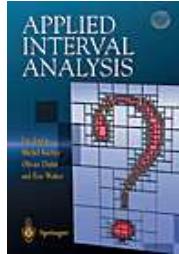


Quelques avancées du calcul par intervalles; applications en robotique mobile



Luc Jaulin, OSM, ENSTA-Bretagne

Douai, le jeudi 7 avril 2011

1 Approche ensembliste

1.1 Calcul par intervalles

$$\begin{array}{lcl} [-1,3]+[2,5] & = & [1,8], \\ [-1,3].[2,5] & = & [-5,15], \\ [-2,6]/[2,5] & = & [-1,3]. \end{array}$$

Si f est donné par

Algorithm f (in: $\mathbf{x} = (x_1, x_2, x_3)$, out: $\mathbf{y} = (y_1, y_2)$)

1 $z := x_1;$ 2 for $k := 0$ to 100 3 $z := x_2(z + kx_3);$ 4 next; 5 $y_1 := z;$ 6 $y_2 := \sin(zx_1);$

alors sa fonction d'inclusion naturelle est

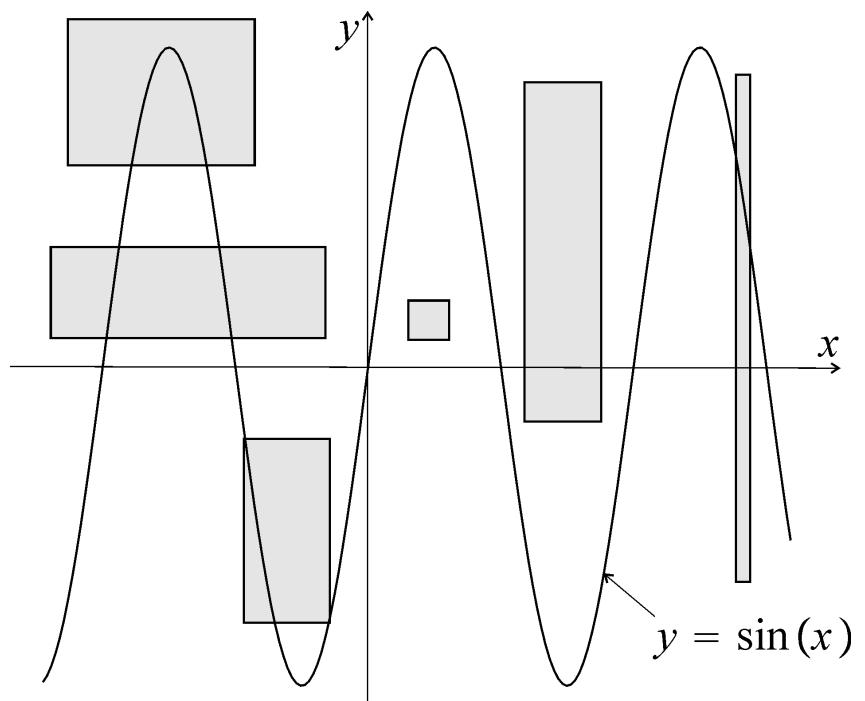
Algorithm [f](in: [x], out: [y])	
1	$[z] := [x_1];$
2	for $k := 0$ to 100
3	$[z] := [x_2] * ([z] + k * [x_3]);$
4	next;
5	$[y_1] := [z];$
6	$[y_2] := \sin([z] * [x_1]);$

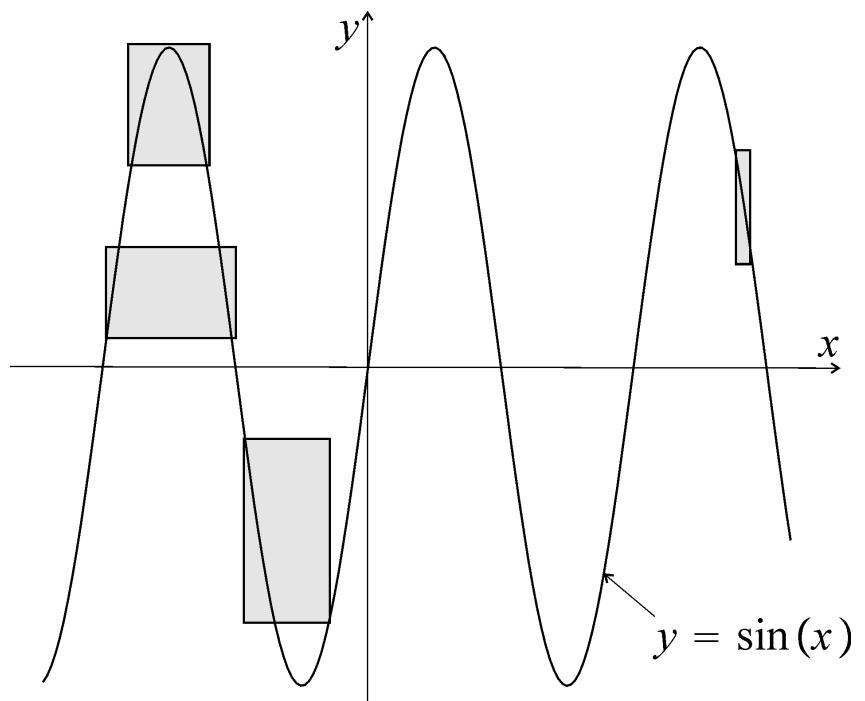
Montrer setdemo

1.2 Contracteurs

L'opérateur $\mathcal{C} : \mathbb{IR}^n \rightarrow \mathbb{IR}^n$ est un *contracteur* pour l'équation $f(\mathbf{x}) = 0$, si

$$\forall [\mathbf{x}] \in \mathbb{IR}^n, \left\{ \begin{array}{l} \mathcal{C}([\mathbf{x}]) \subset [\mathbf{x}] \\ \mathbf{x} \in [\mathbf{x}] \text{ et } f(\mathbf{x}) = 0 \Rightarrow \mathbf{x} \in \mathcal{C}([\mathbf{x}]) \end{array} \right.$$





intersection	$(\mathcal{C}_1 \cap \mathcal{C}_2)([x]) \stackrel{\text{def}}{=} \mathcal{C}_1([x]) \cap \mathcal{C}_2([x])$
union	$(\mathcal{C}_1 \cup \mathcal{C}_2)([x]) \stackrel{\text{def}}{=} [\mathcal{C}_1([x]) \cup \mathcal{C}_2([x])]$
composition	$(\mathcal{C}_1 \circ \mathcal{C}_2)([x]) \stackrel{\text{def}}{=} \mathcal{C}_1(\mathcal{C}_2([x]))$
répétition	$\mathcal{C}^\infty \stackrel{\text{def}}{=} \mathcal{C} \circ \mathcal{C} \circ \mathcal{C} \circ \dots$

1.3 Algorithme de propagation-bissection

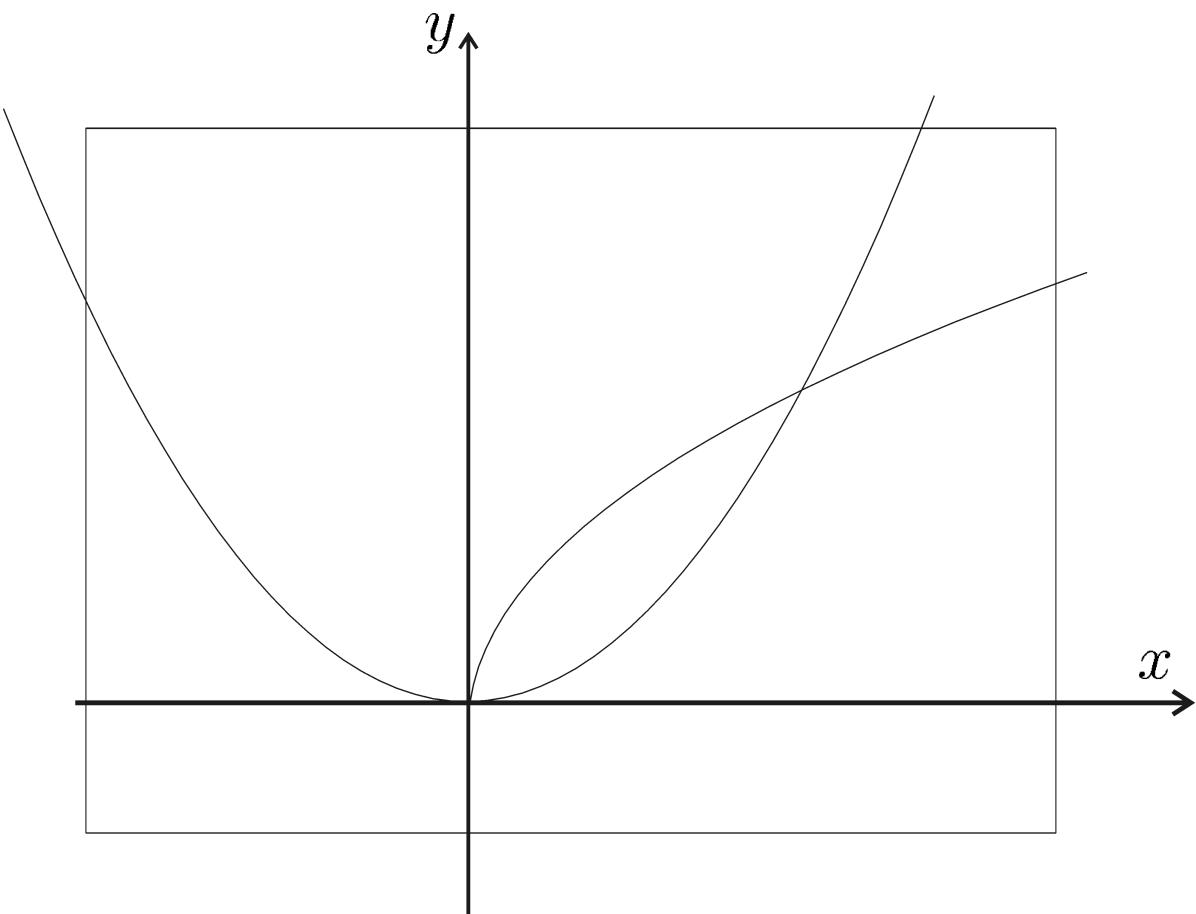
Exemple. Cherchons à résoudre.

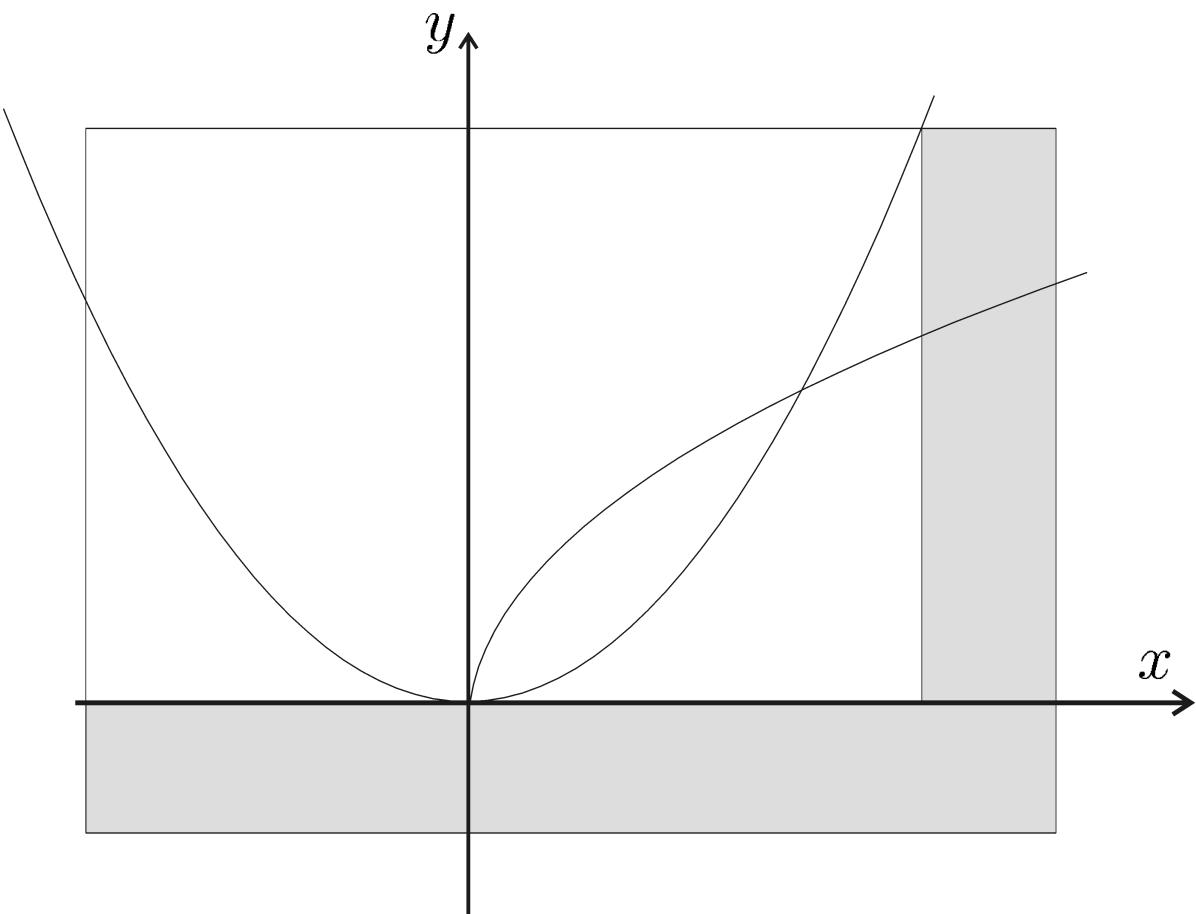
$$\begin{aligned}y &= x^2 \\y &= \sqrt{x}.\end{aligned}$$

