

SLAM Visual Puro

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1. El problema de SLAM

2. EKF SLAM

3. SLAM visual puro

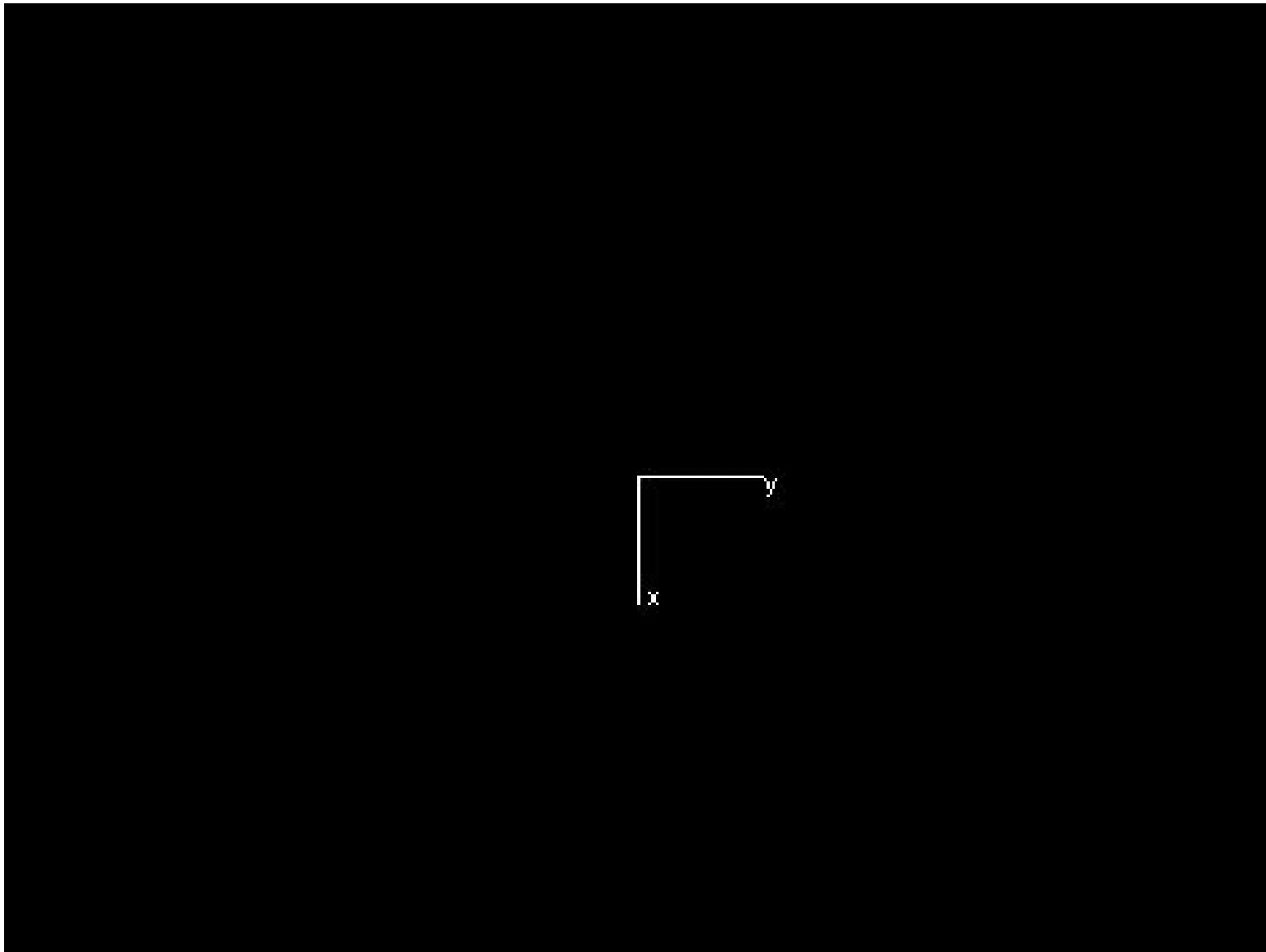
- Monocular
- Estéreo

4. Perspectiva

1. El problema de SLAM

¿Es posible, comenzando en **posición inicial desconocida**, en un **entorno desconocido**, utilizar un vehículo para construir un mapa del entorno **incrementalmente**, y **al mismo tiempo** utilizar el mapa para determinar la localización del vehículo?

El problema de SLAM



(video: Paul Newman)

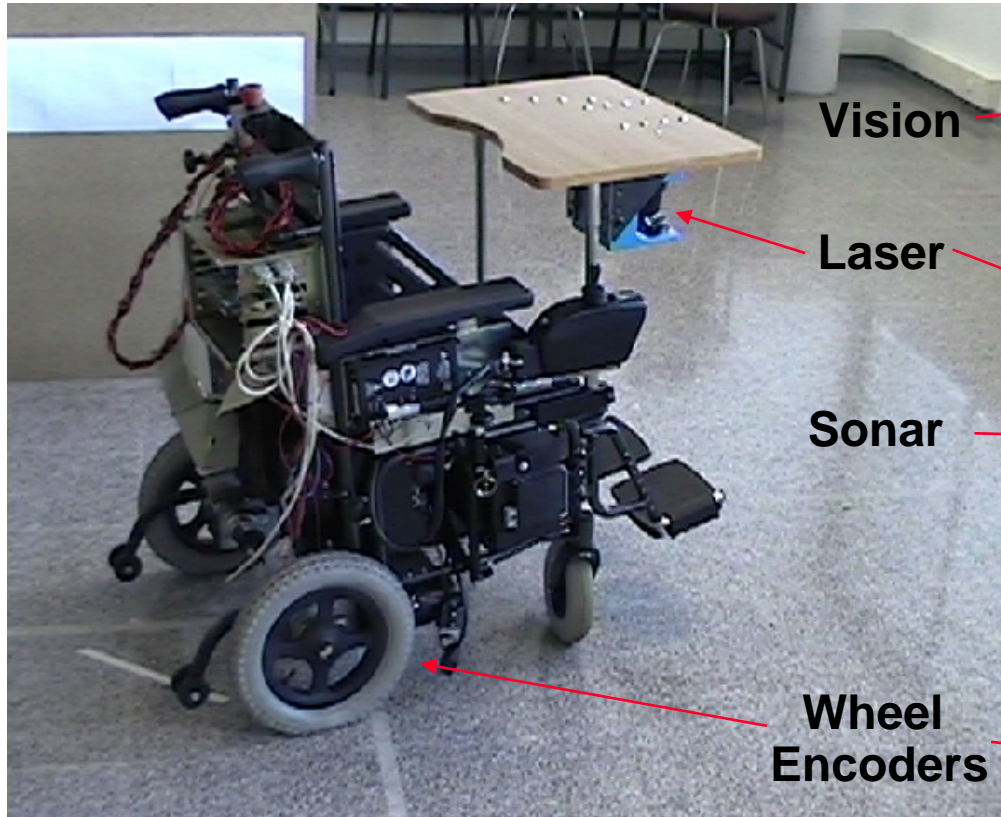
SLAM

The solution to the SLAM problem is, in many respects, a 'Holy Grail' of the autonomous robot research community, as the ability to build a map and navigate simultaneously would indeed make a robot 'autonomous'.

