

Mobile robot algebraic localizability

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- 2 Setup and assumptions for localization of unicycle
- 3 Localizability
- 4 Simulation and experimental result
- 5 Conclusion

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Introduction: What is localization ?

Challenge for autonomous navigation: "Where am I?"

👉 **real-time localization problem:**

Real time estimation of the robot's **pose**
(or posture = **position** + **orientation**)
using **noisy measurements**

Introduction: Absolute positioning with Landmarks

- ☞ **landmarks** = features with known coordinates (relative measure).
- ☞ “**human made**” can be passive or active (ex. radio signal).
 - *active landmarks* as in [14] (wifi infrastructure) and [15] (bluetooth protocol): lack of accuracy.
 - [16] uses magnetic patterns (active landmarks): needs environment modifications to work (drawback).
- ☞ Avoid to modify the environment \Rightarrow **natural landmarks**: laser scanners, ultrasound sensors (distance) or cameras (distance, angle).

- Trends for AGV: move to **optically** guided systems since the above mentioned solutions (GPS, active landmarks and wire-guided solutions) have important drawbacks.
- **Our goal**: design and analyze **landmark based solution for a unicycle mobile robot equipped with a monocular camera** (with **one** or two landmarks).
- Monocular camera (extract natural landmarks): corner points ([17, 18]) + other algorithms SIFT [19] or SURF [20].
- Single landmark based solution can be used also in the multi-landmarks case by fusing the data in order to improve the localization algorithm.

- ☞ Step 1: Vision sensors \Rightarrow information,
- ☞ Localization problem \sim observation problem [26]:
 - Step 2: localizability is related to the observability problem (see [27, 28, 29]).
 - Step 3 observer/estimator design.
- ☞ Here in our algebraic approach Step 2 and 3 and merged.

Step 2: Localizability/observability:

- Linearized approximations: **NO** ([27]),
- NL observability Hermann and Krener [30, 31]: **YES** ([28]).

Step 3: Observer design [26]:

- [28]: nonlinear Luenberger-like observer combined with the projection of stationary landmarks,
- [27]: extended Kalman filter (EKF) in leader-follower context and observability can be tested through the Extended Output Jacobian matrix.
- [28, 29] (extension to the SLAM problem): CNS (observable) = two landmarks, estimation error is minimized using some optimal control methods/

- ✎ EKF cons.: needs the inputs knowledge + noise,
- ✎ Our solution based on differential algebraic setting + efficient numerical derivation of noisy signals = good real-time localization (estimation of pose and velocities) using bearing only measurements.

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Setup and assumptions for localization of unicycle

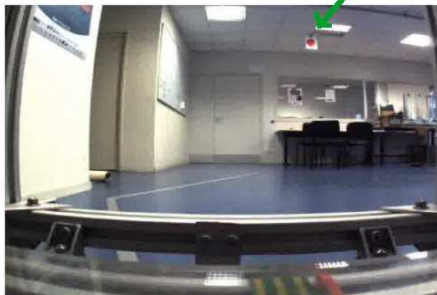
Localization = pose estimation w.r.t fixed frame.

Setup:

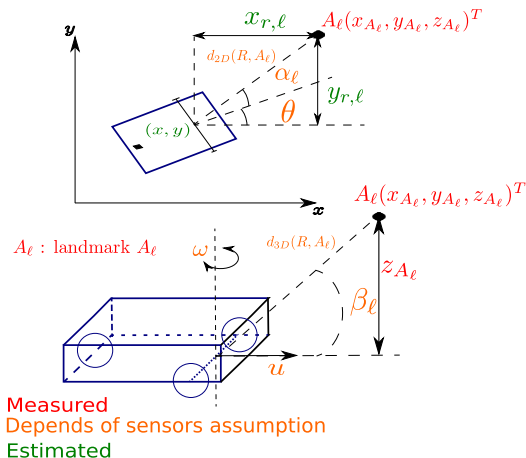
- mobile robot with its kinematic model,
- sensors with its measurement model