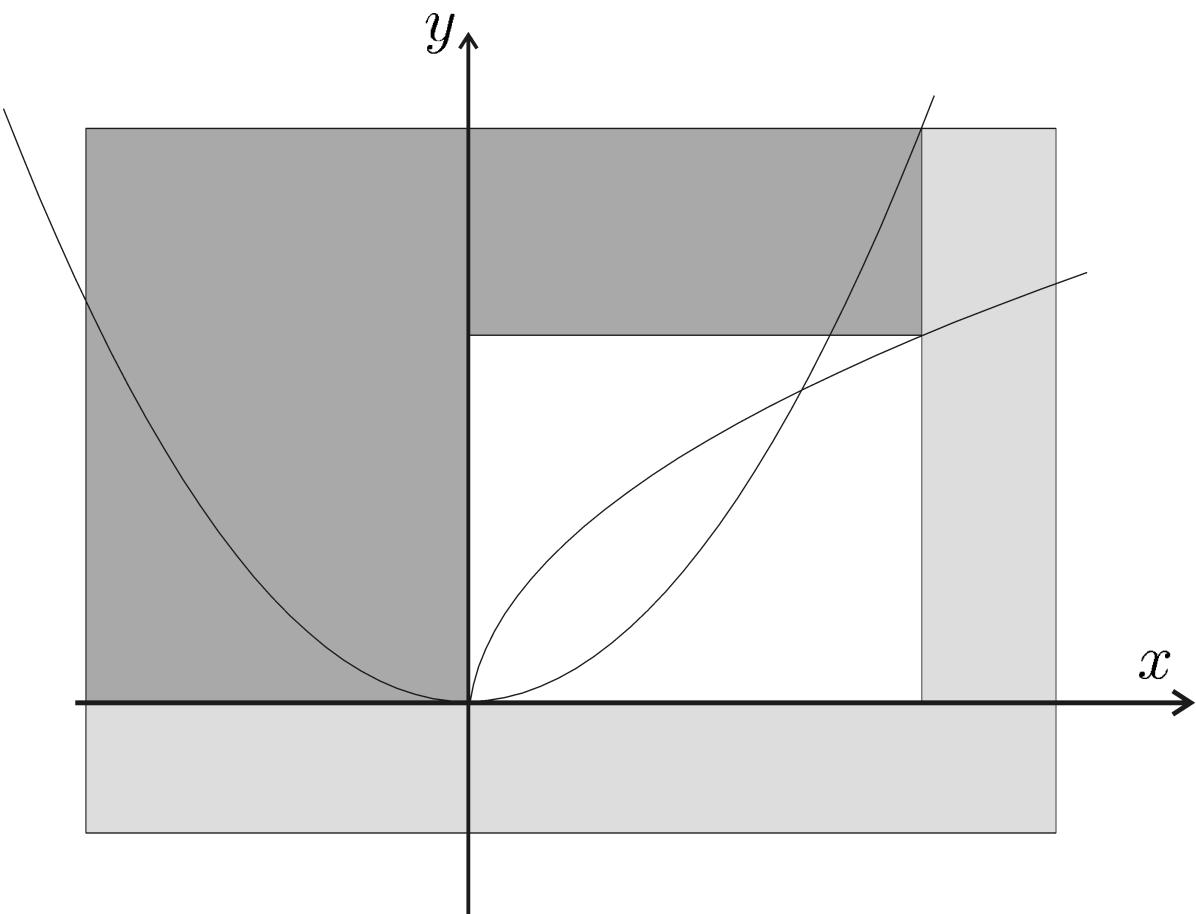
On a deux contracteurs

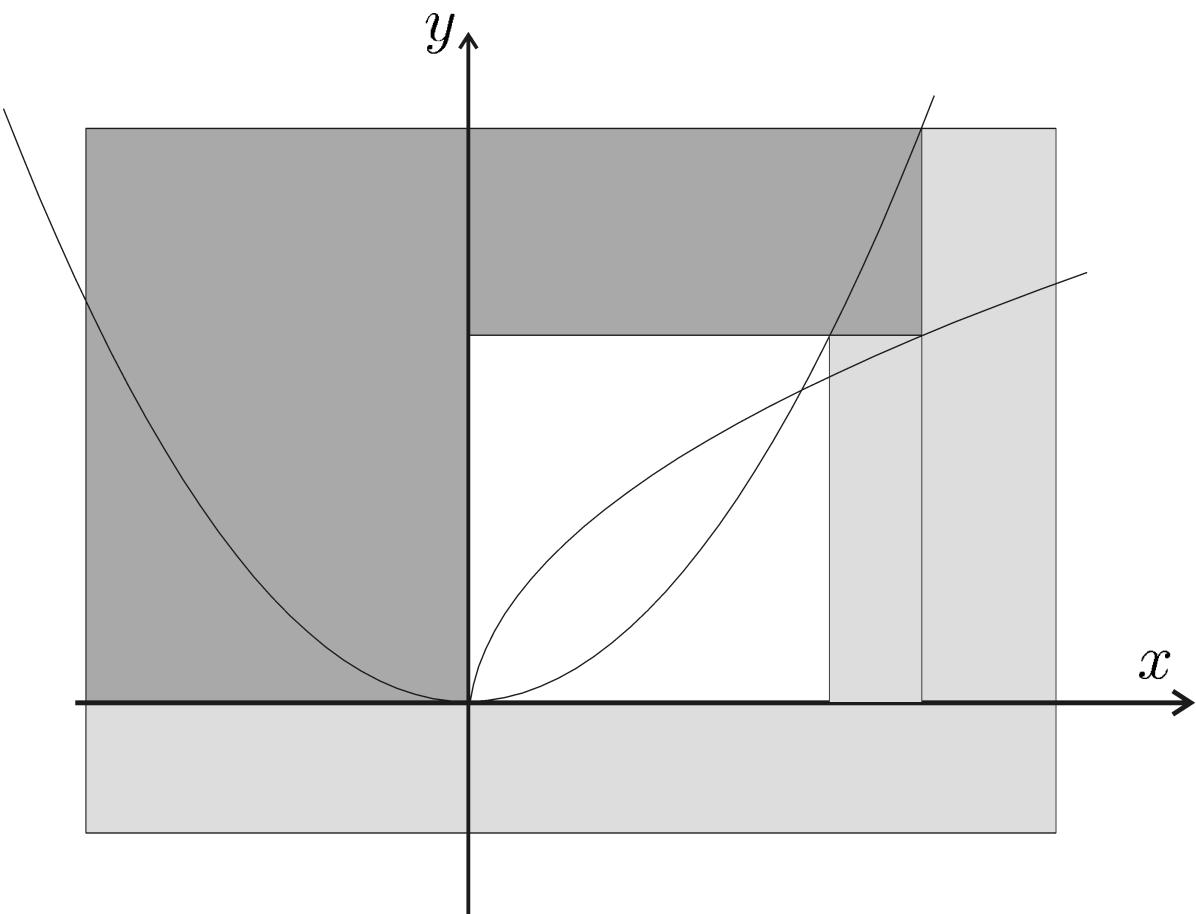
$$\mathcal{C}_1 : \begin{cases} [y] = [y] \cap [x]^2 \\ [x] = [x] \cap \sqrt{[y]} \end{cases} \text{ associé à } y = x^2$$

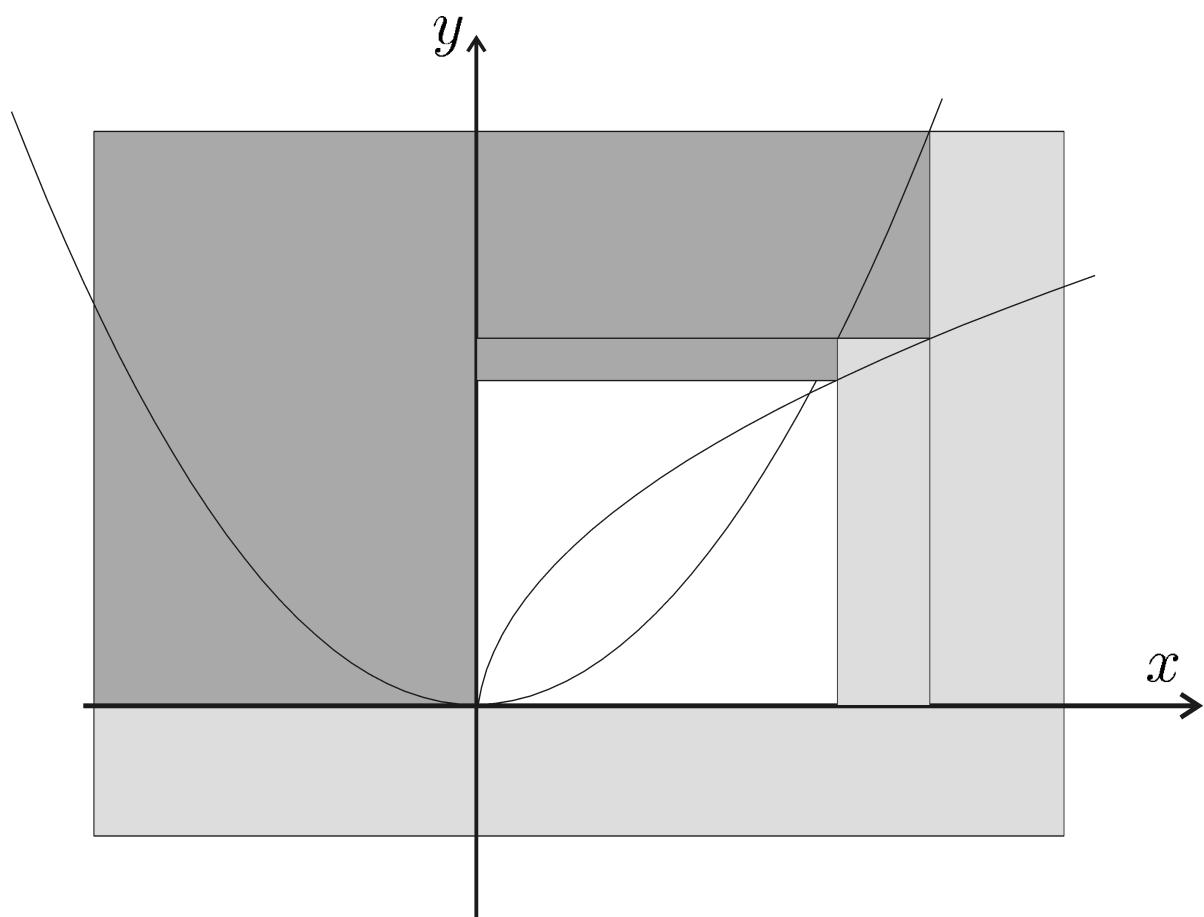
$$\mathcal{C}_2 : \begin{cases} [y] = [y] \cap \sqrt{[x]} \\ [x] = [x] \cap [y]^2 \end{cases} \text{ associé à } y = \sqrt{x}$$