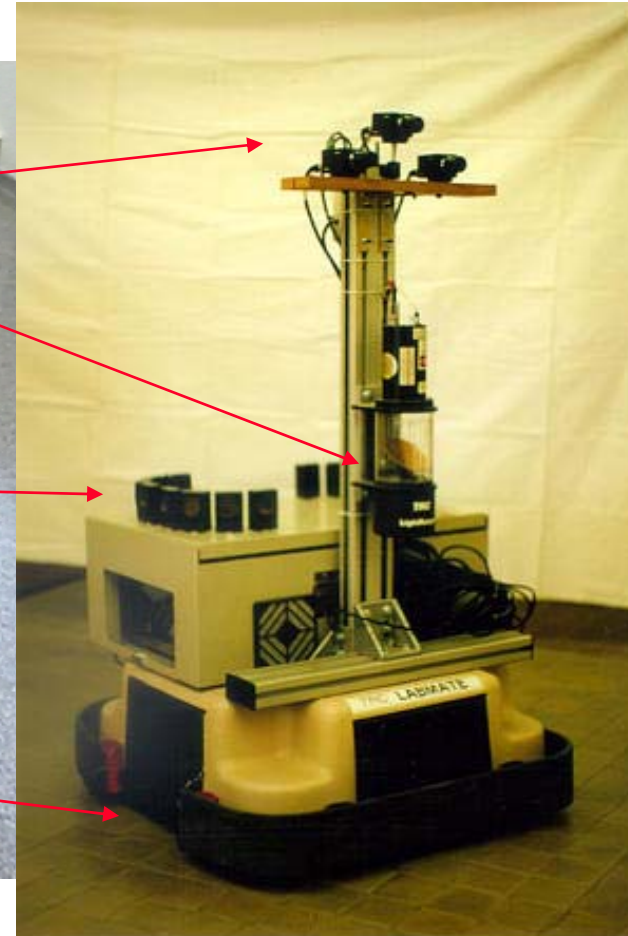
(Newman 1999, Leonard 2000, Thrun 2001)

- Es **posible**
- Proporciona al vehículo **autonomía real**
- Hay una gran cantidad de **aplicaciones potenciales**

Orígenes: el problema de la localización



Triton



Otilio

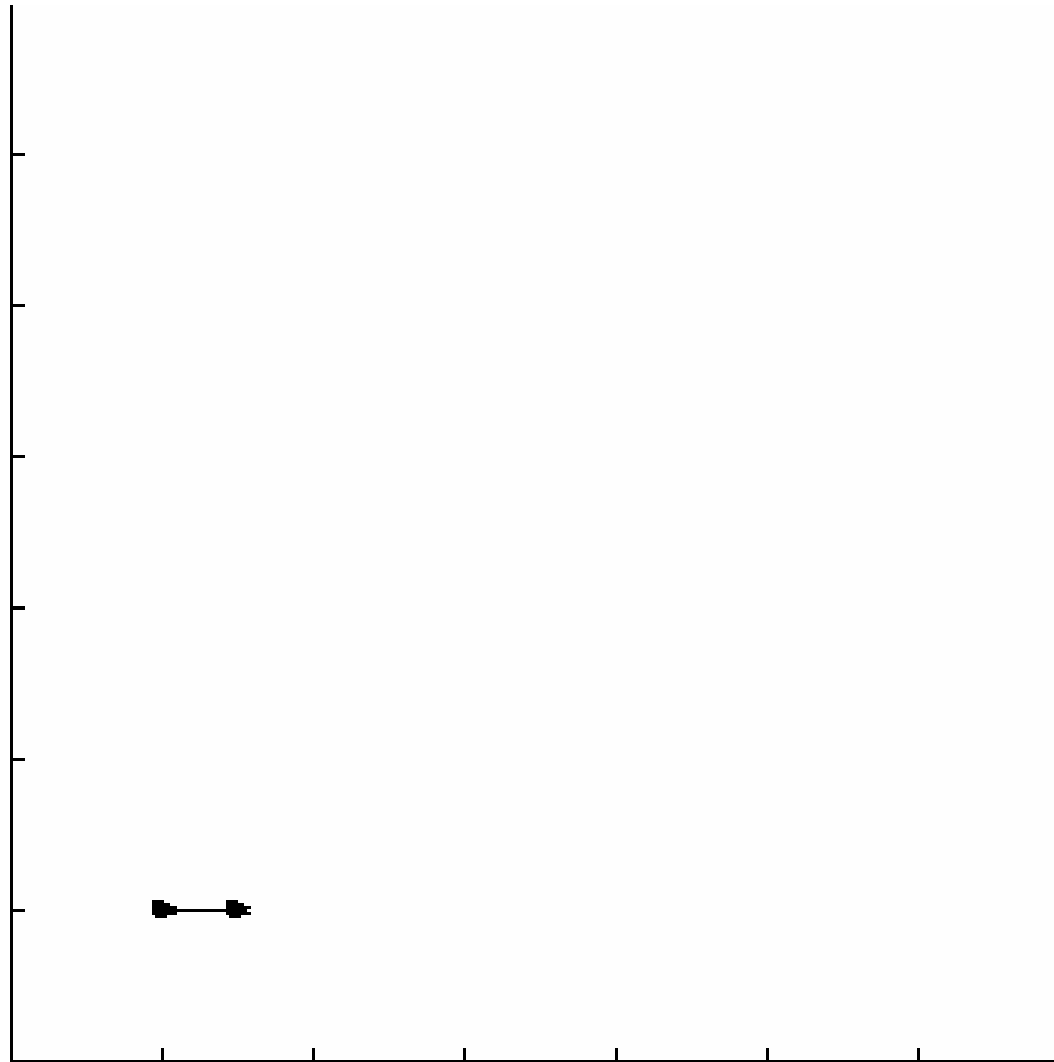
Vision

Laser

Sonar

Wheel Encoders

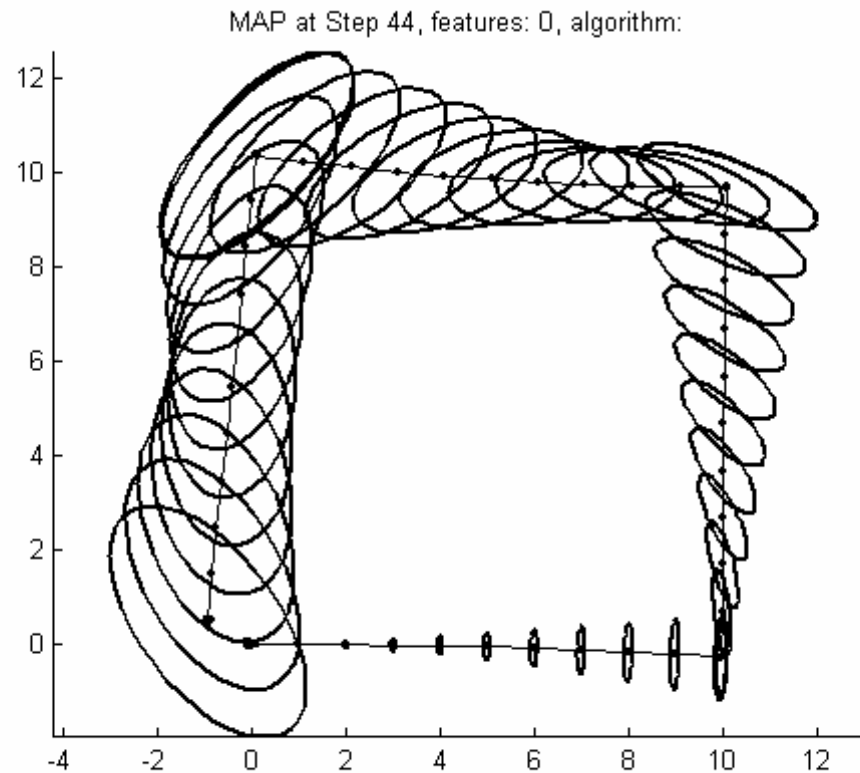
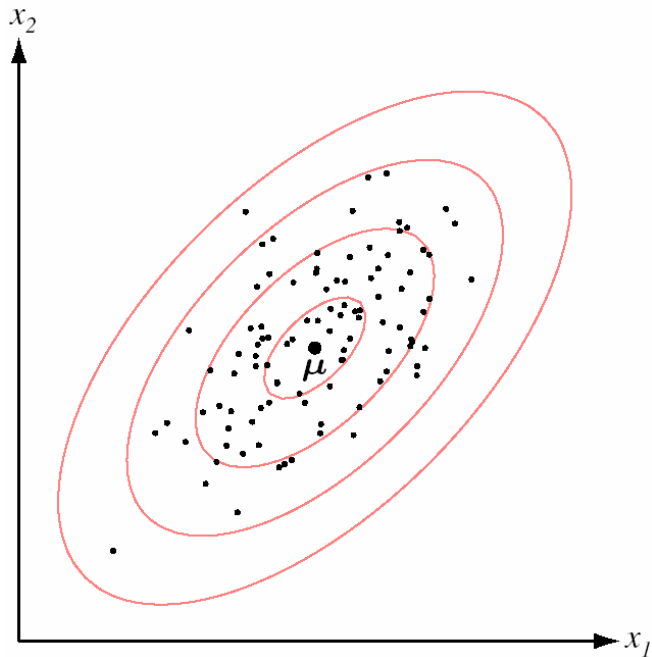
Odometría en 2D