Camera + IMU



The robot - An image of the camera



Robot and landmark notation for the localization

Setup and assumptions for localization of unicycle

POI + image processing = angles:

$$\alpha_\ell = \arctan\left(\frac{y_{r,\ell}}{x_{r,\ell}}\right) - \theta, \quad (1)$$

$$\beta_\ell = \arctan\left(\frac{z_{A_\ell}}{\sqrt{(x_{r,\ell})^2 + (y_{r,\ell})^2}}\right). \quad (2)$$

Measured output:

$$\mathbf{y}_m = \mathbf{y} + \varpi, \quad (3)$$

Setup and assumptions for localization of unicycle

Any other practical sensor setup could be consider as soon as we arrive at one of the following fives cases given in table:

Measurement assumptions	Number of Landmarks	Measures	Output (3)
<u>MA1</u>	1	azimuth angle elevation angle	$\mathbf{y} = \begin{pmatrix} \alpha_1 \\ \beta_1 \end{pmatrix}$
<u>MA2</u>	1 + Compass	azimuth angle elevation angle orientation	$\mathbf{y} = \begin{pmatrix} \alpha_1 \\ \beta_1 \\ \theta \end{pmatrix}$
<u>MA3</u>	2	2 elevation angles	$\mathbf{y} = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}$
<u>MA4</u>	2	2 azimuth angles	$\mathbf{y} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix}$
<u>MA5</u>	2	azimuth angle of A_1 elevation angle of A_2	$\mathbf{y} = \begin{pmatrix} \alpha_1 \\ \beta_2 \end{pmatrix}$

Measurement assumptions: α_ℓ and β_ℓ are given by (1), (2) together Notations.

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 - Observability vs. Localizability
 - Algebraic localizability
 - Localization as a numerical differentiation problem
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Localizability: definition and remarks

- ☞ Unicycle robot: localizability = observability.
- ☞ Car (see [8, 38]), the state vector is $(x, y, \theta, \varphi)^T$ and its kinematic model is:

$$\begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \\ \dot{\varphi} \end{pmatrix} = \begin{pmatrix} L \cos(\theta) \sin(\varphi) & 0 \\ -L \sin(\theta) \sin(\varphi) & 0 \\ \cos(\varphi) & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} v \\ \omega \end{pmatrix}. \quad (4)$$

pose is a sub-vector of the state vector.

- ☞ observability \Rightarrow localizability (reverse is false).

Localizability: definition and remarks

- ☞ Similarity between localizability/observability was already mentioned in [27, 28, 29].
- ☞ linearized approximations can be non observable [27], thus localization is not possible using such approximations.
- ☞ differential nonlinear systems theory proves the feasibility to reconstruct the state, thus the localization problem is solvable (see [28] and [29]).
- ☞ Usually, real-time localization solutions relies on non linear observer design.

Hermann and Krener in [30] obtained sufficient conditions *local observability rank condition* from which we can deduce:

Theorem

A unicycle type mobile robot is **localizable** at a point \mathbf{x}_0 if the co-distribution of observability is of the form $d\mathcal{O}_{\mathbf{x}_0}(\mathbf{h}) = \mathcal{O}(\mathbf{x}_0)(dx, dy, d\theta)^T$ with $\text{rank}(\mathcal{O}(\mathbf{x}_0)) = 3$.

Measures: $\mathbf{y} = \mathbf{h}(\mathbf{x})$

State: \mathbf{x} . Here for (??), we have $\mathbf{x} = \mathbf{p}$.

Pose: $\mathbf{p} = (x, y, \theta)$.

Example (Trivial case: the position is measured)

➤ Measured output: $\mathbf{y} = \mathbf{h}(\mathbf{x}) = (x, y)^T$.

➤ $d\mathcal{O}_{\mathbf{x}_0}(\mathbf{h}) = \text{span}\{dx, dy, d(u \cos(\theta)), d(u \sin(\theta))\} = \text{span}\{dx, dy, d\theta\}$.

➤ $\dim d\mathcal{O}_{\mathbf{x}_0}(\mathbf{h}) = 3 \Rightarrow$ **localizable**.