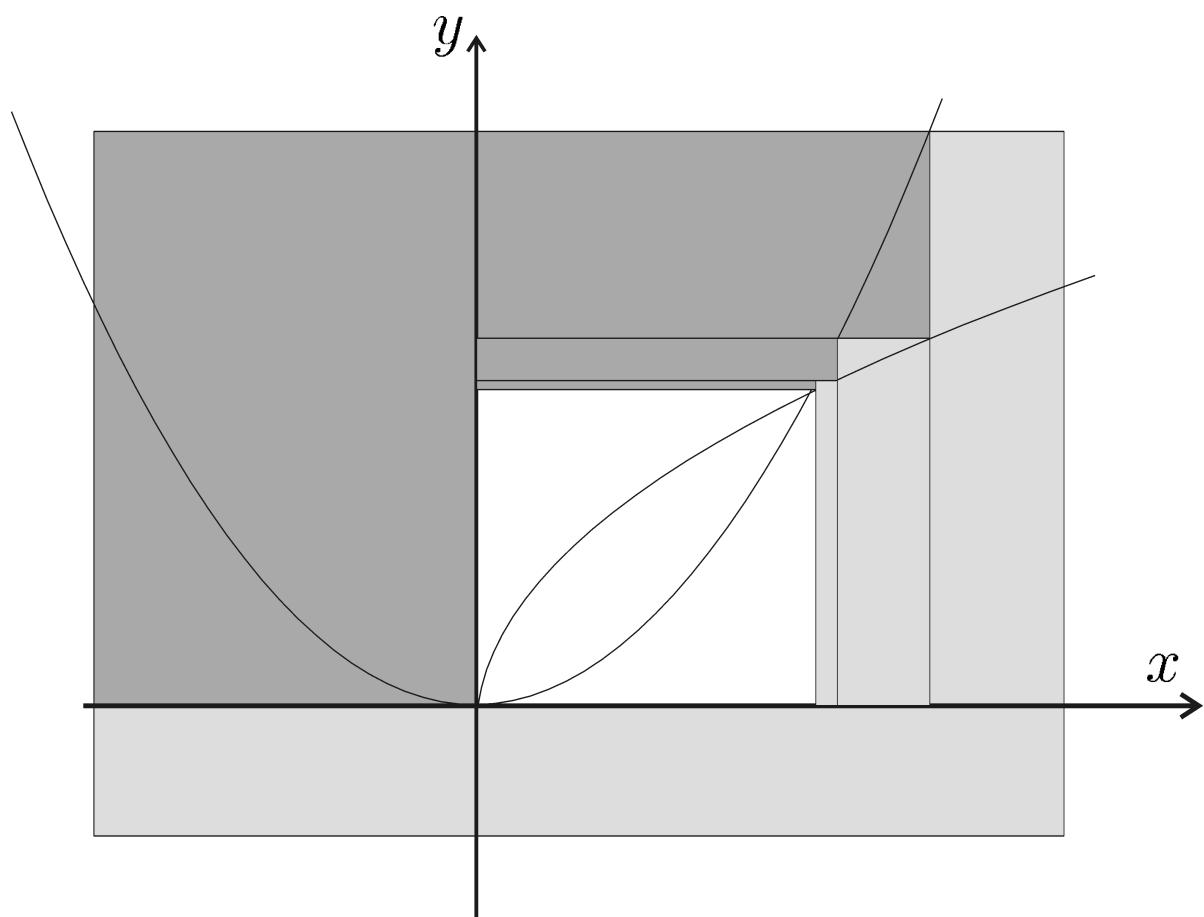


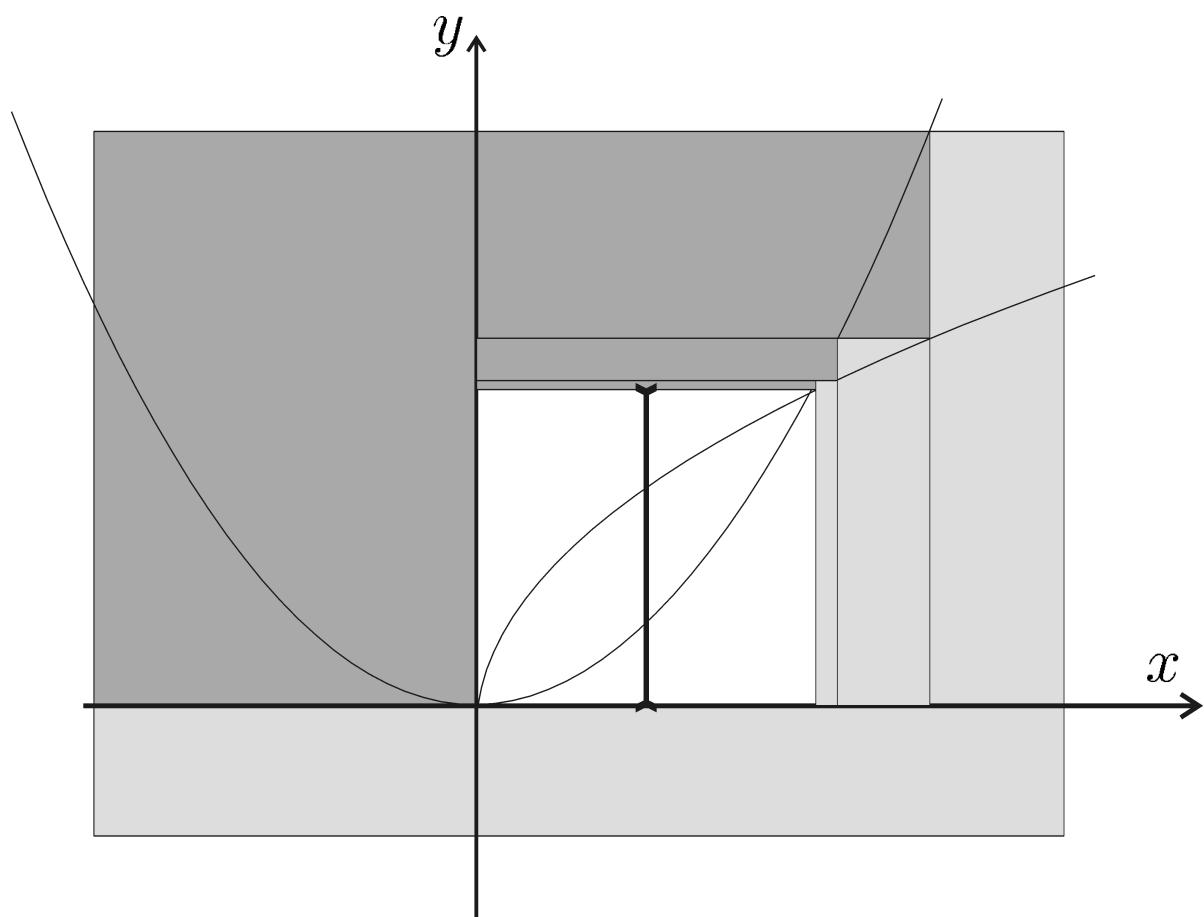


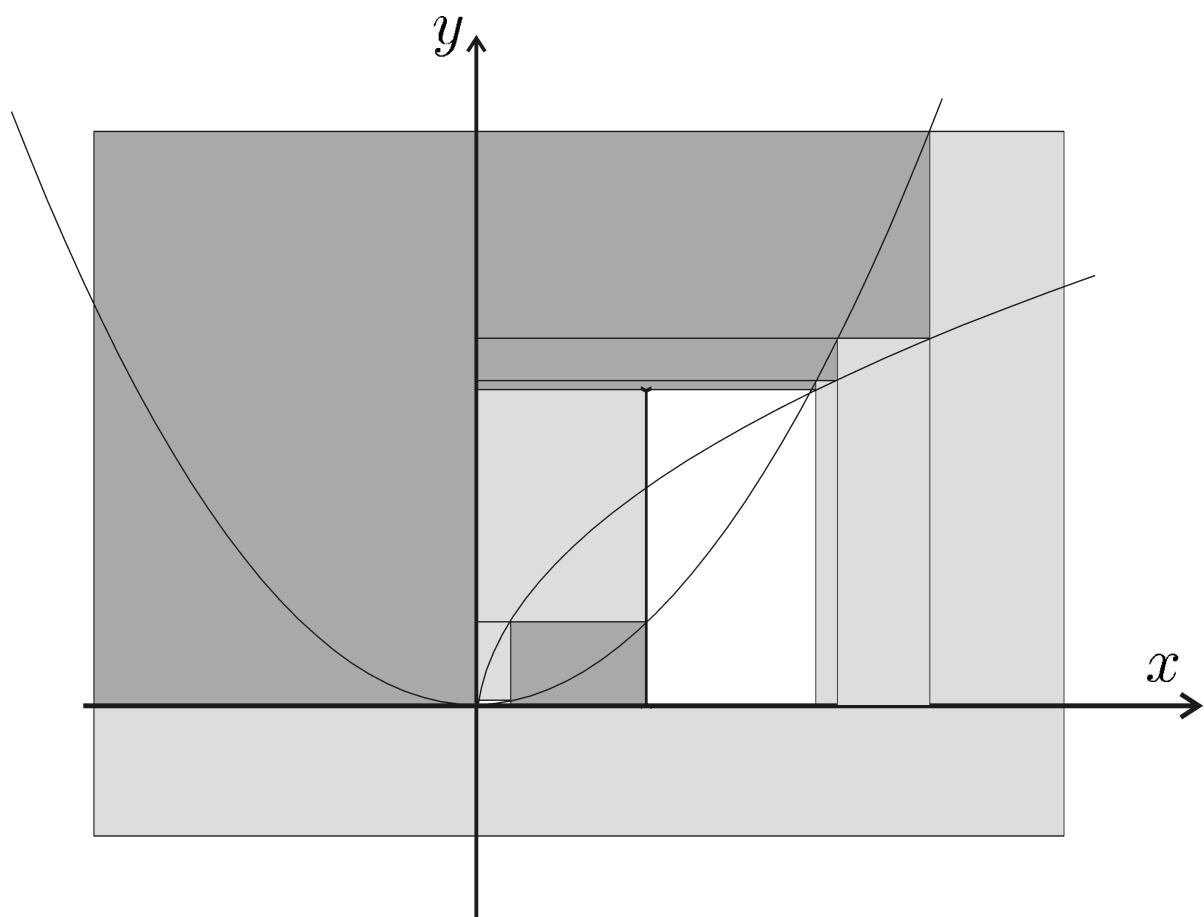


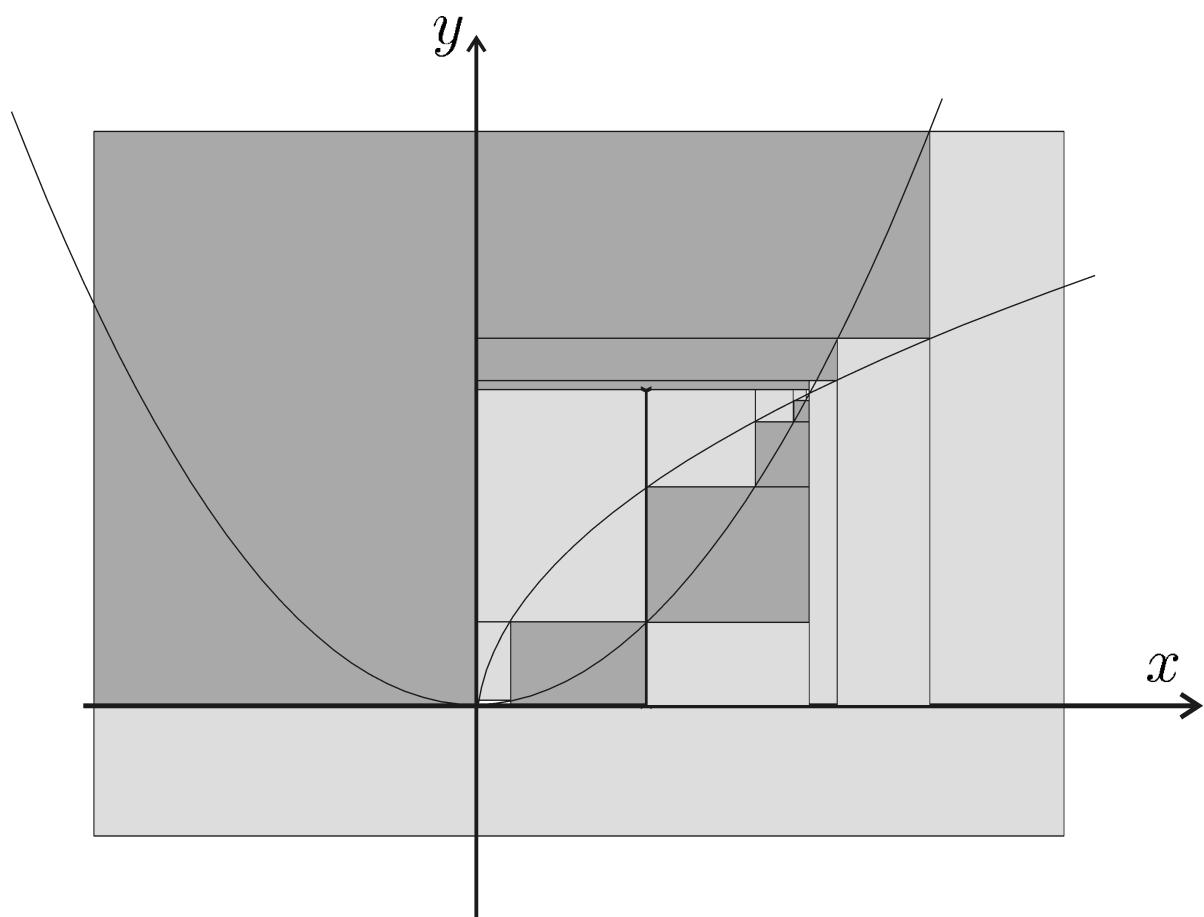












1.4 Décomposition

Pour les contraintes plus complexes, il nous décomposer :

$$\begin{aligned}x + \sin(xy) &\leq 0, \\x &\in [-1, 1], y \in [-1, 1]\end{aligned}$$

se décompose en

$$\left\{ \begin{array}{ll} a = xy & x \in [-1, 1] \quad a \in]-\infty, \infty[\\ b = \sin(a) & , \quad y \in [-1, 1] \quad b \in]-\infty, \infty[\\ c = x + b & \quad \quad \quad c \in]-\infty, 0] \end{array} \right.$$

1.5 QUIMPER

Quimper : QUick Interval Modeling and Programming
in a bounded-ERror context.

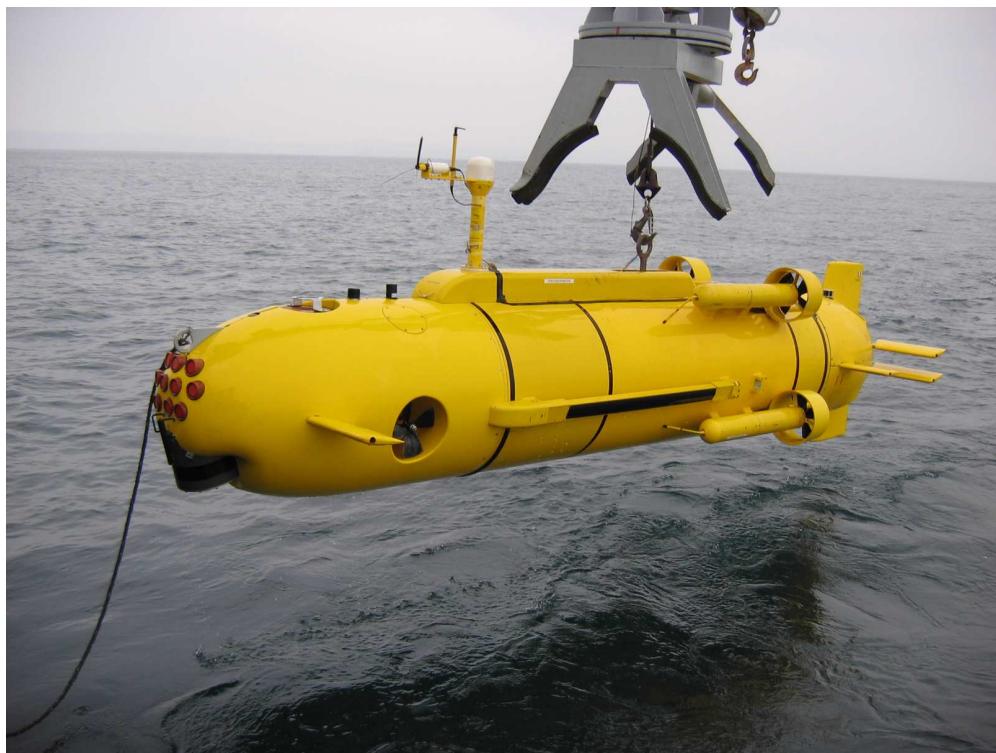
Quimper est un langage interprété pour le calcul en-
sembliste.