¿Cómo evitar la deriva?

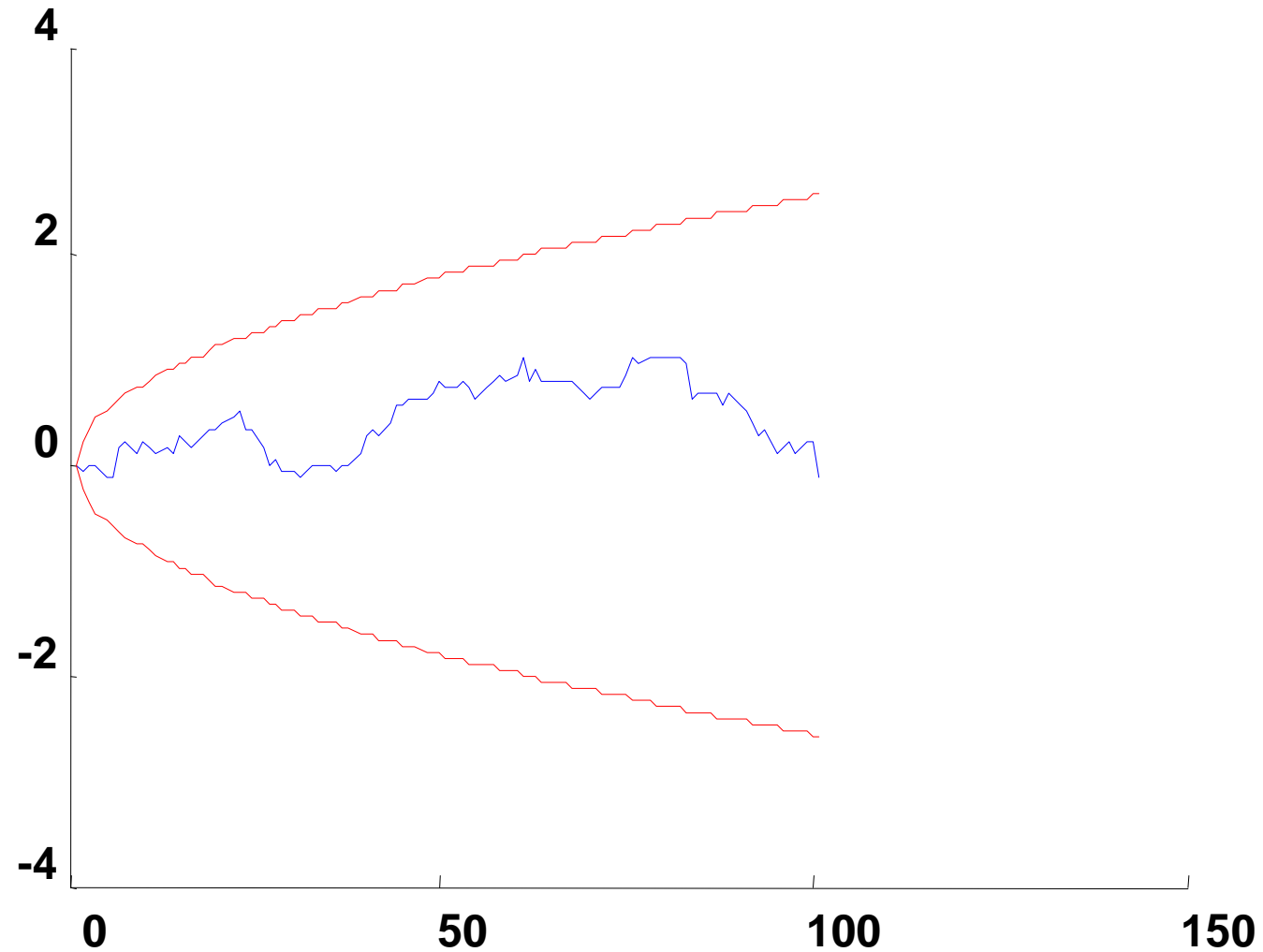
Odometría en 2D

- Suponemos que el error sigue una distribución Gaussiana



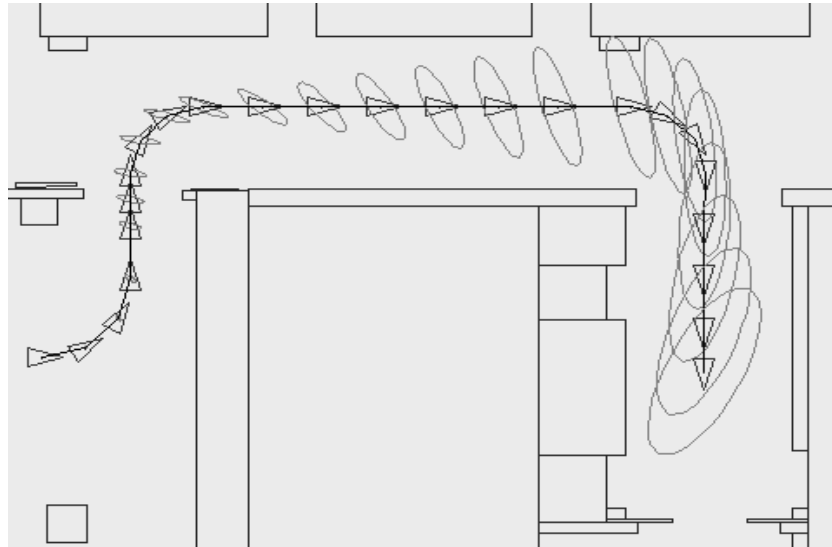
Odometría en 2D

Vehicle error in theta (deg)