Example (Case 1: the bearing angles are measured for one landmark (MA1))

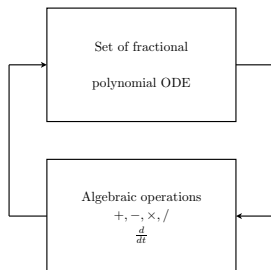
- One landmark A_1 + measurement $\mathbf{h}(\mathbf{p}) = (\alpha_1, \beta_1)^T$,
- There is no closed form for $dL_f^{\ell-1} \mathbf{h}(\mathbf{x})$.
- Lengthy computation of $d\mathcal{O}_{\mathbf{x}_0}(\mathbf{h})$ prove that the rank is 2: the unicycle mobile robot is not localizable with only one landmark.

- local observability rank condition is concerned with the successive output **time derivatives**.
- For an introduction to Diff. Algebra (for more details see [39, 40, 41, 34, 42, 43]).

Some hints about the algebraic concepts and tools:

- Ring (or Field) \rightarrow differential Ring (Field) (as soon as derivation is defined Leibniz rule),
- differential ideal,
- differential extension (\mathbf{L}/\mathbf{F} : one is bigger than the other $\mathbf{F} \subset \mathbf{L}$),
- notion of basis (generator and freeness), dimension of the basis is the differential transcendence degree,
- etc ...

I will not give details but will give a down to earth vision.



☞ **suitable for all real processes:** exp, log trigonometric functions and so on satisfy ODE.

$$x_1 \ddot{x}_1 + x_1^2 \dot{x}_1 + x_1^2 + \exp(x_1) = 0 \quad \Leftrightarrow \quad \begin{aligned} x_1 \ddot{x}_1 + x_1^2 \dot{x}_1 + x_1^2 + x_2 &= 0, \\ x_2 - x_2 \dot{x}_1 &= 0. \end{aligned}$$

$x_2 = \exp(x_1)$

Observability review: differential algebraic framework

Practical guide to differential Algebraic framework

$$\dot{\mathbf{p}} = \mathbf{f}(\mathbf{p}, \mathbf{u}) = \begin{pmatrix} v \cos(\theta) \\ v \sin(\theta) \\ \omega \end{pmatrix}, \quad (5)$$

Fit this framework (trigonometric functions) using:

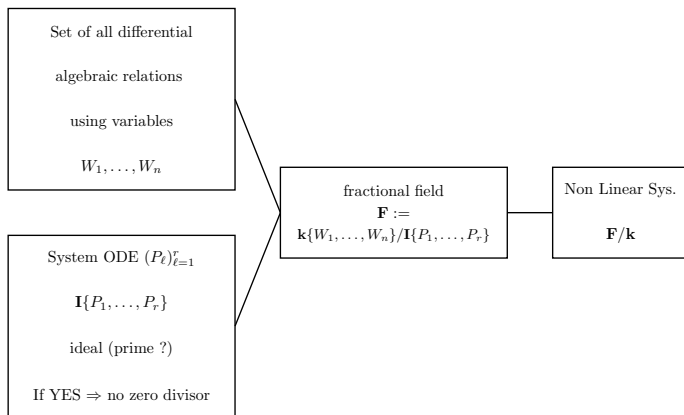
$$\begin{cases} z &= x + iy \\ \Theta &= \exp(i\theta) \end{cases}, \quad (6)$$

(5) can be rewritten as:

$$\dot{z} = \Theta v, \quad (7)$$

$$\dot{\Theta} = i\Theta\omega. \quad (8)$$

Observability review: differential algebraic framework



Properties: invertibility, flatness, ...

Simple characterization of the intrinsic properties of a system: **invertibility**, **flatness** (closed to controllability) [45, 46, 47, 48, 38], ...

Observability review: differential algebraic framework

Observability: (see [39] and [40])

Definition

$\zeta \in \mathbf{F}$ is **observable** w.r.t. $\mathbf{z} := \{z_\ell : \ell \in I\} \subset \mathbf{F}$ if it is algebraic over $\mathbf{k}\langle \mathbf{z} \rangle$.

☞ ζ = algebraic function of the components of \mathbf{z} and a finite number of their derivatives.

Theorem

A non linear system is observable if, and only if, any state variable is a function of the input and the output variables and their derivatives up to some finite order.

$$\begin{aligned}\dot{x}_1 &= x_2 + f_1(x_1), \\ \dot{x}_2 &= f_2(x_1, x_2), \\ y &= x_1\end{aligned}$$

Theorem

A mobile robot is **localizable** with respect to \mathbf{u}, \mathbf{y} if, and only if, there is a non-zero irreducible differential polynomial linking the pose to the measured output \mathbf{y} , the input \mathbf{u} and a finite number of their time derivatives.

