begin{pmatrix} \cos\left(\frac{\pi}{4}\right) x_1 - \sin\left(\frac{\pi}{4}\right) x_2 \\ \cos\left(\frac{\pi}{4}\right) x_2 + \sin\left(\frac{\pi}{4}\right) x_1 \end{pmatrix}$$



#### Lie symmetry

#### Definition (Lie symmetry)

 $g \in diff(\mathbb{R}^n)$  is a symmetry of f if the action  $\bullet$  of g on f leaves f unchanged i.e

 $\mathbf{g} \bullet \mathbf{f} = \mathbf{f}.$ 

Lie symmetries are also called **stabilisers**.

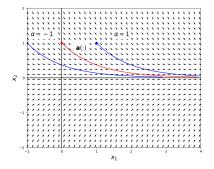
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$$\begin{aligned} \mathbf{g}_{\alpha} \bullet \mathbf{f}(\mathbf{x}) &= \left(\frac{d\mathbf{g}_{\alpha}}{d\mathbf{x}} \circ \mathbf{g}_{\alpha}^{-1}\right) \cdot \left(\mathbf{f} \circ \mathbf{g}_{\alpha}^{-1}\right)(\mathbf{x}) \\ &= \left(\frac{d\mathbf{g}_{\alpha}}{d\mathbf{x}} \cdot \mathbf{f}\right) \circ \mathbf{g}_{\alpha}^{-1}(\mathbf{x}) \\ &= \left(\left(\begin{array}{cc}1 & 0\\0 & 1\end{array}\right) \cdot \left(\begin{array}{c}1\\-x_2\end{array}\right)\right) \circ \left(\begin{array}{c}x_1 - \alpha\\x_2\end{array}\right) \\ &= \left(\begin{array}{c}1\\-x_2\end{array}\right) \\ &= \mathbf{f}(\mathbf{x}) \end{aligned}$$



#### Mirror-symmetry

$$\mathbf{g}_{\boldsymbol{\beta}}: \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \mapsto \begin{pmatrix} x_1 \\ \boldsymbol{\beta} x_2 \end{pmatrix}$$

### Mirror-symmetry

g

$$\mathbf{g}_{\beta} : \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \mapsto \begin{pmatrix} x_1 \\ \beta x_2 \end{pmatrix}$$

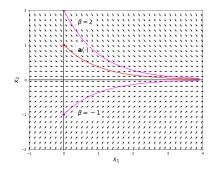
$$\mathbf{g} \bullet \mathbf{f}(\mathbf{x}) = \left( \frac{d\mathbf{g}_{\beta}}{d\mathbf{x}} \circ \mathbf{g}_{\beta}^{-1} \right) \cdot \left( \mathbf{f} \circ \mathbf{g}_{\beta}^{-1} \right) (\mathbf{x})$$

$$= \left( \frac{d\mathbf{g}_{\beta}}{d\mathbf{x}} \cdot \mathbf{f} \right) \circ \mathbf{g}_{\beta}^{-1} (\mathbf{x})$$

$$= \left( \begin{pmatrix} 1 & 0 \\ 0 & \beta \end{pmatrix} \cdot \begin{pmatrix} 1 \\ -x_2 \end{pmatrix} \right) \circ \begin{pmatrix} x_1 \\ \frac{x_2}{\beta} \end{pmatrix}$$

$$= \begin{pmatrix} 1 \\ -x_2 \end{pmatrix}$$

$$= \mathbf{f}(\mathbf{x})$$



# Complete symmetry

$$\mathbf{g}_{\mathbf{P}}: \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \mapsto \begin{pmatrix} x_1 + \mathbf{p}_1 \\ \mathbf{p}_2 x_2 \end{pmatrix}$$

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Definition (Lie group of symmetry)

Consider a state equation  $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x})$  and a manifold  $\mathbb{P}$ . A Lie group  $G_{\mathbf{p}}$  of symmetries is a family of diffeomorphisms  $\mathbf{g}_{\mathbf{p}} \in \text{diff}(\mathbb{R}^n)$  parameterised by  $\mathbf{p} \in \mathbb{P}$  such that:

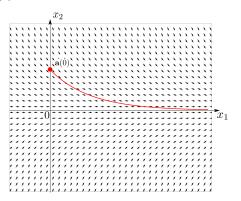
- $G_p$  is a Lie group with respect to the composition  $\circ$ ,
- $\blacktriangleright \ \forall p \in \mathbb{P}, g_p \bullet f = f.$

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We have:

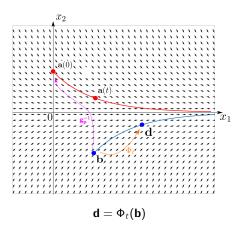
- A reference trajectory denoted a(·) (painted red)
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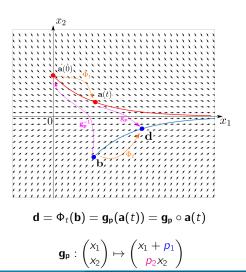
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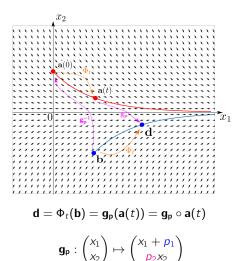
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Therefore

$$\Phi_t(x) = \mathbf{g}_{\mathbf{p}} \circ \mathbf{a}(t)$$



To find the right value of **p**, we must solve

 $\mathbf{g}_{\mathbf{p}}(\mathbf{a}(0)) = \mathbf{b}_{\mathbf{x}}$ 

in order to express  $\mathbf{p}$  using only  $\mathbf{a}(0)$  and  $\mathbf{b}$ .

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Using the previous example :

$$\mathbf{g}_{\mathbf{p}}(\mathbf{a}(0)) = \mathbf{b} \iff \begin{pmatrix} a_1 + p_1 \\ p_2 a_2 \end{pmatrix} = \mathbf{b}$$
$$\iff \mathbf{p} = \begin{pmatrix} b_1 - a_1 \\ \frac{b_2}{a_2} \end{pmatrix}$$

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We introduce a new tool, the **transport function** denoted h(x, a) such that:

$$\mathbf{p} = \mathbf{h}(\mathbf{b}, \mathbf{a}) = \begin{pmatrix} b_1 - a_1 \\ \frac{b_2}{a_2} \end{pmatrix}.$$

#### Definition (Transport function)

Consider a transitive Lie group of symmetries  $G_{\mathbf{p}}$  (i.e it only has one orbit). In this case, there exists a function  $\mathbf{h} : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{P}$  such that  $\mathbf{h}(\mathbf{x}, \mathbf{a})$  corresponds to the displacement  $\mathbf{p}$  to be chosen so that the point  $\mathbf{a}$  is moved to  $\mathbf{x}$  by  $\mathbf{g}_{\mathbf{p}}$ , which means:

 $g_{h(\boldsymbol{x},\boldsymbol{a})}(\boldsymbol{a}) = \boldsymbol{x}$ 

#### Reference:

$$\mathbf{a}(t)\in [\mathbf{a}](t)$$
,  $\mathbf{a}(0)=egin{pmatrix}0\1\end{pmatrix}$ 

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Symmetry:

$$\mathbf{g}_{\mathbf{p}}: \begin{pmatrix} u_1\\ u_2 \end{pmatrix} \mapsto \begin{pmatrix} u_1+p_1\\ p_2u_2 \end{pmatrix}$$
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$$\Phi_t(\mathbf{x}) = \mathbf{g}_{\mathbf{p}} \circ \mathbf{a}(t)$$
  
=  $\mathbf{g}_{\mathbf{h}(\mathbf{x}, \mathbf{a}_0)} \circ \mathbf{a}(t)$   
=  $\mathbf{g}_{x_1, x_2} \circ \begin{pmatrix} a_1(t) \\ a_2(t) \end{pmatrix}$   
=  $\begin{pmatrix} a_1(t) + x_1 \\ x_2 \cdot a_2(t) \end{pmatrix}$   
=  $\begin{pmatrix} t + x_1 \\ x_2 \cdot e^{-t} \end{pmatrix}$ 

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Transport function:

$$\mathbf{h}(\mathbf{x},\mathbf{a}) = \begin{pmatrix} x_1 - \partial_1 \\ \frac{x_2}{\partial_2} \end{pmatrix},$$

$$\begin{aligned} \mathbf{f}_{t}(\mathbf{x}) &= \mathbf{g}_{\mathbf{p}} \circ \mathbf{a}(t) \\ &= \mathbf{g}_{\mathsf{h}(\mathbf{x}, \mathbf{a}_{0})} \circ \mathbf{a}(t) \\ &= \mathbf{g}_{x_{1}, x_{2}} \circ \begin{pmatrix} a_{1}(t) \\ a_{2}(t) \end{pmatrix} \\ &= \begin{pmatrix} a_{1}(t) + x_{1} \\ x_{2} \cdot a_{2}(t) \end{pmatrix} \\ &= \begin{pmatrix} t + x_{1} \\ x_{2} \cdot e^{-t} \end{pmatrix} \end{aligned}$$

Φ

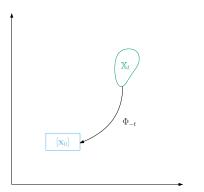
We finally have a analytic expression for the flow !