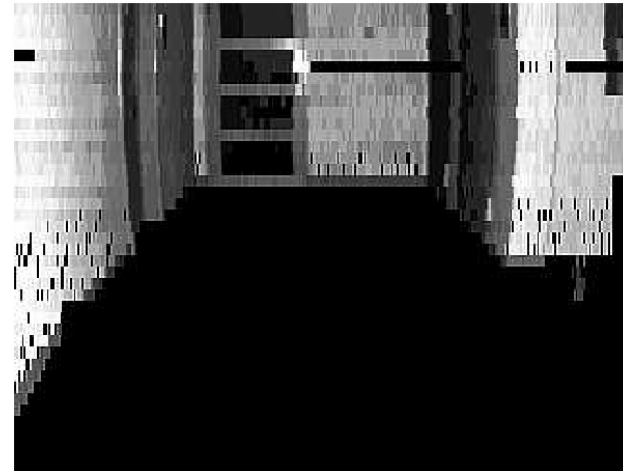
Localización basada en mapas

- Error acumulativo en odometría

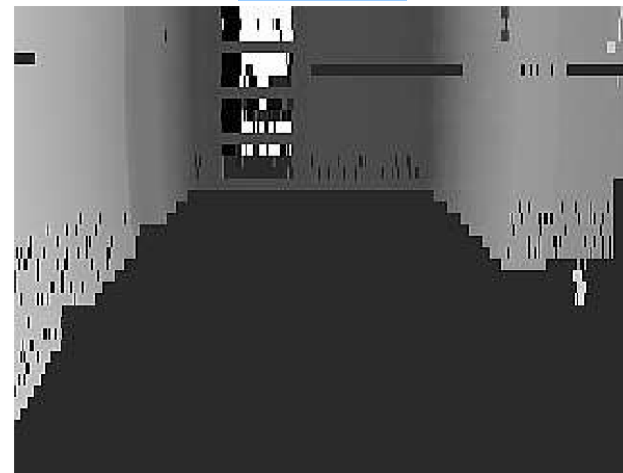


J. Neira, J.D. Tardós, J. Horn and G. Schmidt:
Fusing Range and Intensity Images for Mobile Robot Localization, IEEE Trans. Robotics and Automation, Vol. 15, No. 1, Feb 1999, pp 76-84.

- Mapa a priori + sensores



Vision

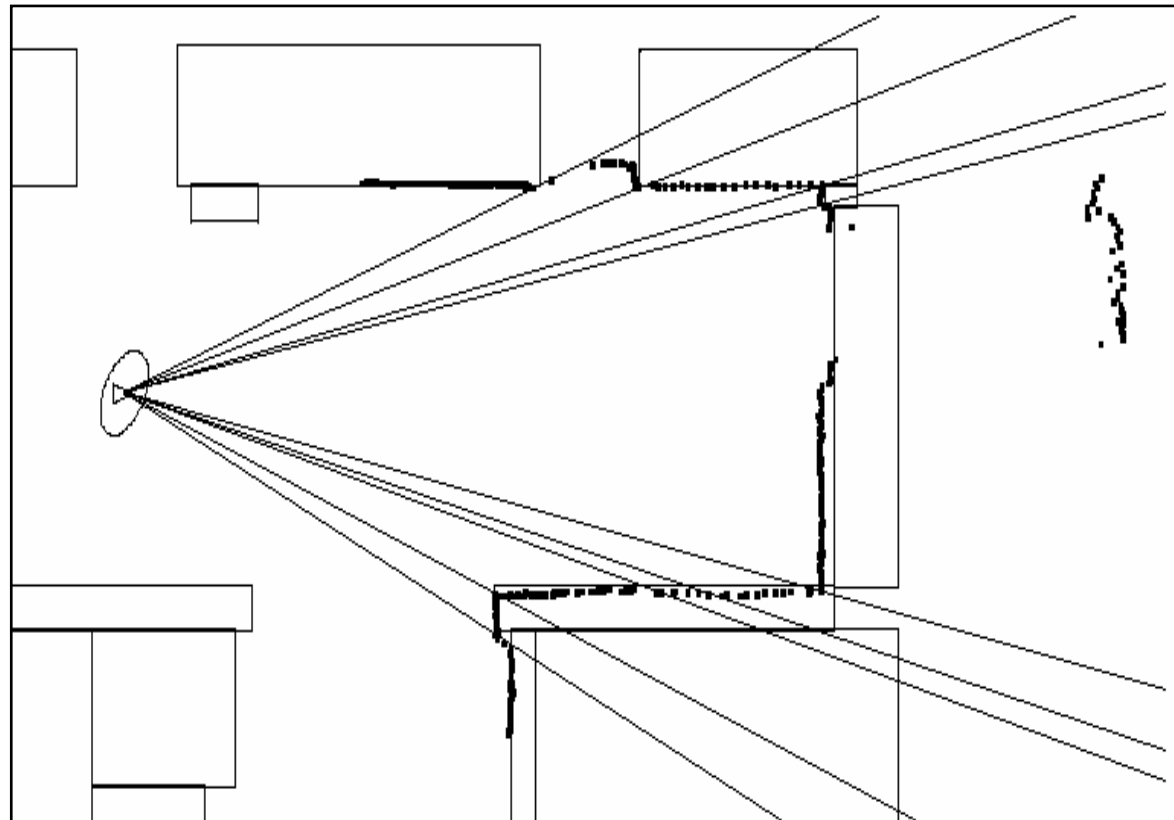


Laser

La necesidad de SLAM

- En muchas aplicaciones el entorno es desconocido
- Los mapas apriori usualmente son:

- Costosos
- Imprecisos
- Incompletos
- Desfasados



Índice

1. El problema de SLAM

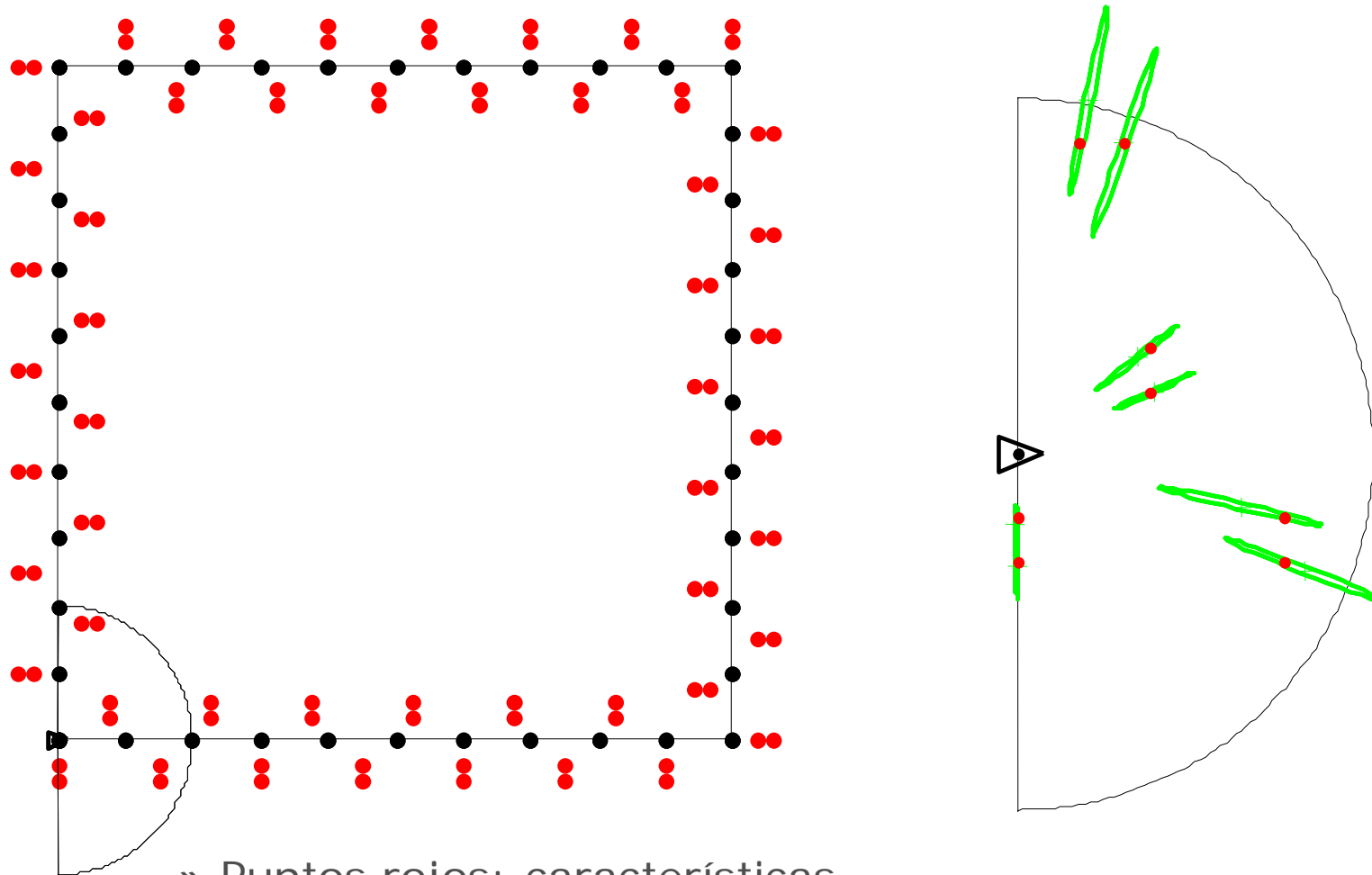
2. EKF SLAM

3. SLAM visual

- Monocular
- Estéreo

4. Perspectiva

Ejemplo: SLAM en un claustro



- » Puntos rojos: características
- » Línea negra: trayectoria robot
- » Semicírculo negro: rango del sensor

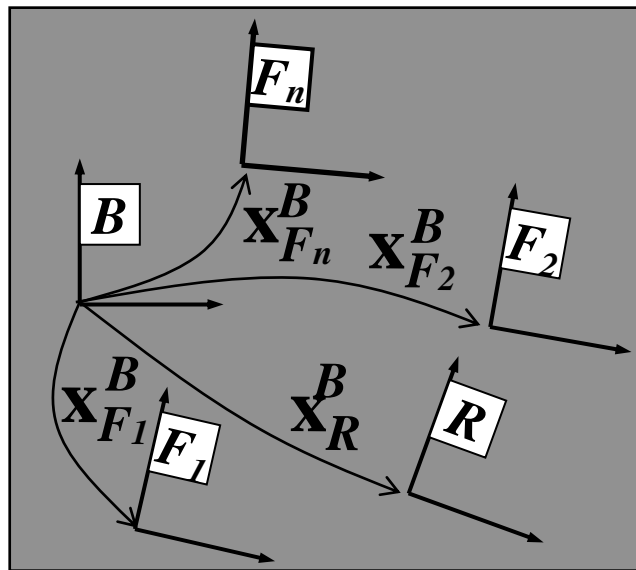
Mapas estocásticos

- Información relacionada con elementos del entorno:

$$\mathcal{F} = \{B, R, F_1, \dots, F_n\}$$

- Se representa en un **mapa estocástico**:

$$\mathcal{M}^B = (\hat{\mathbf{x}}^B, \mathbf{P}^B)$$



$$\hat{\mathbf{x}}^B = \begin{bmatrix} \hat{\mathbf{x}}_R^B \\ \vdots \\ \hat{\mathbf{x}}_{F_n}^B \end{bmatrix}$$

$$\mathbf{P}^B = \begin{bmatrix} \mathbf{P}_{RR}^B & \cdots & \mathbf{P}_{RF_n}^B \\ \vdots & \ddots & \vdots \\ \mathbf{P}_{F_n R}^B & \cdots & \mathbf{P}_{F_n F_n}^B \end{bmatrix}$$

EKF SLAM

Algorithm 1 SLAM:

$\mathbf{x}_0^B = \mathbf{0}; \mathbf{P}_0^B = \mathbf{0}$ { *Map initialization* }

$[\mathbf{z}_0, \mathbf{R}_0] = \text{get_measurements}$

$[\mathbf{x}_0^B, \mathbf{P}_0^B] = \text{add_new_features}(\mathbf{x}_0^B, \mathbf{P}_0^B, \mathbf{z}_0, \mathbf{R}_0)$

for $k = 1$ to steps **do**

$[\mathbf{x}_{R_k}^{R_{k-1}}, \mathbf{Q}_k] = \text{get_odometry}$

$[\mathbf{x}_{k|k-1}^B, \mathbf{P}_{k|k-1}^B] = \text{EKF_prediction}(\mathbf{x}_{k-1}^B, \mathbf{P}_{k-1}^B, \mathbf{x}_{R_k}^{R_{k-1}}, \mathbf{Q}_k)$

$[\mathbf{z}_k, \mathbf{R}_k] = \text{get_measurements}$

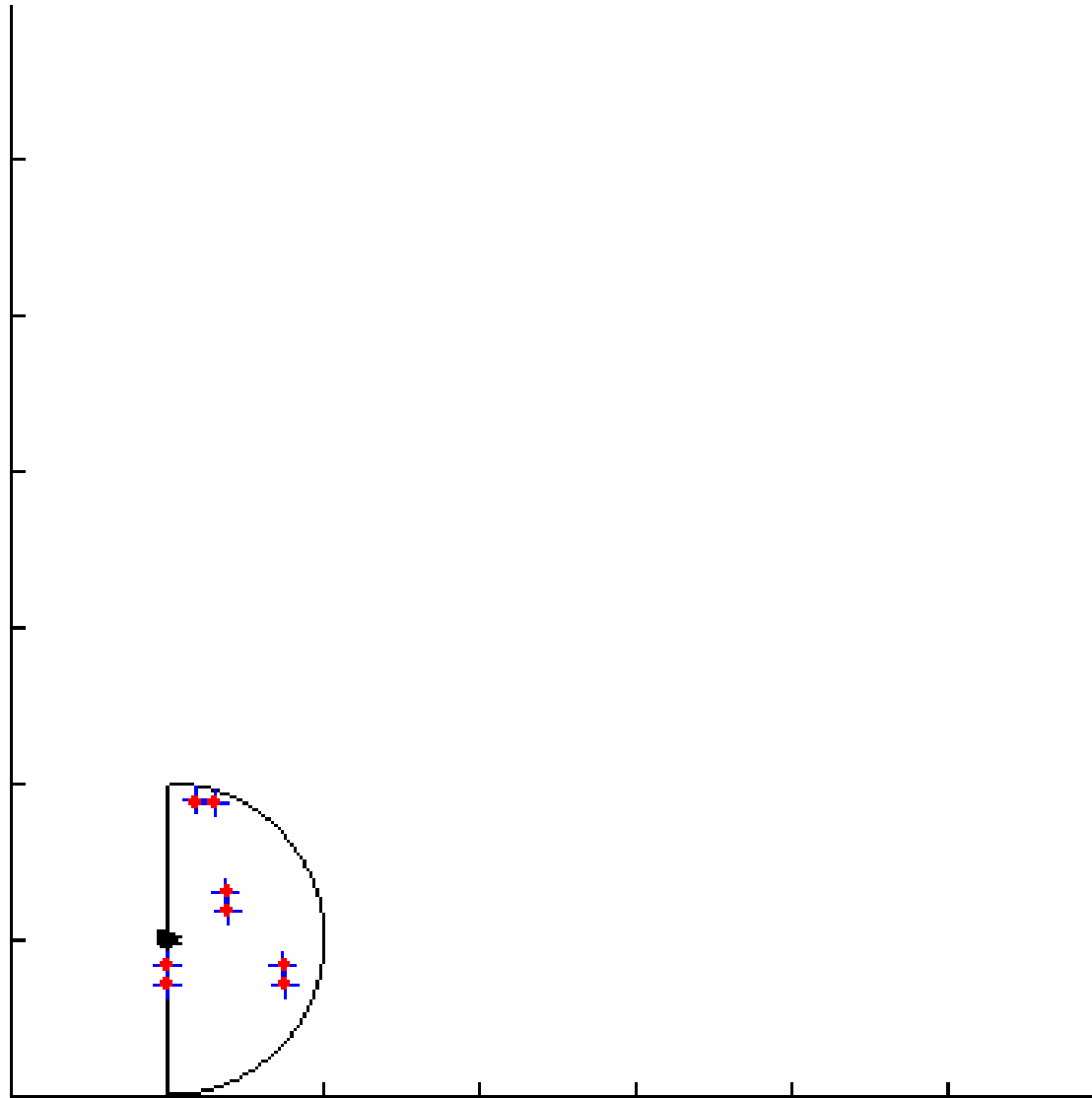
$\mathcal{H}_k = \text{data_association}(\mathbf{x}_{k|k-1}^B, \mathbf{P}_{k|k-1}^B, \mathbf{z}_k, \mathbf{R}_k)$