Un programme Quimper se décrit par un ensemble de
contracteurs.

Quimper est un logiciel libre.

2 SLAM

2.1 Redermor



Redermor, GESMA
(Groupe d'Etude Sous-Marine de l'Atlantique)



Montrer Daurade

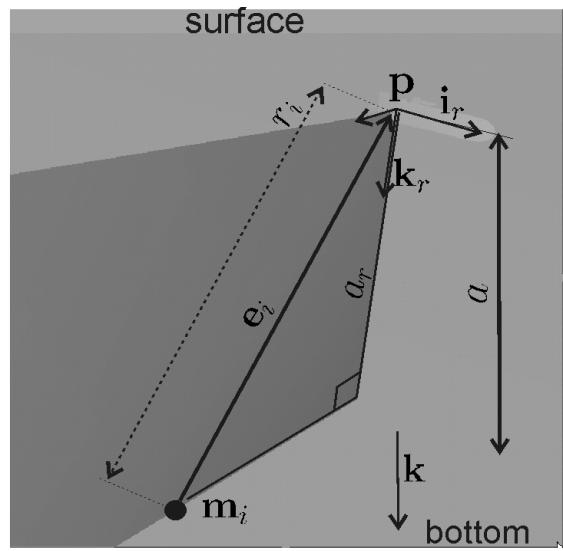
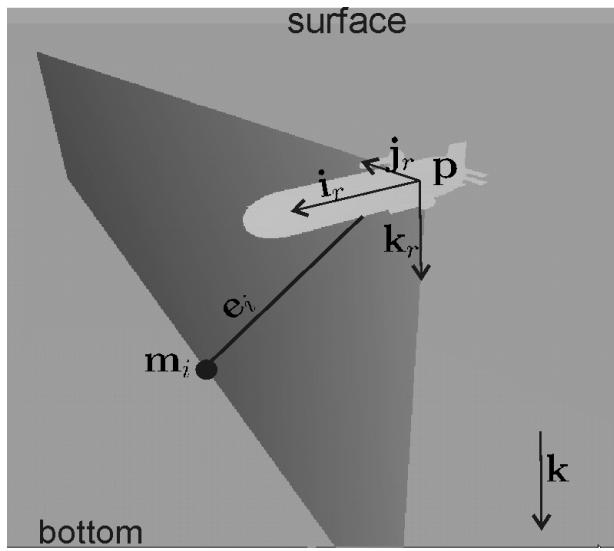
2.1.1 Sensors

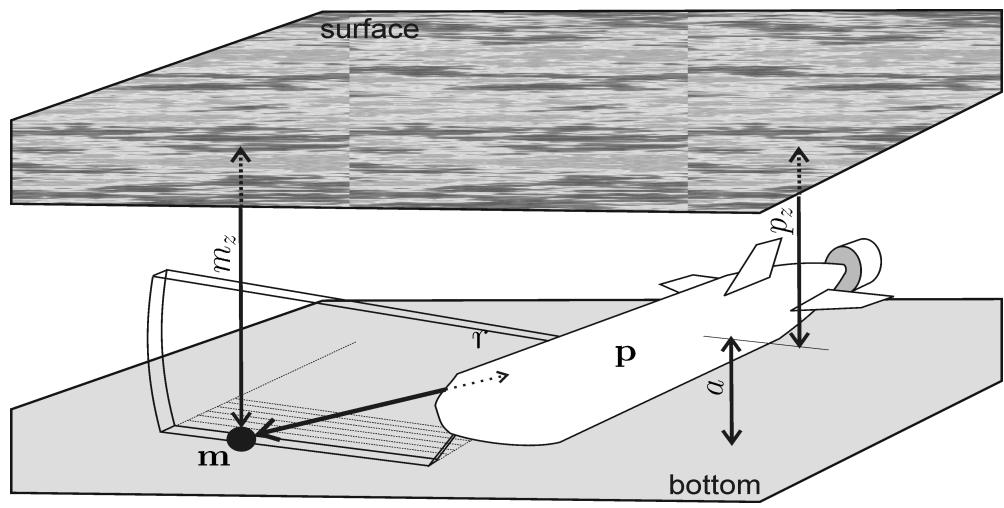
GPS (Global positioning system), only at the surface.

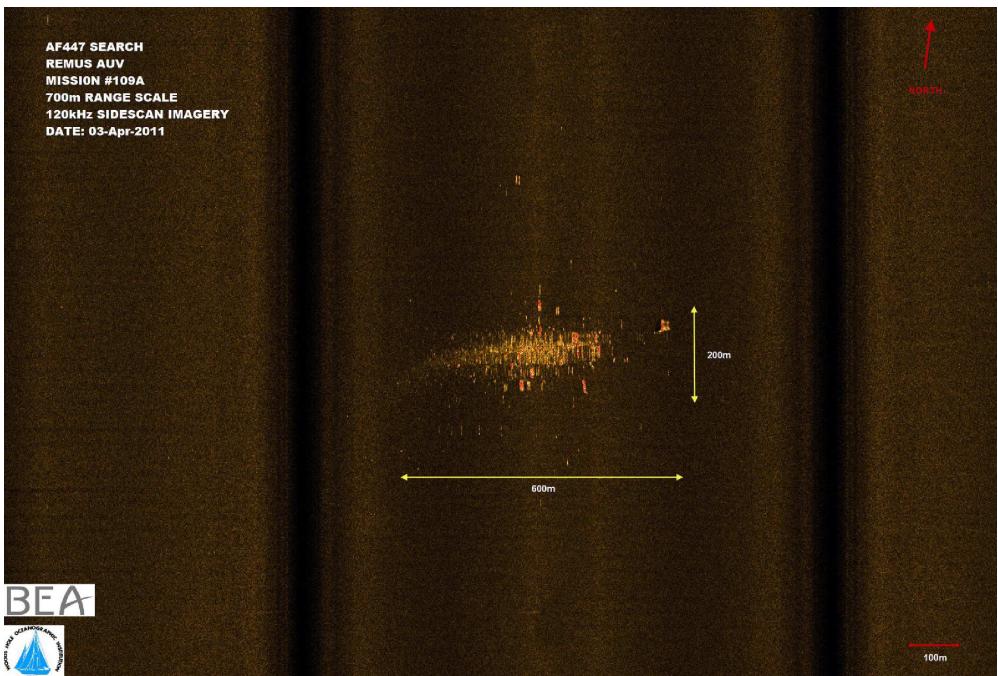
$$t_0 = 6000 \text{ s}, \quad \ell^0 = (-4.4582279^\circ, 48.2129206^\circ) \pm 2.5m$$

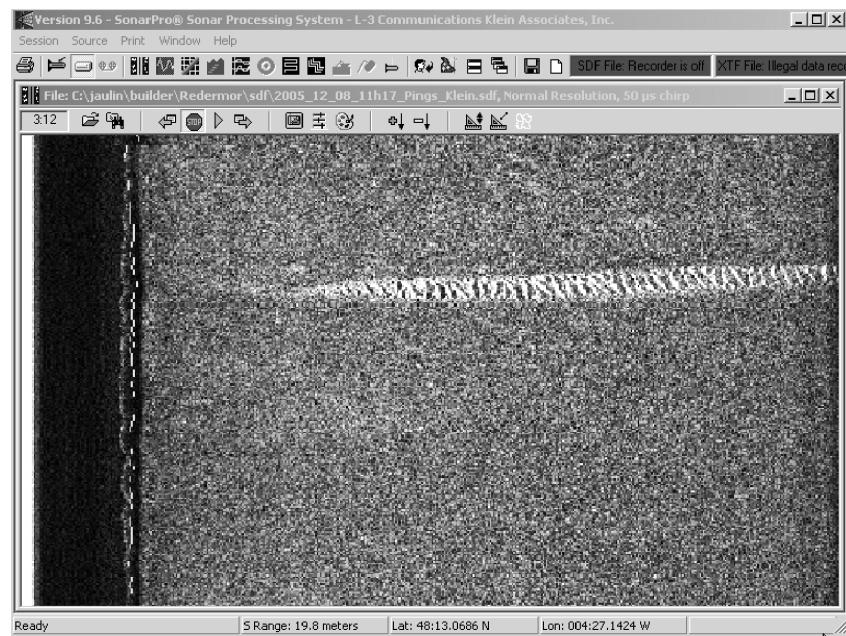
$$t_f = 12000 \text{ s}, \quad \ell^f = (-4.4546607^\circ, 48.2191297^\circ) \pm 2.5m$$

Sonar (KLEIN 5400 side scan sonar).

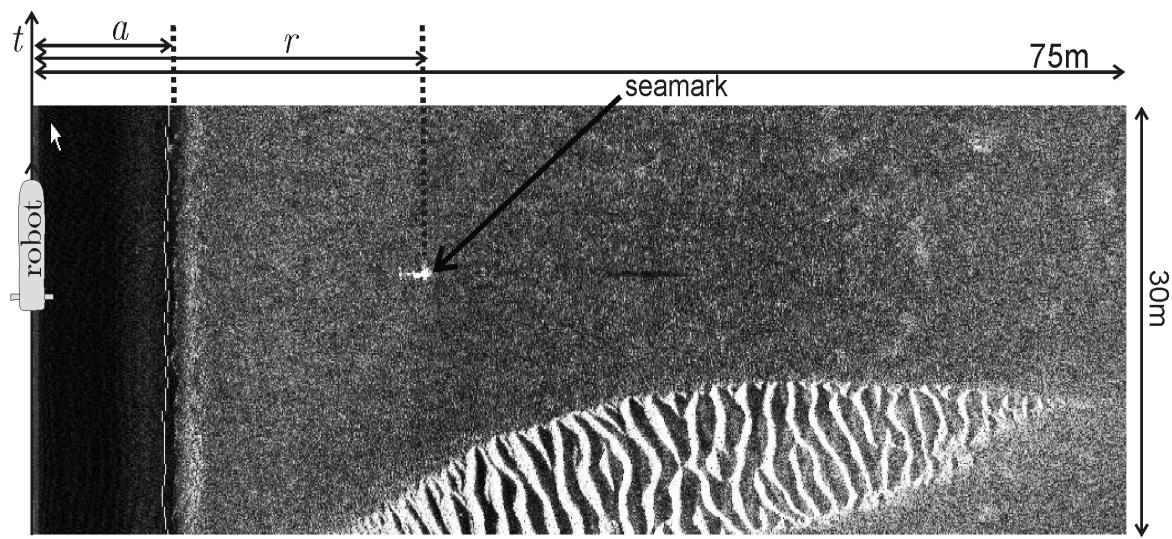








Screenshot of SonarPro



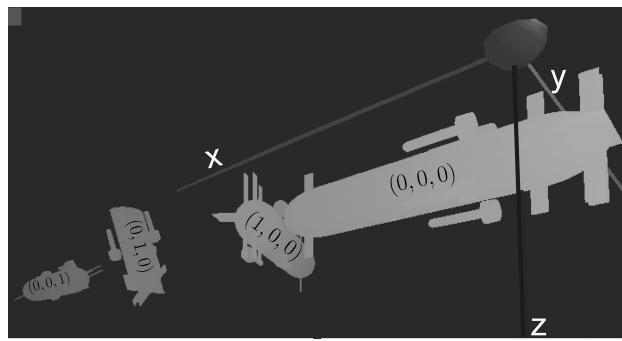
Mine detection with SonarPro

Loch-Doppler returns the speed robot \mathbf{v}_r .

$$\mathbf{v}_r \in \tilde{\mathbf{v}}_r + 0.004 * [-1, 1] . \tilde{\mathbf{v}}_r + 0.004 * [-1, 1].$$

Inertial central (Octans III from IXSEA).

$$\begin{pmatrix} \phi \\ \theta \\ \psi \end{pmatrix} \in \begin{pmatrix} \tilde{\phi} \\ \tilde{\theta} \\ \tilde{\psi} \end{pmatrix} + \begin{pmatrix} 1.75 \times 10^{-4} \cdot [-1, 1] \\ 1.75 \times 10^{-4} \cdot [-1, 1] \\ 5.27 \times 10^{-3} \cdot [-1, 1] \end{pmatrix}.$$



Six marks have been detected.

i	0	1	2	3	4	5
$\tau(i)$	7054	7092	7374	7748	9038	9688
$\sigma(i)$	1	2	1	0	1	5
$\tilde{r}(i)$	52.42	12.47	54.40	52.68	27.73	26.98

6	7	8	9	10	11
10024	10817	11172	11232	11279	11688
4	3	3	4	5	1
37.90	36.71	37.37	31.03	33.51	15.05