#### A set inversion problem

With the flow function  $\Phi_t$ , performing a guaranteed integration for an uncertain initial condition is equivalent to solving a set inversion problem.

Consider a uncertain initial box  $[x_0]$  for which we want to find the image set by  $\Phi_t$ . We want to find the set  $X_t$  such that

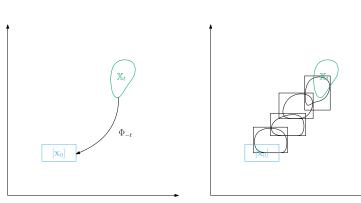
$$\mathbb{X}_t = \Phi_{-t}^{-1}([\mathbf{x}_0]).$$



#### A set inversion problem

With the flow function  $\Phi_t$ , performing a guaranteed integration for an uncertain initial condition is equivalent to solving a set inversion problem.

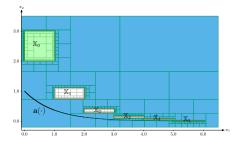
Consider a uncertain initial box  $[x_0]$  for which we want to find the image set by  $\Phi_t$ . We want to find the set  $X_t$  such that



$$\mathbb{X}_t = \Phi_{-t}^{-1}([\mathbf{x}_0])$$

# Applying a SIVIA algorithm

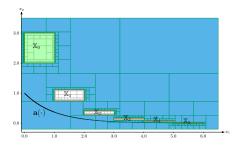
• 
$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) = \begin{pmatrix} 1 \\ -x_2 \end{pmatrix}$$
  
•  $[\mathbf{x}_0] = [0, 1] \times [2, 3]$ 



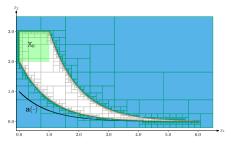
Discrete sets computation (Lie 70 ms, CAPD 300 ms)

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Discrete sets computation (Lie 70 ms, CAPD 300 ms)



Continous set computation (229 ms)

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Julien Damers, Luc Jaulin, Simon Rohou. "Lie symmetries applied to interval integration". Accepted in: Automatica 2022

#### Section 4

# Solving the localisation problem for an unknown initial condition

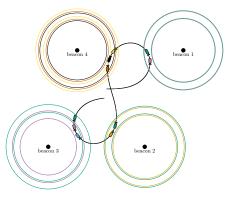
# Problem presentation

#### Hypotheses:

- 1 robot
- 4 beacons
- Completely unknown inital condition
- Range only measurements

Objectives:

- Estimate the initial condition
- Locate the robot



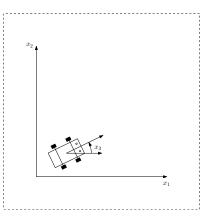
# The tank-like robot model

Let us consider the system defined by:

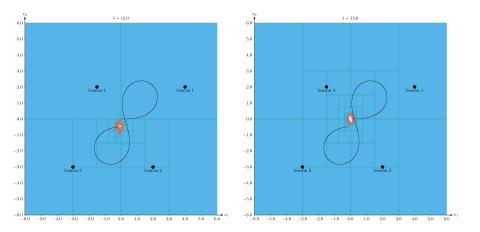
$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}(t)) = \begin{pmatrix} u_1(t) \cos(x_3) \\ u_1(t) \sin(x_3) \\ u_2(t) \end{pmatrix}$$

- General kinematic model
- Can be applied to a large group of robots

In our example u(t) is known for all t



# Result



#### Section 5

# Conclusion

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Prospects:

- Solve differential inclusions  $\dot{\mathbf{x}} \in \mathbf{F}(\mathbf{x}, \mathbf{u})$
- ► Handle both space and time displacement (sliding window)
- Apply symmetries in other context than interval analysis (particle filter)
- Compute the transport function automatically

Thank you for your attention

#### Conclusio

# Codac code

// The uncertain initial condition
<pre>IntervalVector x_0({{0,1},{2,3}});</pre>
// The space to explore for the set inversion
IntervalVector m({{-0.1,6.5}, {-0.2,3.5}});
double epsilon = 0.01; // define accuracy of paving
<pre>// define transformation function</pre>
Function phi("x1","x2","t","(x1+t;x2*exp(-t))");
// Create the general separator on phi t with [z 0] as constraint
SepFwdBwd SepPhi(phi,x_0);
// Define the time for which we want to perform the integration
Interval t(-3,-3);
// Create the projected separator object
SepProj sepProj(SepPhi,t,epsilon);
// Perform the set inversion algorithm
vector <vector<intervalvector>&gt; pavings = sivia(m,sepProj,epsilon);</vector<intervalvector>