$[\mathbf{x}_k^B, \mathbf{P}_k^B] = \text{EKF_update}(\mathbf{x}_{k|k-1}^B, \mathbf{P}_{k|k-1}^B, \mathbf{z}_k, \mathbf{R}_k, \mathcal{H}_k)$

$[\mathbf{x}_k^B, \mathbf{P}_k^B] = \text{add_new_features}(\mathbf{x}_k^B, \mathbf{P}_k^B, \mathbf{z}_k, \mathbf{R}_k, \mathcal{H}_k)$

end for

La necesidad de SLAM

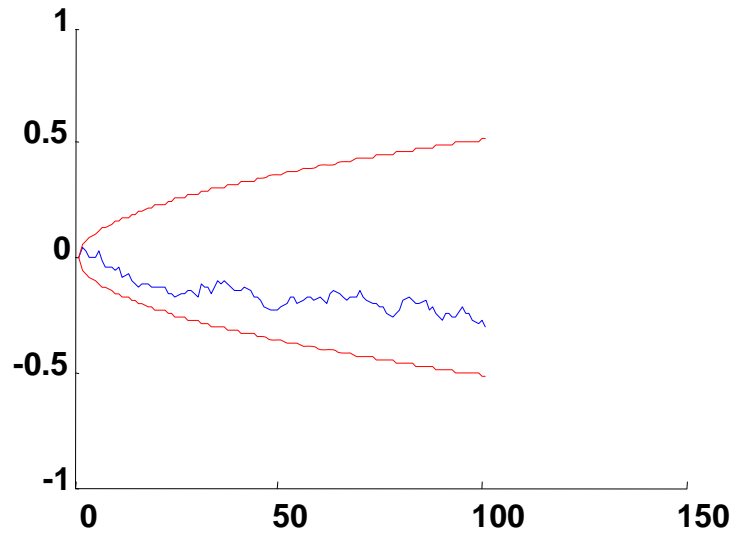


La incertidumbre crece!

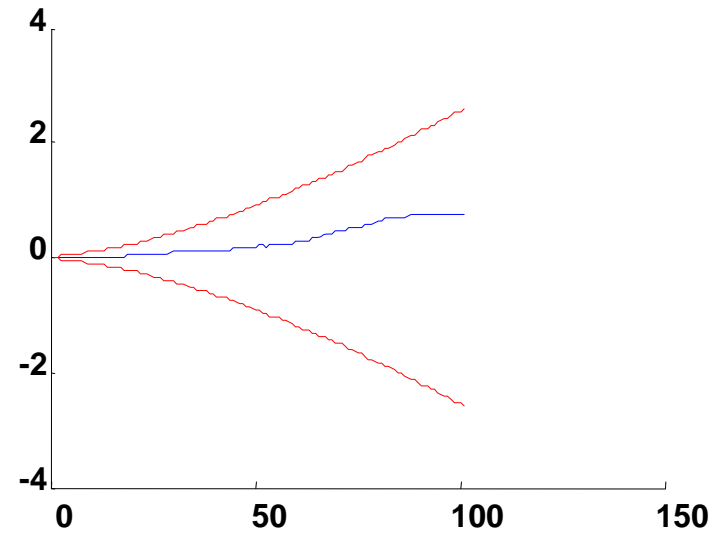
Jornadas Argentinas de Robótica 2008

SLAM en 2D

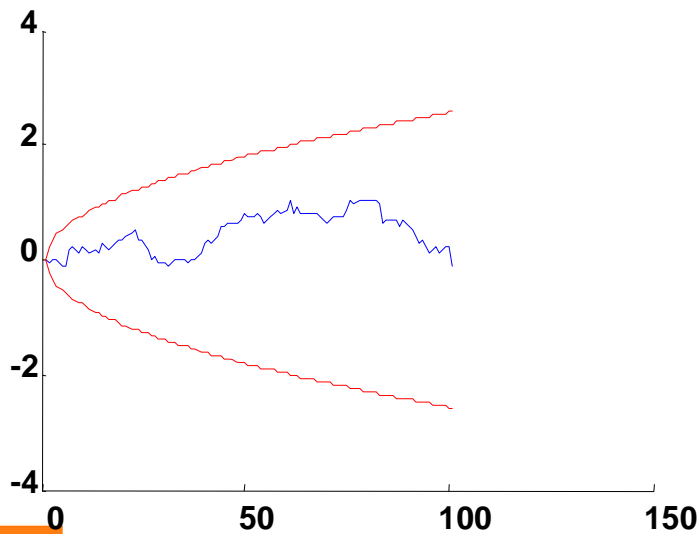
Vehicle error in x (m)



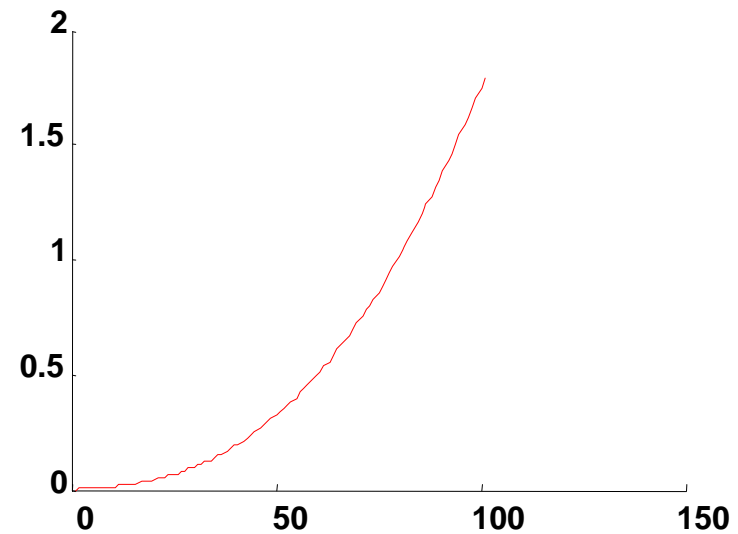
Vehicle error in y (m)