Example (Position is measured)

$$\dot{z} = \Theta v, \quad (9)$$

$$\dot{\Theta} = i\Theta\omega. \quad (10)$$

Output $\mathbf{y} = z = x + iy$ (two sensors).

Observable: $\mathbf{p}_a = \left(\mathbf{y}, \Theta = \frac{\dot{\mathbf{y}}}{v} \right)^T$.

Example (MA1: bearing angles for one landmark)

$$\dot{\mathbf{y}} = -v - i\omega\mathbf{y}. \quad (11)$$

Θ cannot be obtained as an algebraic relation in terms of \mathbf{y}, v, ω and a finite number of their derivatives: **robot is not localizable**.

➡ **localizability defect** is defined using an algebraic setting and corresponds to the number of variables within the list z, Θ to be added to \mathbf{u}, \mathbf{y} in order to retrieve the robot localizability.

Algebraic localizability

- All cases MA2 to MA4 are solved (similar technics).
- Is there anything in between MA1 and MA2 ?

MA1-BIS: azimuth and elevation angles are measured for one landmark and **one target**: 4 outputs y_1, \dots, y_4

$$v = \frac{2z_{A_1} \dot{y}_2 y_1}{(1 + y_1^2) y_2^2} \quad (12)$$

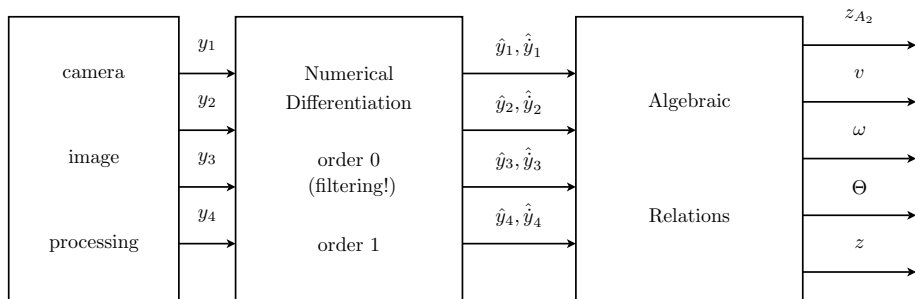
$$z_{A_2} = \frac{z_{A_1} \dot{y}_2 y_1}{(1 + y_1^2) y_2^2} \times \frac{(1 + y_3^2) y_4^2}{\dot{y}_4 y_3} \quad (13)$$

$$\omega = -i \frac{z_{A_1} y_4^2(t) (y_1(t) \dot{y}_2(t) - \dot{y}_1(t) y_2(t)) + z_{A_2} y_2^2(t) (\dot{y}_3(t) y_4(t) - y_3(t) \dot{y}_4(t))}{z_{A_1} y_1(t) y_2(t) y_4^2(t) - z_{A_2} y_2^2(t) y_3(t) y_4(t)} \quad (14)$$

$$\Theta = \Theta(t_0) \frac{z_{A_1} \frac{y_1(t_0)}{y_2(t_0)} - z_{A_2} \frac{y_3(t_0)}{y_4(t_0)}}{z_{A_1} \frac{y_1(t)}{y_2(t)} - z_{A_2} \frac{y_3(t)}{y_4(t)}} \quad (15)$$

$$z(t) = c_{A_1} - z_{A_1} \Theta \frac{y_1(t)}{y_2(t)} \quad (16)$$

Algebraic localizability



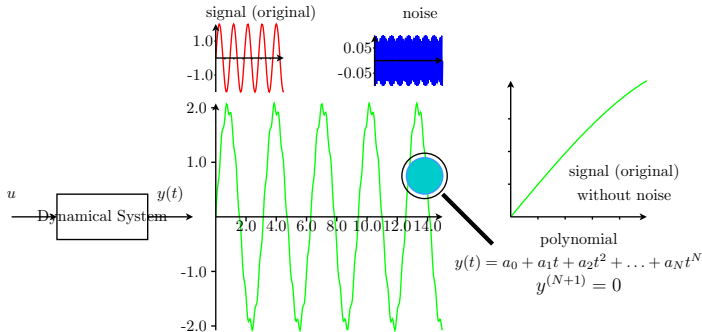
Need good numerical differentiation in noisy environment

Algorithms:	Non-A Algorithm	EKF
Input (known):	NO	YES
Noise characteristics (known)	NO	YES
θ measured	NO	NO
Initialization	NO	YES
Only one landmarks	YES	NO
Confidence interval	NO (TBD)	YES

Table: Algorithms Comparison

Localization as a numerical differentiation problem

All we want to know is in the output signal...