2.1.2 Constraints

$$t \in \{6000.0, 6000.1, 6000.2, \ldots, 11999.4\},$$

$$i \in \{0,1,\dots,11\},$$

$$\left(\begin{array}{c} p_x(t) \\ p_y(t) \end{array}\right)=111120\left(\begin{array}{cc} 0 & 1 \\ \cos\left(\ell_y(t)*\frac{\pi}{180}\right) & 0 \end{array}\right)\left(\begin{array}{c} \ell_x(t)-\ell_x^0 \\ \ell_y(t)-\ell_y^0 \end{array}\right)$$

$${\bf p}(t)=(p_x(t),p_y(t),p_z(t)),$$

$$\mathbf{R}_\psi(t)=\left(\begin{array}{ccc} \cos\psi(t) & -\sin\psi(t) & 0 \\ \sin\psi(t) & \cos\psi(t) & 0 \\ 0 & 0 & 1 \end{array}\right),$$

$$\mathbf{R}_\theta(t)=\left(\begin{array}{ccc} \cos\theta(t) & 0 & \sin\theta(t) \\ 0 & 1 & 0 \\ -\sin\theta(t) & 0 & \cos\theta(t) \end{array}\right),$$

$$\mathbf{R}_\varphi(t)=\left(\begin{array}{ccc}1&0&0\\0&\cos\varphi(t)&-\sin\varphi(t)\\0&\sin\varphi(t)&\cos\varphi(t)\end{array}\right),$$

$$\mathbf{R}(t)=\mathbf{R}_{\psi}(t)\mathbf{R}_{\theta}(t)\mathbf{R}_{\varphi}(t),$$

$$\dot{\mathbf{p}}(t)=\mathbf{R}(t).\mathbf{v}_r(t),$$

$$||\mathbf{m}(\sigma(i)) - \mathbf{p}(\tau(i))||~=r(i),$$

$$\mathbf{R}^\top(\tau(i))\left(\mathbf{m}(\sigma(i))-\mathbf{p}(\tau(i))\right)\in[0]\times[0,\infty]^{\times 2},$$

$$m_z(\sigma(i))-p_z(\tau(i))-a(\tau(i))\in[-0.5,0.5]$$

```
//-----  
Constants  
N = 59996; // Number of time steps  
Variables  
    R[N-1][3][3], // rotation matrices  
    p[N][3], // positions  
    v[N-1][3], // speed vectors  
    phi[N-1],theta[N-1],psi[N-1]; // Euler angles  
    px[N],py[N]; // for display only  
//-----
```

```

function R[3][3]=euler(phi,theta,psi)
cphi = cos(phi);
sphi = sin(phi);
ctheta = cos(theta);
stheta = sin(theta);
cpsi = cos(psi);
spsi = sin(psi);
R[1][1]=ctheta*cpsi;
R[1][2]=-cphi*spsi+stheta*cpsi*sphi;
R[1][3]=spsi*sphi+stheta*cpsi*cphi;
R[2][1]=ctheta*spsi;
R[2][2]=cpsi*cphi+stheta*spsi*sphi;
R[2][3]=-cpsi*sphi+stheta*cphi*spsi;
R[3][1]=-stheta;
R[3][2]=ctheta*sphi;
R[3][3]=ctheta*cphi;
end

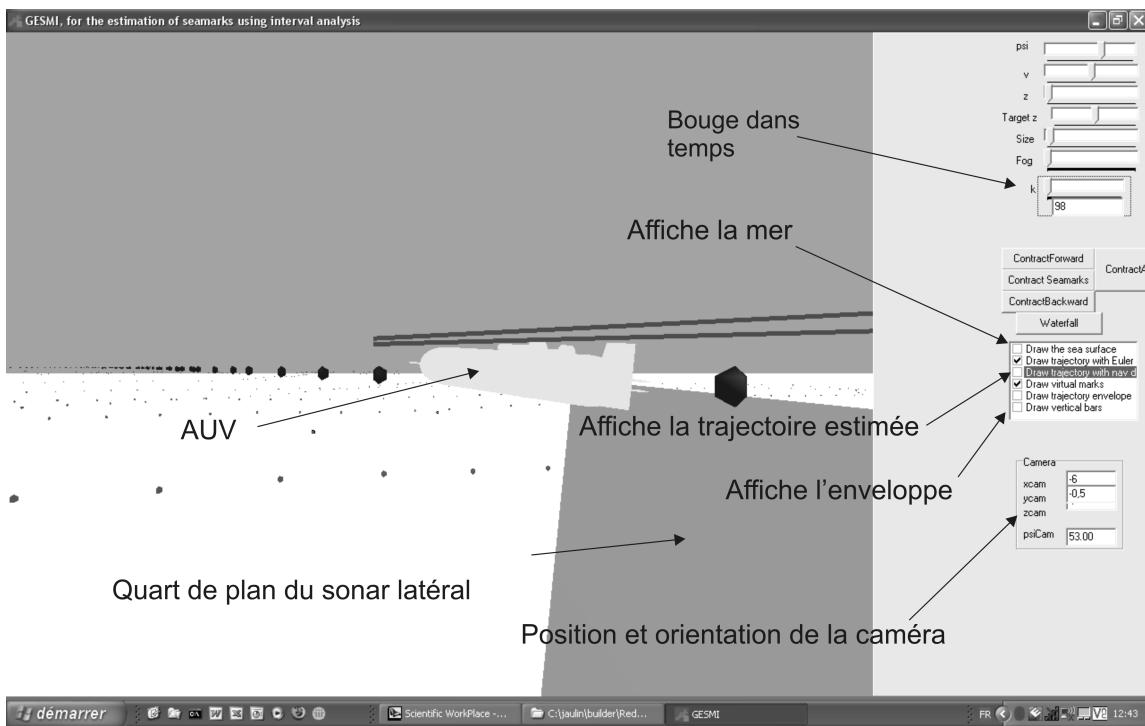
```

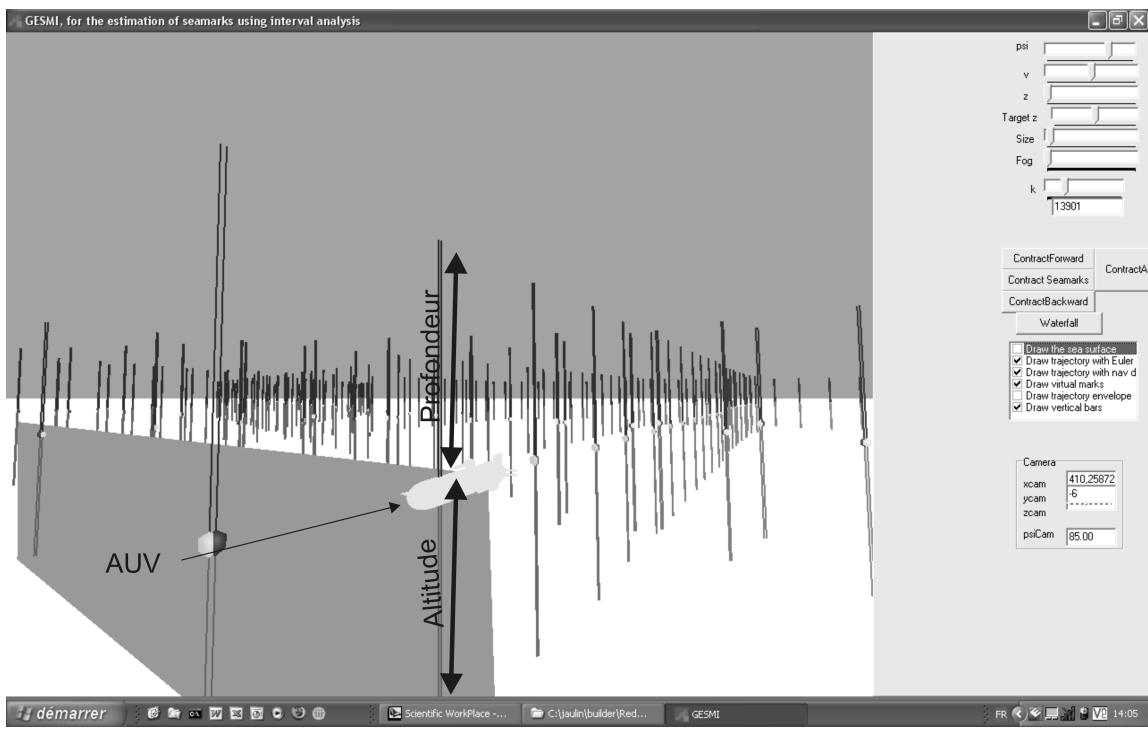
```
contractor-list rotation
  for k=1:N-1;
    R[k]=euler(phi[k],theta[k],psi[k]);
  end
end
//-----
contractor-list statequ
  for k=1:N-1;
    p[k+1]=p[k]+0.1*R[k]*v[k];
  end
end
//-----
contractor init
  inter k=1:N-1;
    rotation(k)
  end
end
```

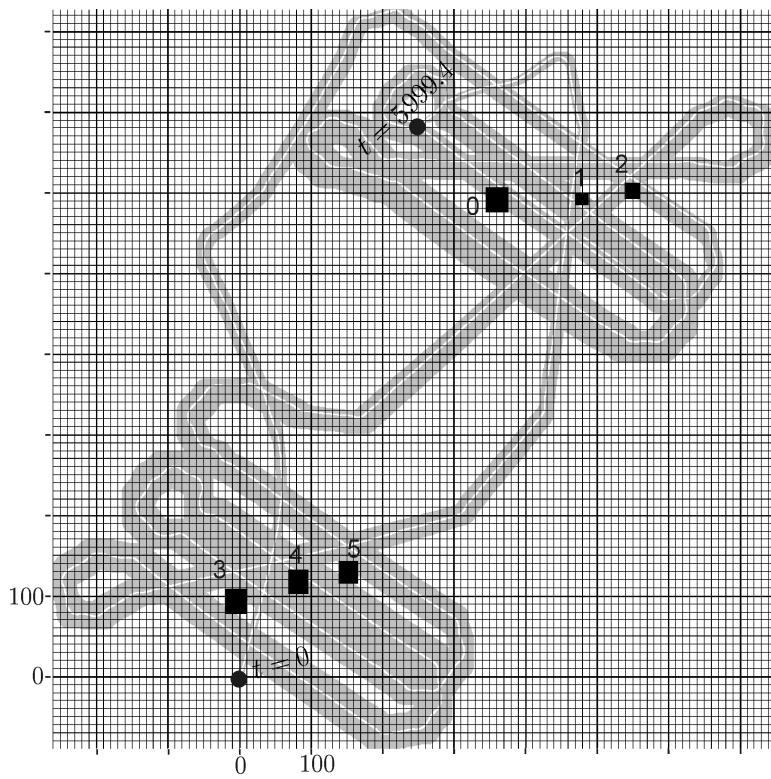
```
contractor fwd
    inter k=1:N-1;
        statequ(k)
    end
end
//-----
contractor bwd
    inter k=1:N-1;
        statequ(N-k)
    end
end
```

```
main
  p[1] :=read("gps_init.dat");
  v :=read("Quimper_v.dat");
  phi :=read("Quimper_phi.dat");
  theta :=read("Quimper_theta.dat");
  psi :=read("Quimper_psi.dat");
  init;
  fwd;
  bwd;
  column(p,px,1);
  column(p,py,2);
  print("---- Robot positions: ----");
  newplot("gesmi.dat");
  plot(px,py,color(rgb(1,1,1),rgb(0,0,0)));
end
```

2.1.3 GESMI

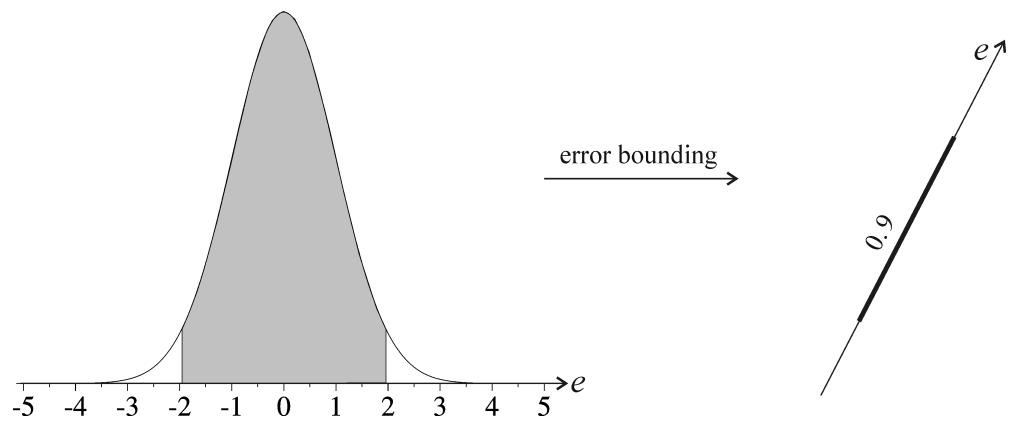


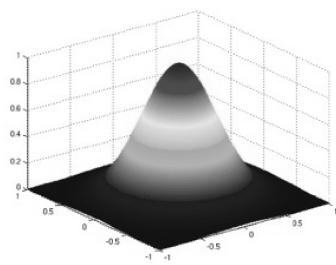




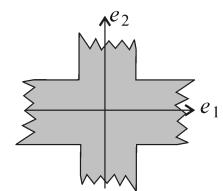
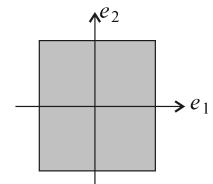
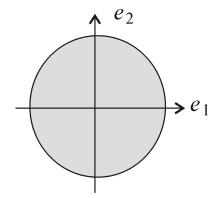
3 Probabilistic-set approach

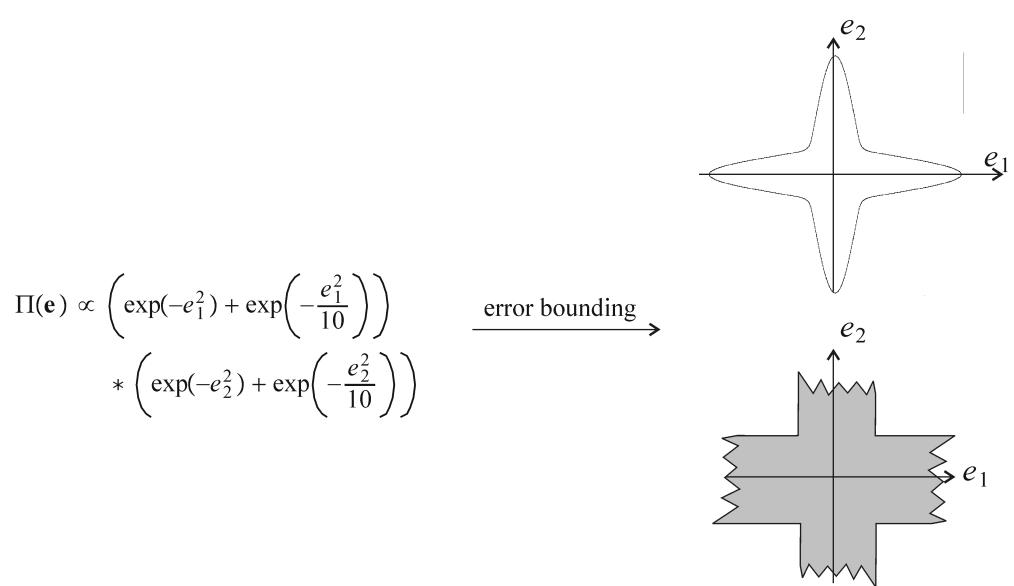
3.1 Error bounding





error bounding





3.2 Principle of the approach

Consider the error model

$$\mathbf{e} = \underbrace{\mathbf{y} - \psi(\mathbf{p})}_{\mathbf{f}(\mathbf{y}, \mathbf{p})}.$$

y_i is an *inlier* if $e_i \in [e_i]$ and an *outlier* otherwise. We assume that

$$\forall i, \Pr(e_i \in [e_i]) = \pi$$

and that all e_i 's are independent.