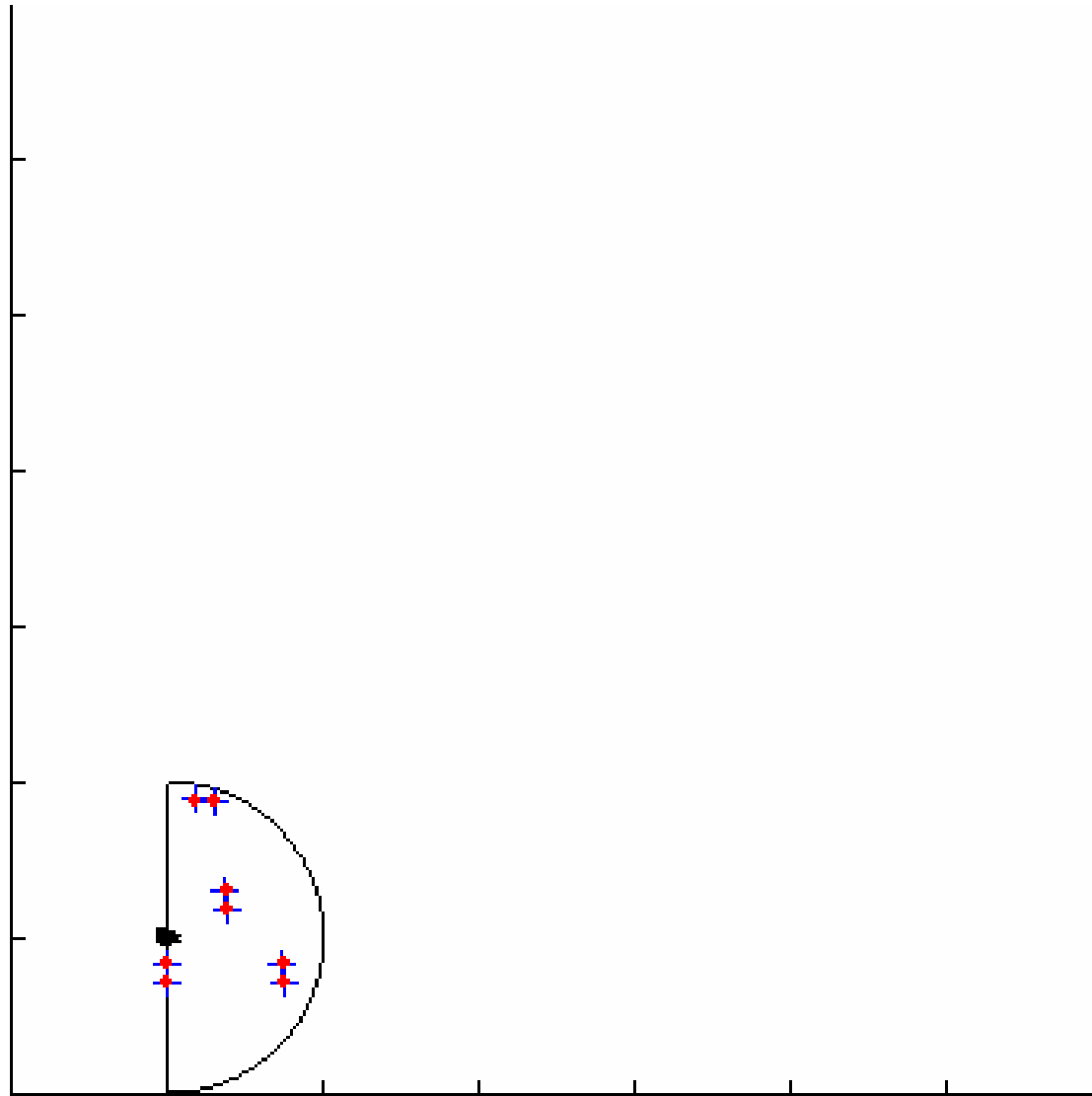
Vehicle error in theta (deg)



$\times 10^{-3}$ sqrt(det(P))



Buenas noticias!



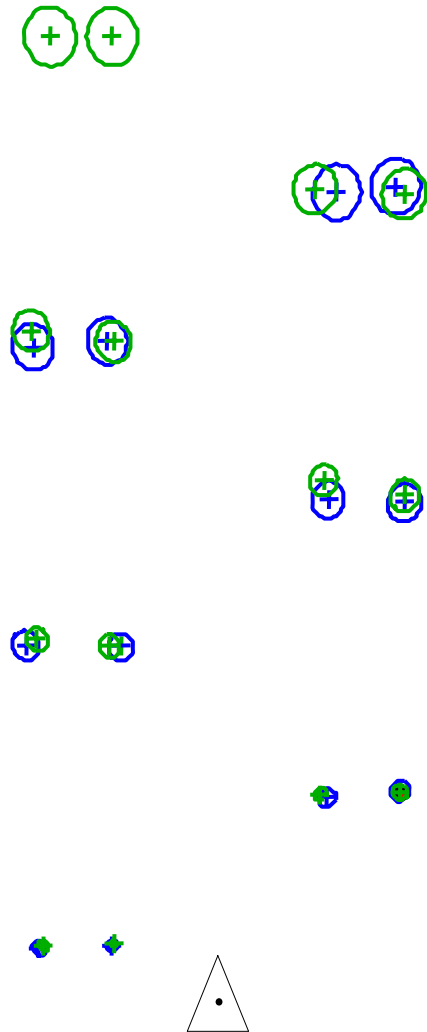
El cerrado de bucle reduce la incertidumbre!

Retos del EKF SLAM

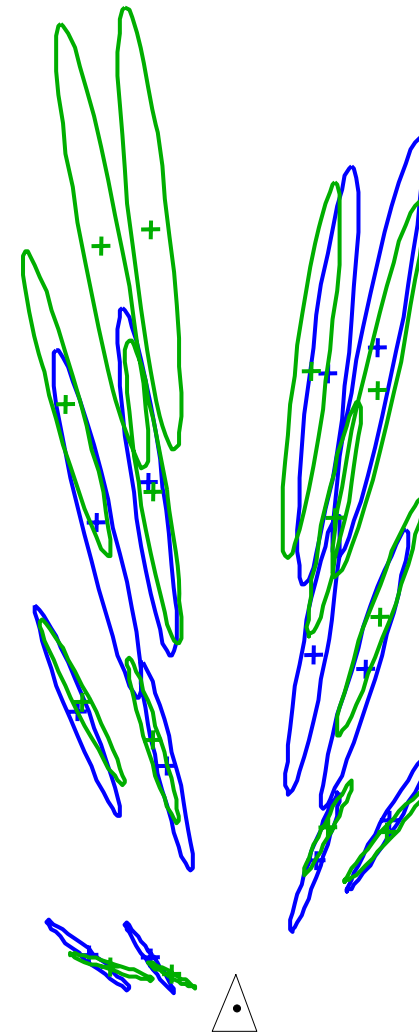
1. Asociación de datos
2. El coste computacional
3. El problema de la consistencia