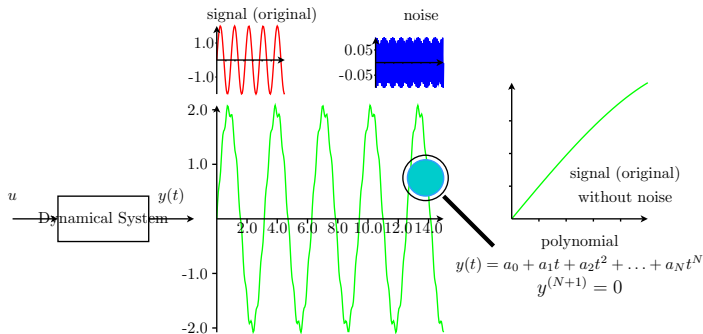


Real-time estimations of derivatives for noisy signals

Takes $x^N = 0$ (Laplace) + alg. annihilator \Rightarrow time domain

Localization as a numerical differentiation problem

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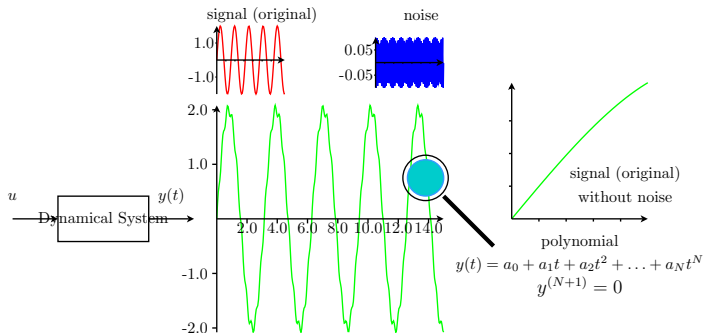


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Real-time estimations of derivatives for noisy signals

Takes $x^N = 0$ (Laplace) + alg. annihilator \Rightarrow time domain

Localization as a numerical differentiation problem

Numerical derivation

Estimate $x^{(2)}(0)$ through the truncated series of order 2:

$$\mathcal{R}: \quad X = \frac{x(0)}{s} + \frac{x^{(1)}(0)}{s^2} + \frac{x^{(2)}(0)}{s^3}$$

Idea: kill undesired terms (blue) except the one to estimate (red)

Step 1 $\times s^2$: $s^2 X = sx(0) + x^{(1)}(0) + \frac{x^{(2)}(0)}{s}$

Step 2 $\frac{d^2}{ds^2}$: $2X + 4s \frac{dX}{ds} + s^2 \frac{d^2 X}{ds^2} = \frac{2}{s^3} x^{(2)}(0)$

Step 3 $\times \frac{1}{s^3}$: $\frac{2}{s^3} X + \frac{4}{s^2} \frac{dX}{ds} + \frac{1}{s} \frac{d^2 X}{ds^2} = \frac{2}{s^6} x^{(2)}(0)$

Step 4 Go back to the time domain:

$$\frac{2T^5}{5!} x^{(2)}(0) = T^3 \int_0^1 (2w^{2,0}(\tau) - 4w^{1,1}(\tau) + w^{0,2}(\tau)) y(T\tau) d\tau$$

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$$2X + 4s \frac{dX}{ds} + s^2 \frac{d^2 X}{ds^2} = \frac{2}{s^3} x^{(2)}(0)$$