Equivalently,

$$\left\{ \begin{array}{ll} f_1(y, p) \in [e_1] & \text{with a probability } \pi \\ \vdots & \vdots \\ f_m(y, p) \in [e_m] & \text{with a probability } \pi \end{array} \right.$$

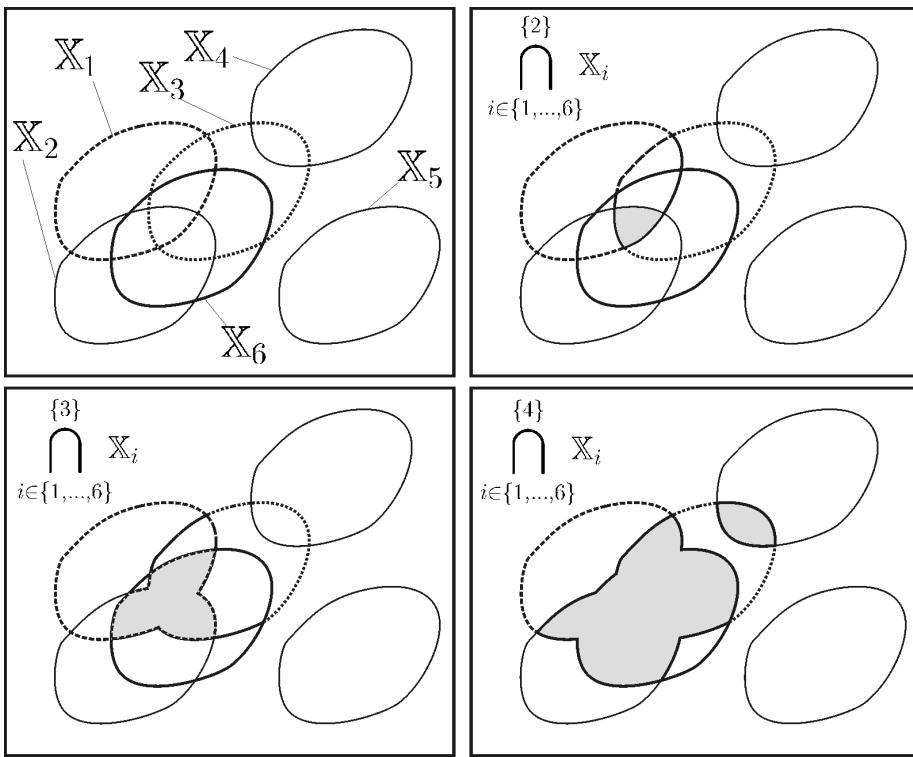
The number k of inliers follows a binomial distribution

$$\frac{m!}{k!(m-k)!} \pi^k \cdot (1 - \pi)^{m-k}.$$

The probability of having more than q outliers is thus

$$\gamma(q, m, \pi) \stackrel{\text{def}}{=} \sum_{k=0}^{m-q-1} \frac{m!}{k!(m-k)!} \pi^k \cdot (1-\pi)^{m-k}.$$

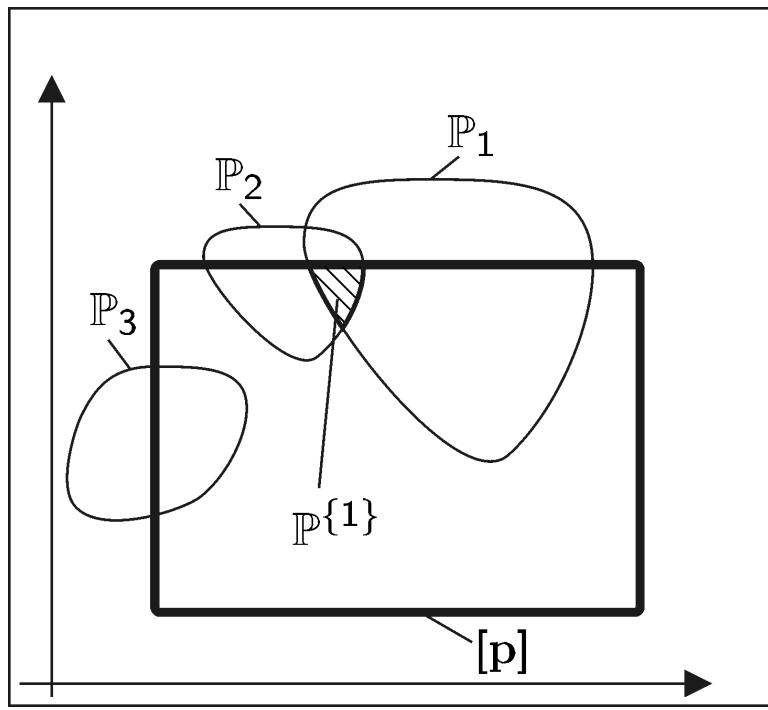
Example. For instance, if $m = 1000$, $q = 900$, $\pi = 0.2$, we get $\gamma(q, m, \pi) = 7.04 \times 10^{-16}$. Thus having more than 900 outliers can be seen as a rare event.

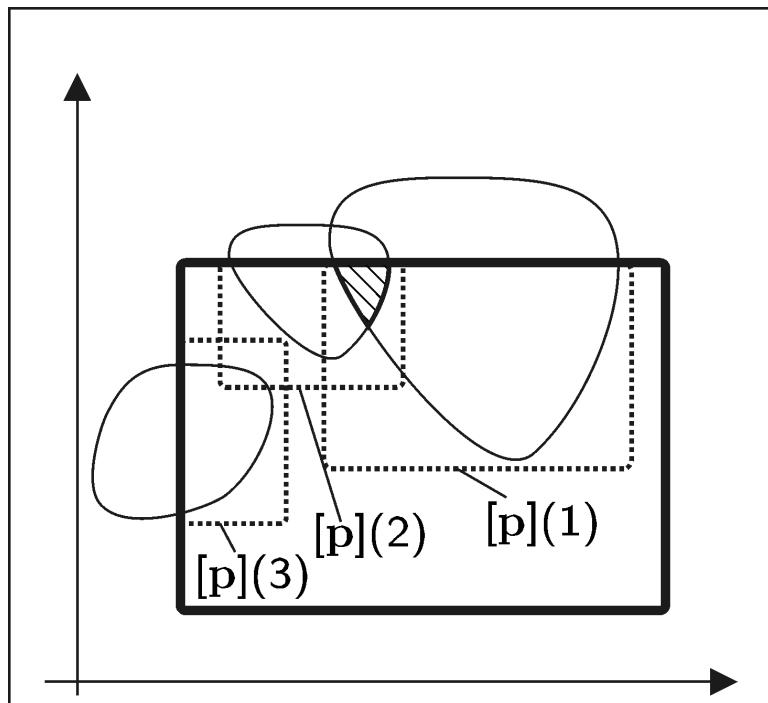


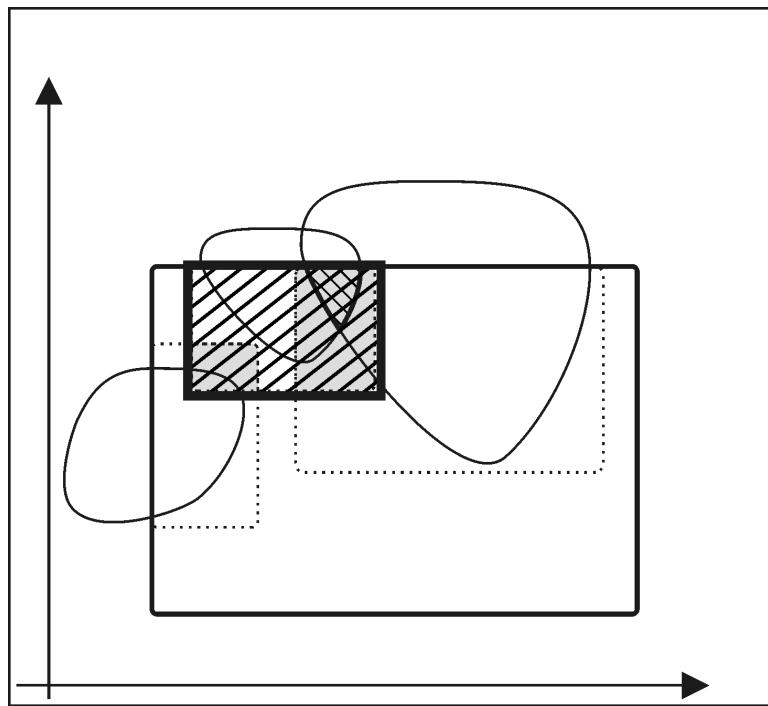
q-intersection

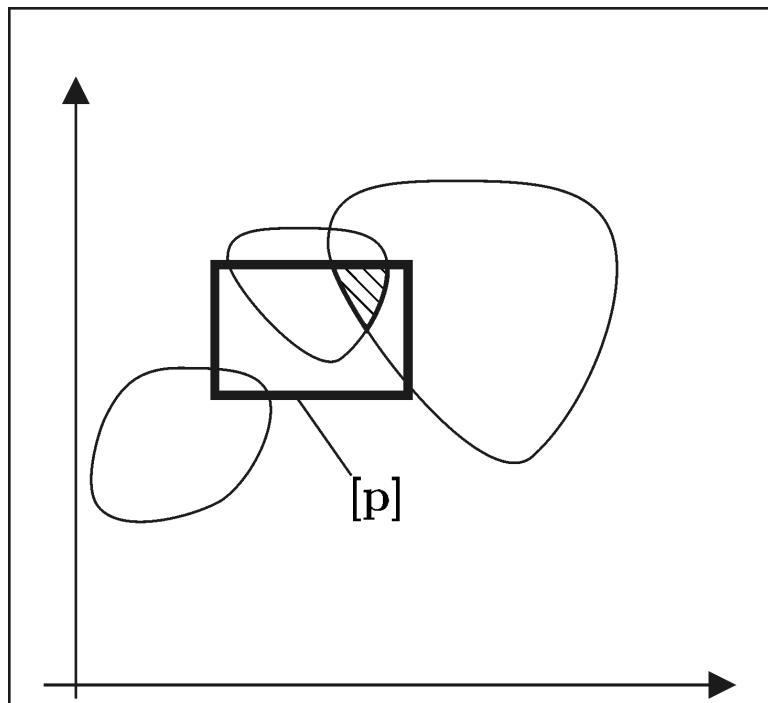
q -intersection de contracteurs.

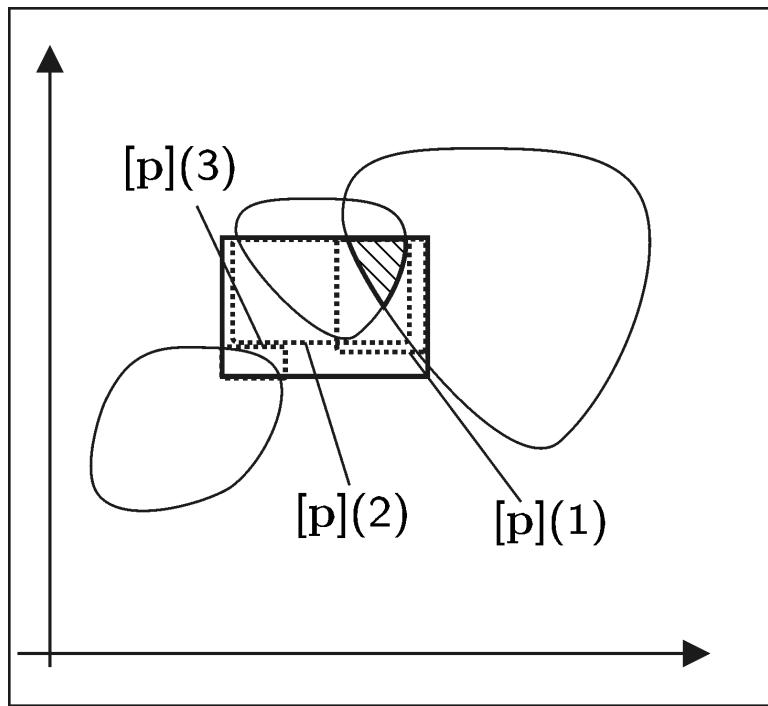
$$\mathcal{C} = \bigcap_{i \in \{1,2,3\}}^{\{1\}} \mathcal{C}_i$$

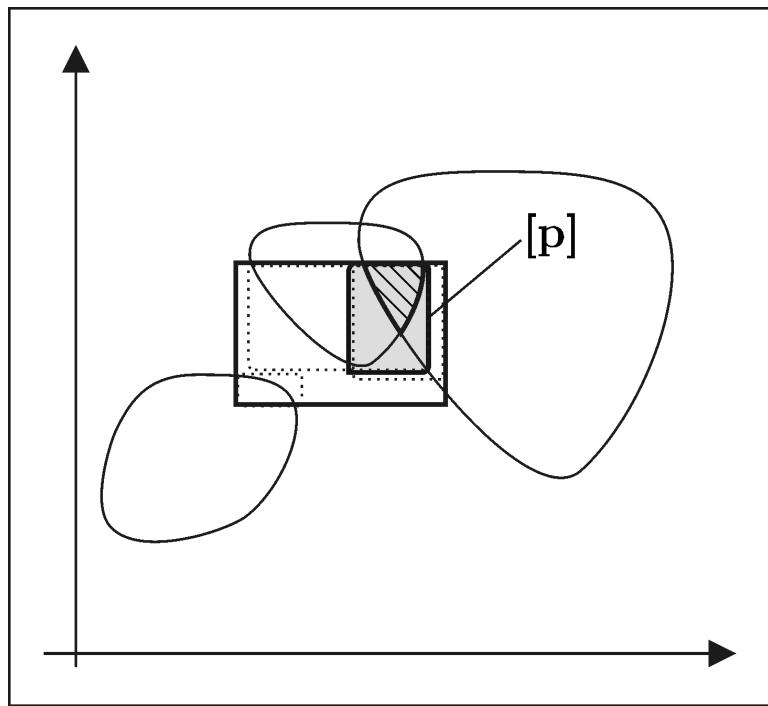












3.3 Test case

Generation of data. $m = 500$ data

$$\begin{cases} y_i = p_1 \sin(p_2 t_i) + e_i, & \text{with a probability 0.2.} \\ y_i = r_1 \exp(r_2 t_i) + e_i, & \text{with a probability 0.2.} \\ y_i = n_i \end{cases}$$

where $t_i = 0.02 \cdot i$, $i \in \{1, 500\}$, $e_i : \mathcal{U}([-0.1, 0.1])$ and $n_i : \mathcal{N}(2, 3)$.

We took $\mathbf{p}^* = (2, 2)^\top$ and $\mathbf{r}^* = (4, -0.4)^\top$.

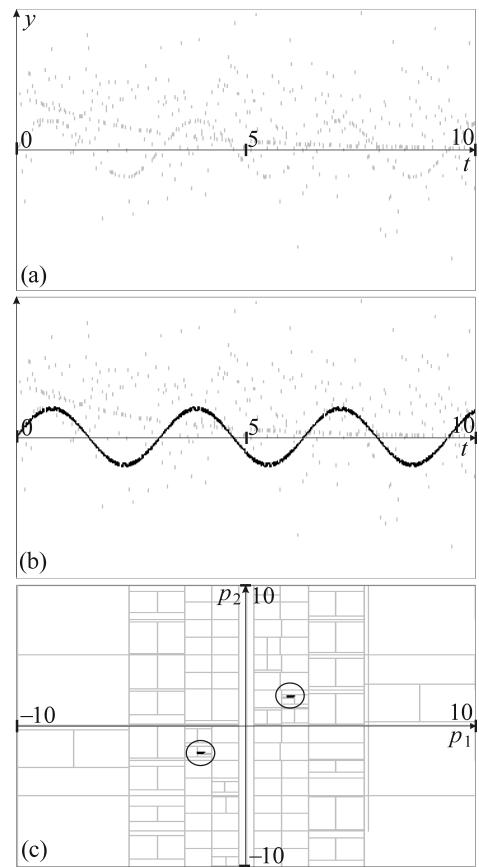
Estimation. We only know that

$$y_i = p_1 \sin(p_2 t_i) + e_i, \text{ with a probability 0.2.}$$

We want

$$\Pr(p^* \in \hat{\mathbb{P}}) \geq 0.95$$

Since $\gamma(414, 500, 0.2) = 0.0468$ and $\gamma(413, 500, 0.2) = 0.12$, we should assume $q = 414$ outliers.



3.4 State estimation

$$\begin{cases} \mathbf{x}(k+1) &= \mathbf{f}_k(\mathbf{x}(k), \mathbf{n}(k)) \\ \mathbf{y}(k) &= \mathbf{g}_k(\mathbf{x}(k)), \end{cases}$$

with $\mathbf{n}(k) \in \mathbb{N}(k)$ and $\mathbf{y}(k) \in \mathbb{Y}(k)$.

Without outliers

$$\mathbb{X}(k+1) = \mathbf{f}_k\left(\mathbb{X}(k), \mathbb{N}(k)\right) \cap \mathbf{g}_{k+1}^{-1}\left(\mathbb{Y}(k+1)\right).$$

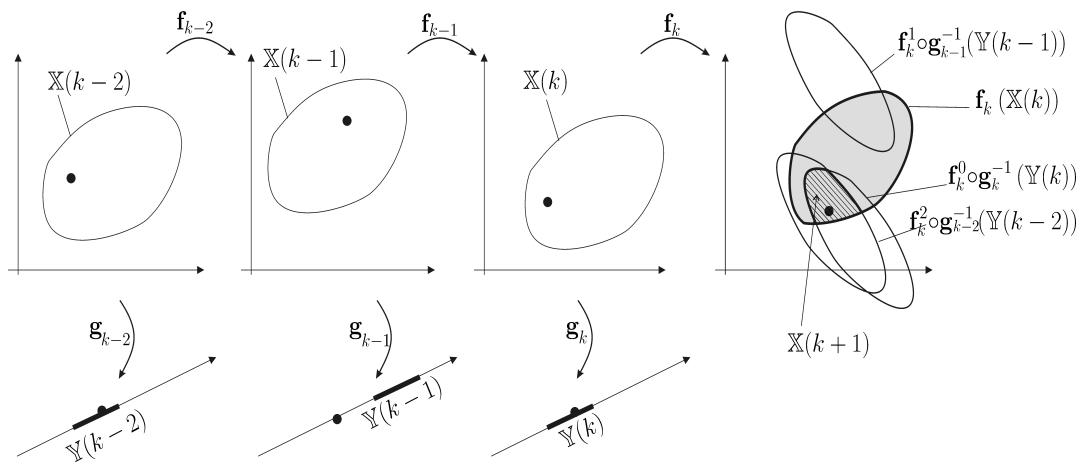
Define

$$\begin{cases} \mathbf{f}_{k:k}(\mathbb{X}) & \stackrel{\text{def}}{=} \mathbb{X} \\ \mathbf{f}_{k_1:k_2+1}(\mathbb{X}) & \stackrel{\text{def}}{=} \mathbf{f}_{k_2}(\mathbf{f}_{k_1:k_2}(\mathbb{X}), \mathbb{N}(k_2)), \quad k_1 \leq k_2. \end{cases}$$

The set $\mathbf{f}_{k_1:k_2}(\mathbb{X})$ represents the set of all $\mathbf{x}(k_2)$, consistent with $\mathbf{x}(k_1) \in \mathbb{X}$.

Consider the set state estimator

$$\left\{ \begin{array}{ll} \mathbb{X}(k) &= \mathbf{f}_{0:k}(\mathbb{X}(0)) \quad \text{if } k < m, \text{ (initialization step)} \\ \mathbb{X}(k) &= \mathbf{f}_{k-m:k}(\mathbb{X}(k-m)) \cap \\ &\qquad \bigcap_{\substack{i \in \{1, \dots, m\}}}^{\{q\}} \mathbf{f}_{k-i:k} \circ \mathbf{g}_{k-i}^{-1}(\mathbb{Y}(k-i)) \quad \text{if } k \geq m \end{array} \right.$$



We assume

- (i) within any time window of length m we have less than q outliers and
- (ii) $\mathbb{X}(0)$ contains $\mathbf{x}(0)$, then $\mathbb{X}(k)$ encloses $\mathbf{x}(k)$.

What is the probability of this assumption ?

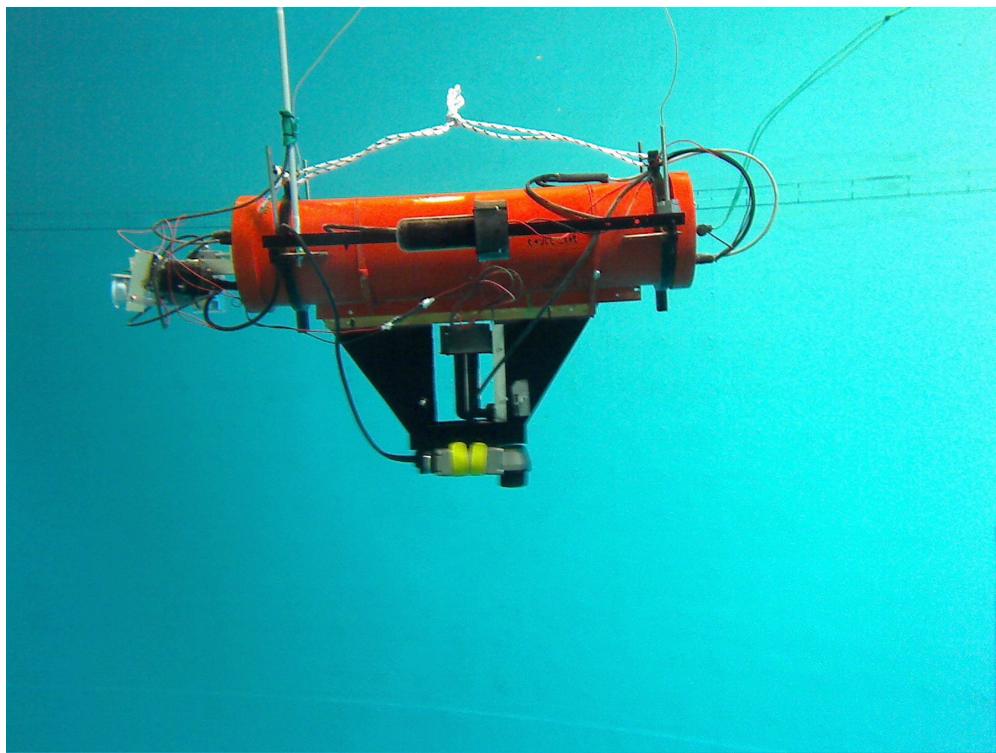
Theorem. Consider the sequence of sets $\mathbb{X}(0), \mathbb{X}(1), \dots$ built by the set observer. We have

$$\Pr(\mathbf{x}(k) \in \mathbb{X}(k)) \geq \alpha * \Pr(\mathbf{x}(k-1) \in \mathbb{X}(k-1))$$