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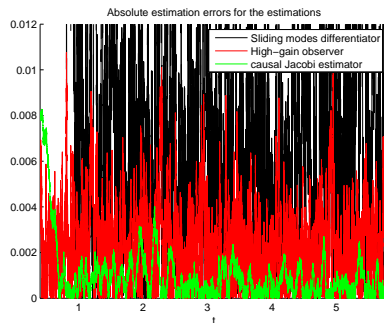
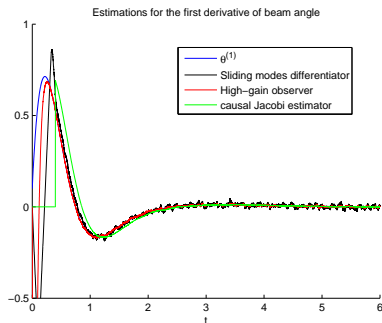
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Localization as a numerical differentiation problem

Numerical differentiation: causal Jacobi estimators

The Ball and Beam system:



$SNR = 24.5\text{dB}$ and $T_s = 10^{-4}$

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Simulations: EKF knows the noise characteristic

Algorithm	Results			
	distance error mean	distance error variance	v error mean	ω error mean
NON-A-MA1BIS	0.2196	0.0040	0.0334	0.0015
NON-A-MA2	0.1422	0.0034	0.0286	3.2435e-006
NON-A-MA3	0.1869	0.0033	0.5000	0.0100
EKF-MA3	0.2219	0.0122	X	X
NON-A-MA4	1.6806	1.8969	X	X
NON-A-MA5	1.3127	1.4534	X	X

Simulations: EKF does not know the noise characteristic

Algorithm	Results			
	distance error mean	distance error variance	v error mean	ω error mean
NON-A-MA1BIS	0.2081	0.0039	0.0334	0.0015
NON-A-MA2	0.1436	0.0035	0.0287	3.2435e-006
NON-A-MA3	0.1839	0.0034	0.5000	0.0100
EKF-MA3	1.0382	0.0403	X	X
NON-A-MA4	1.7047	1.9789	X	X
NON-A-MA5	1.3421	1.5717	X	X

- NON-A algorithms require less hypothesis than EKF (easier to implement),
- All results MA1-BIS, MA2 and MA3 are better than EKF,
- MA4 and MA5 are not so useful even if better than EKF (with the same outputs).

- Robot is equipped with an Imaging Source camera and an inertial sensor for MA2,
- Reference localization is obtained using luminous pattern hanging from the ceiling,
- The Imaging Source camera is used to get the relative angle between the robot and two points (landmark and/or target),
- This measures are process using Matlab to estimate the posture.

Experimental Results: MA1-BIS

	error mean (<i>cm</i>)	error standard deviation (<i>cm</i>)
NON-A- MA1-BIS	11	5

Table: Experimental results of NON-A algorithm

Experimental Results: MA1-BIS

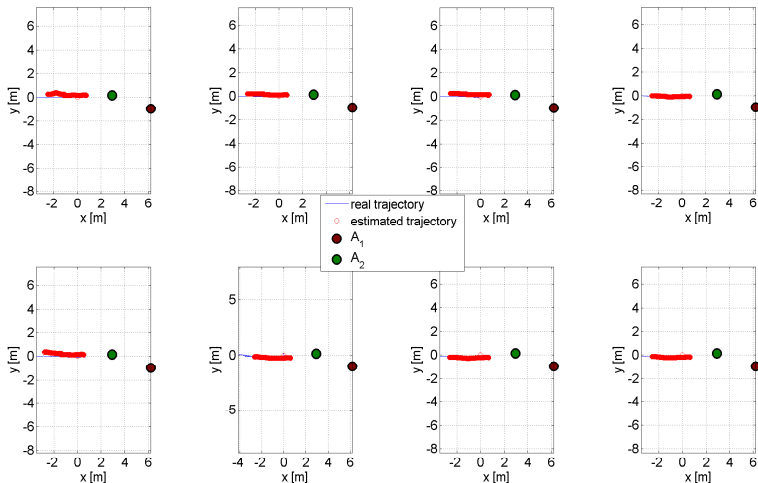


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- Localization framework: bearing only measurement cases using optic flow information and natural landmarks.
- Localizability is defined in a differential algebraic framework (notion of localizability defect)
- Localization \Leftrightarrow numerical differentiation problem in noisy environment.
- Our solution provides pose and velocities reconstruction.

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