where

$$\alpha = \sqrt[m]{\sum_{i=m-q}^m \frac{m! \pi^i (1-\pi)^{m-i}}{i! (m-i)!}}.$$

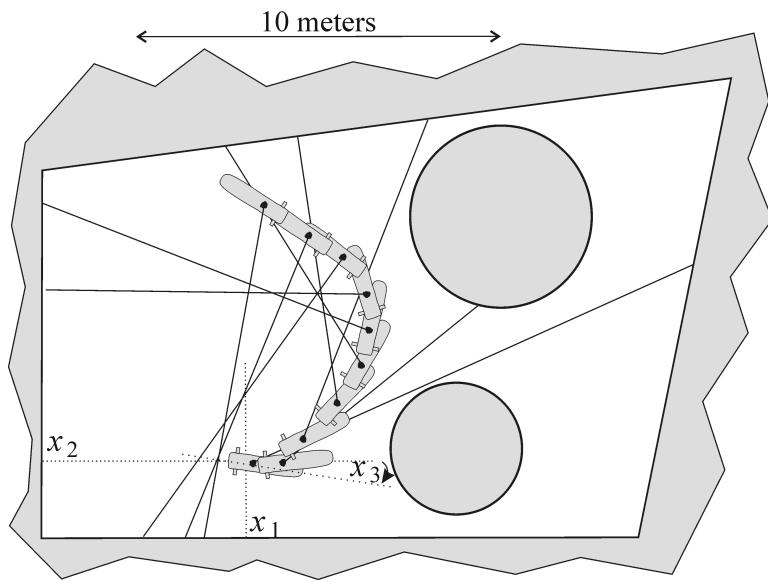
4 Application to localization



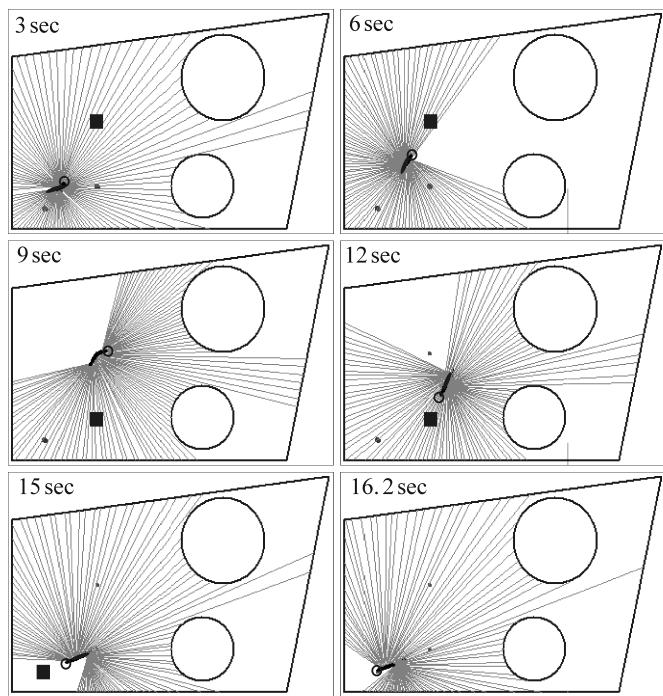
SAUCISSE inside a swimming pool

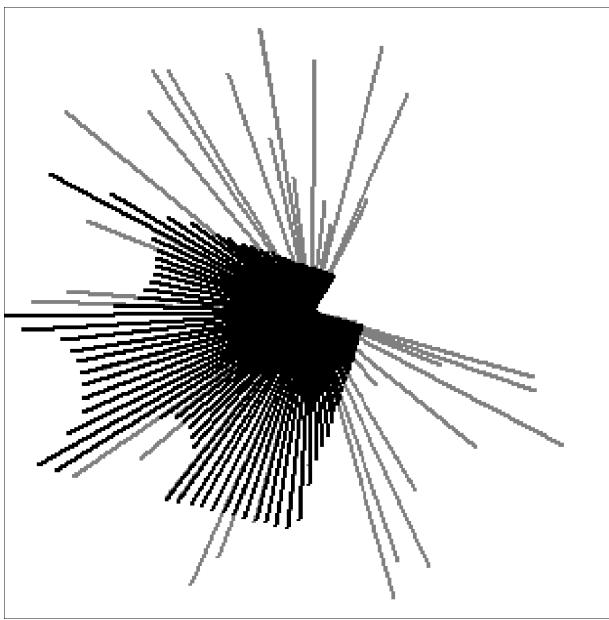
The robot evolution is

$$\begin{cases} \dot{x}_1 = x_4 \cos x_3 \\ \dot{x}_2 = x_4 \sin x_3 \\ \dot{x}_3 = u_2 - u_1 \\ \dot{x}_4 = u_1 + u_2 - x_4, \end{cases}$$

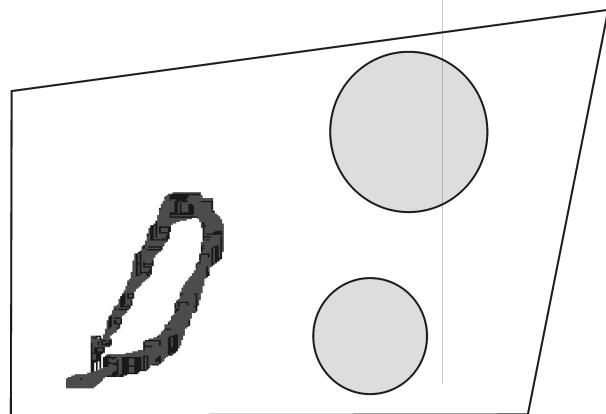
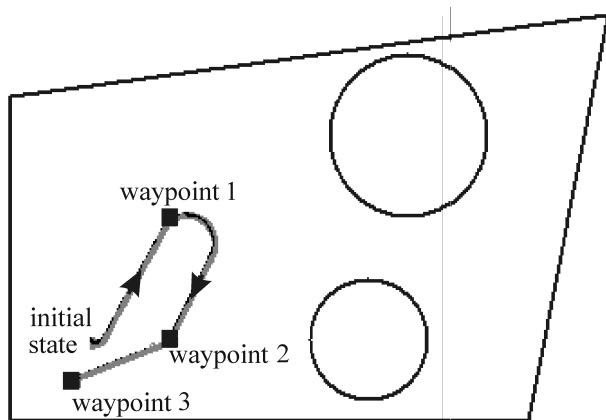


Underwater robot moving inside a pool



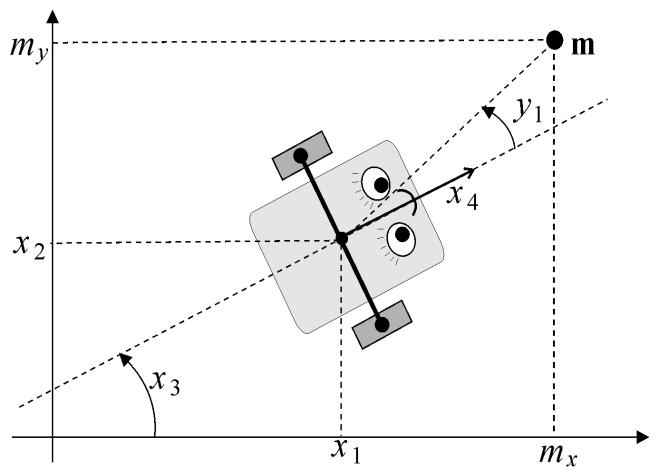


Emmision diagram at time $t = 16.2 \text{ sec}$



$t(\text{sec})$	$\Pr(x \in \mathbb{X})$	Outliers
3.0	≥ 0.965	58
6.0	≥ 0.932	50
9.0	≥ 0.899	42
12.0	≥ 0.869	51
15.0	≥ 0.838	51
16.2	≥ 0.827	49

5 Comparison with the Kalman filter



A robot (unicycle type) which measures the angle y_1 corresponding to the mark **m**

$$\begin{cases} \dot{x}_1 = x_4 \cos x_3 \\ \dot{x}_2 = x_4 \sin x_3 \\ \dot{x}_3 = u_1 \\ \dot{x}_4 = u_2 \end{cases}$$

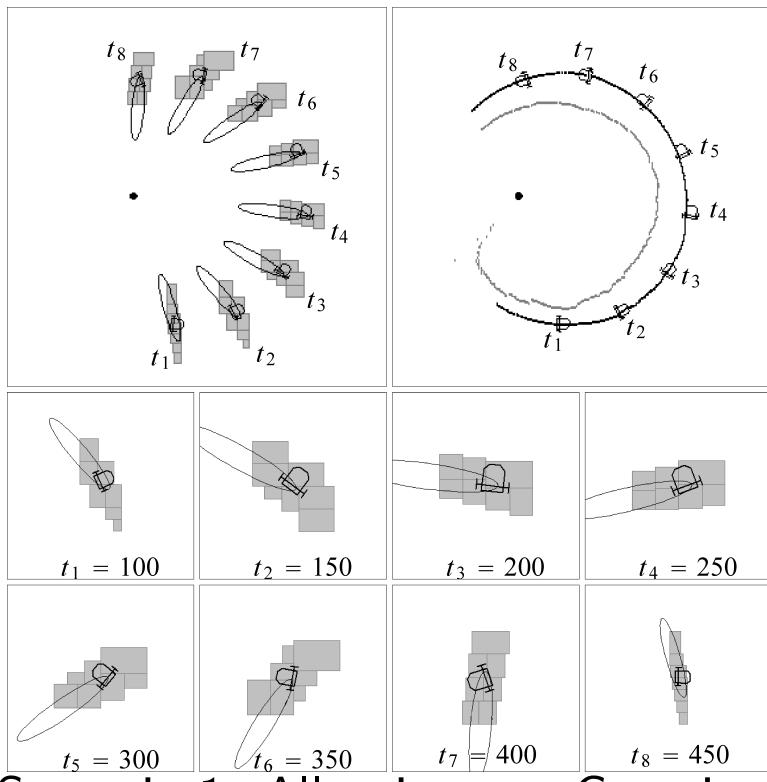
$$\begin{cases} y_1 = \text{atan2}(m_y - x_2, m_x - x_1) + x_3, & k \in \mathbb{Z} \\ y_2 = x_3 \\ y_3 = x_4. \end{cases}$$

Scenario 1. The measurement noises as well as the state noises are all Gaussian and centered with a variance of 0.01.

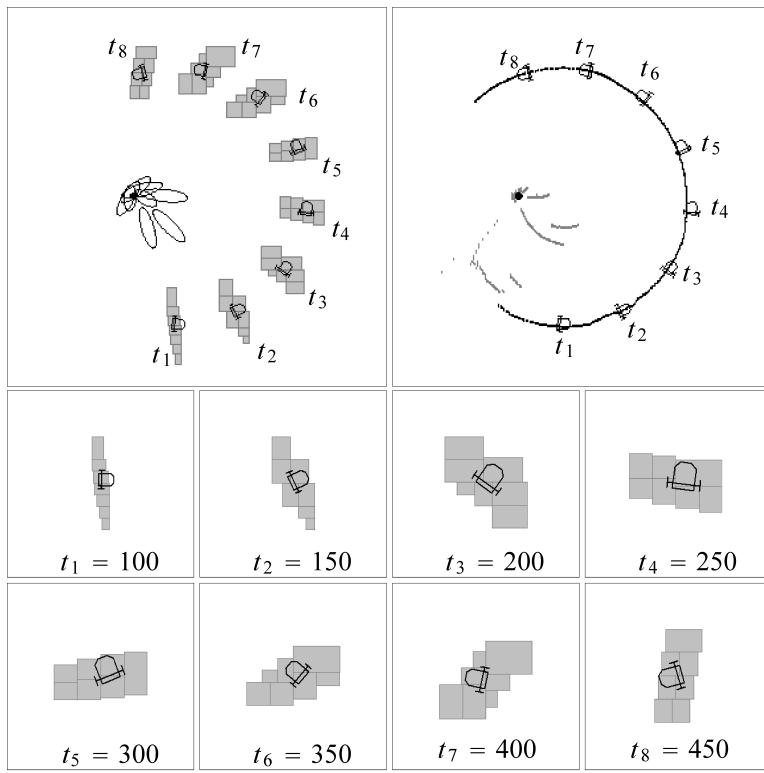
Scenario 2. With a probability of 5%, an outlier for y_1 is generated.

Scenario 3. This scenario is similar to Scenario 1 but a bias of 0.5 is added to y_1 .

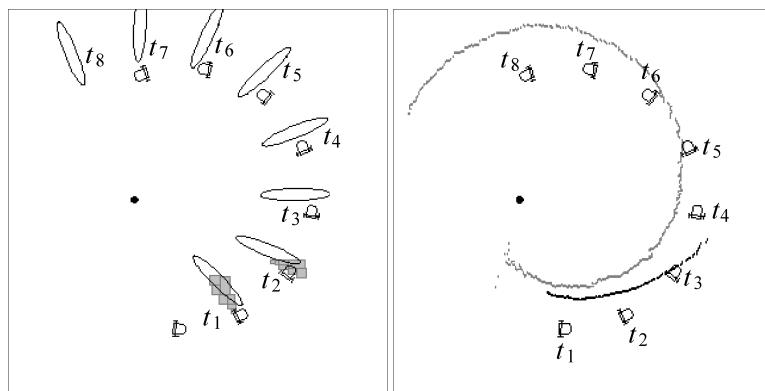
For RSO, $m = 50, q = 10$.



Scenario 1: All noises are Gaussian



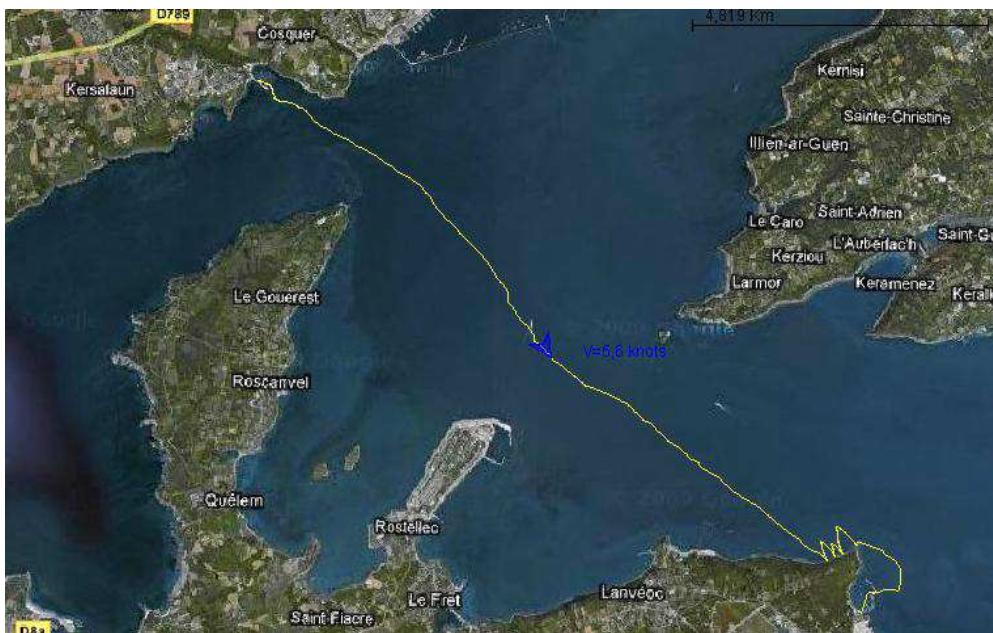
Scenario 2: 1% of the data are outliers



Scenario 3. An unknown bias has been added to y_1 .

6 Robot voilier





7 Conclusion

- 1) Les équations représentent les relations entre des variables mal connues. On leur associe un contracteur.
- 2) La méthode se distribue et se parallélise facilement.
- 3) La méthode ne linéarise pas.
- 4) Elle permet de prendre en compte des variables discrètes (entières, booléennes, . . .).
- 5) Elle est robuste par rapport aux outliers.
- 6) Venez tous à SWIM'11, June 14-15, 2011 à Bourges.