La asociación de datos

- Sensor preciso

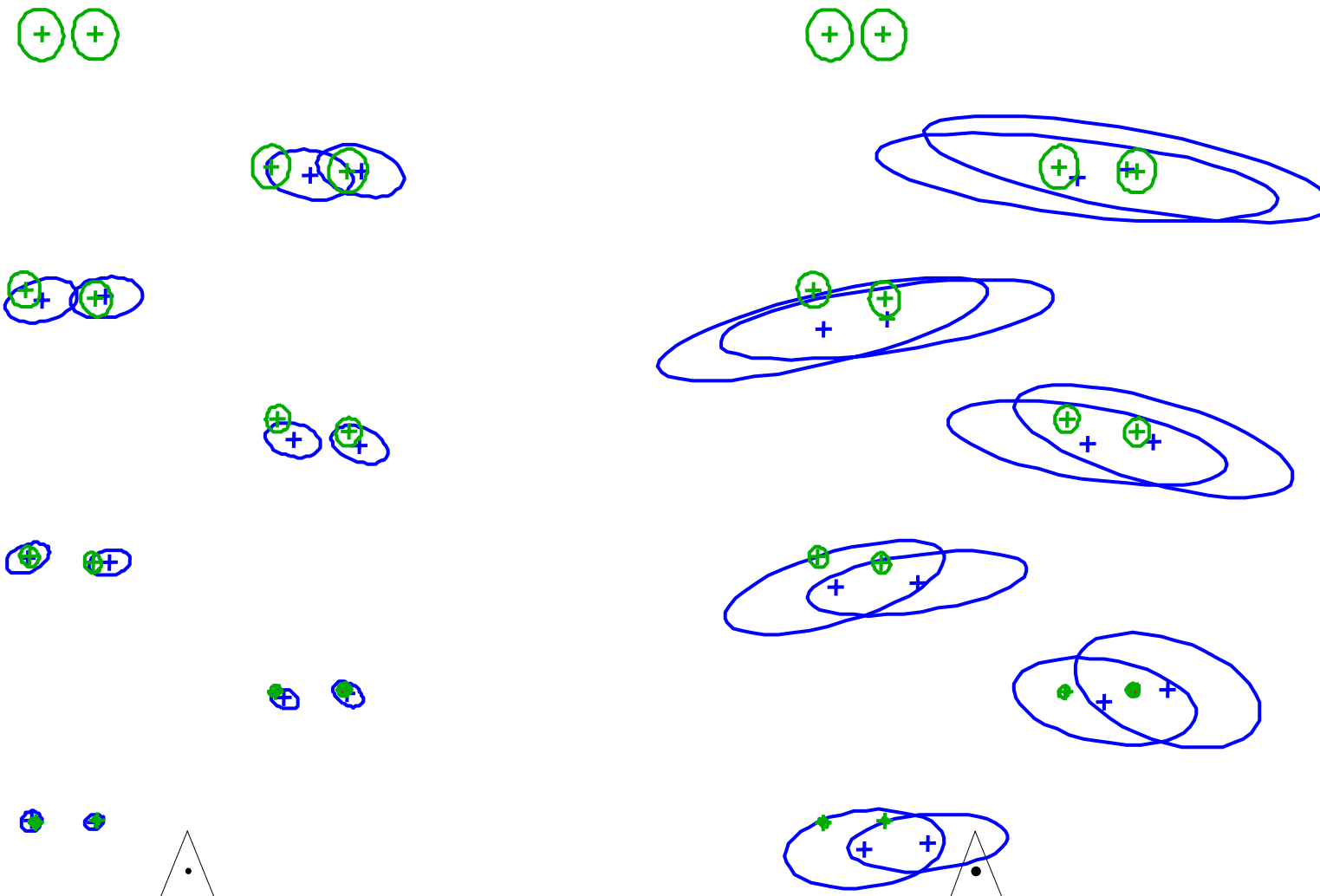


- Sensor impreciso



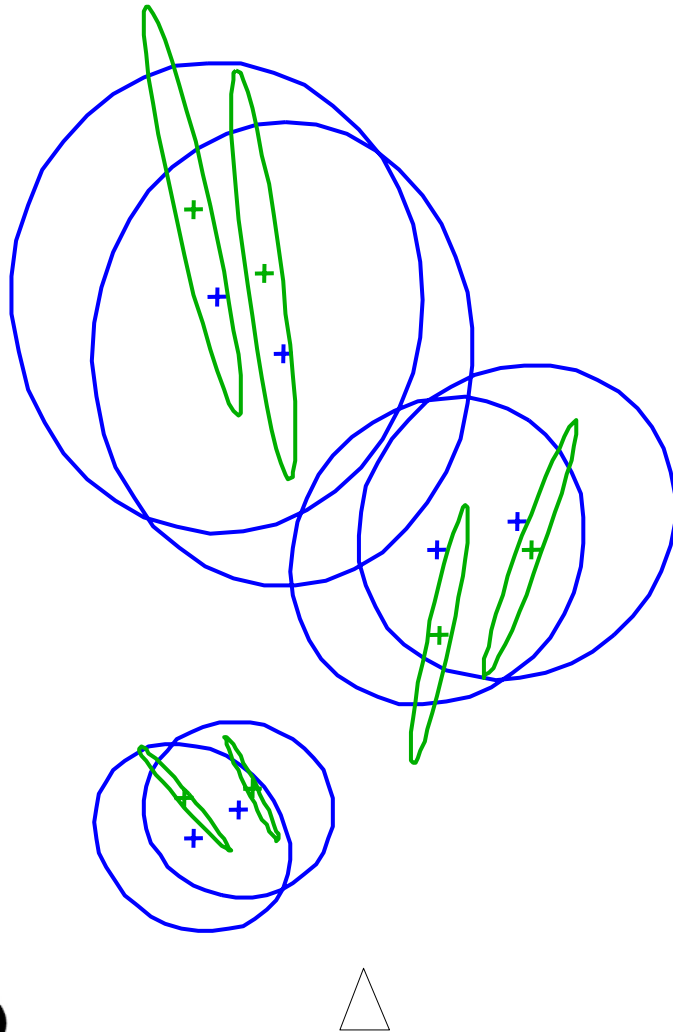
Asociación de datos

- Poco error de odometría
- Mucho error de odometría



La asociación de datos

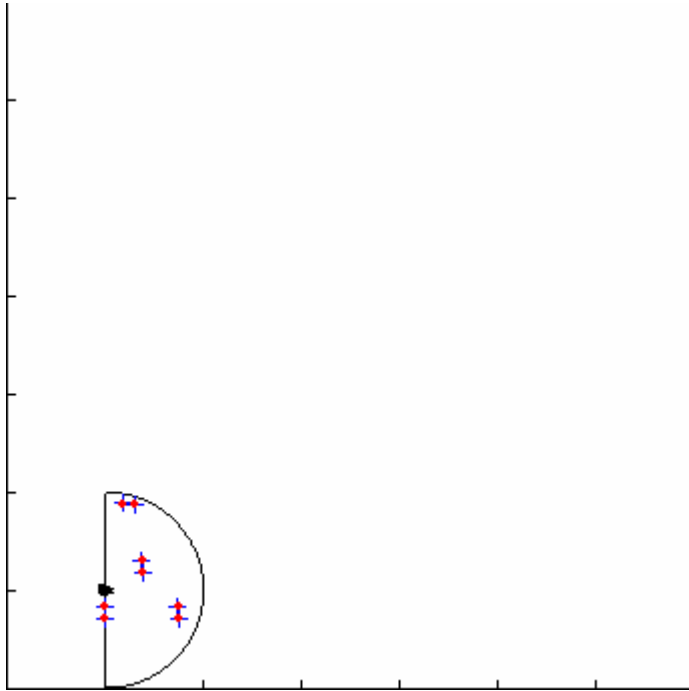
- Baja densidad de características



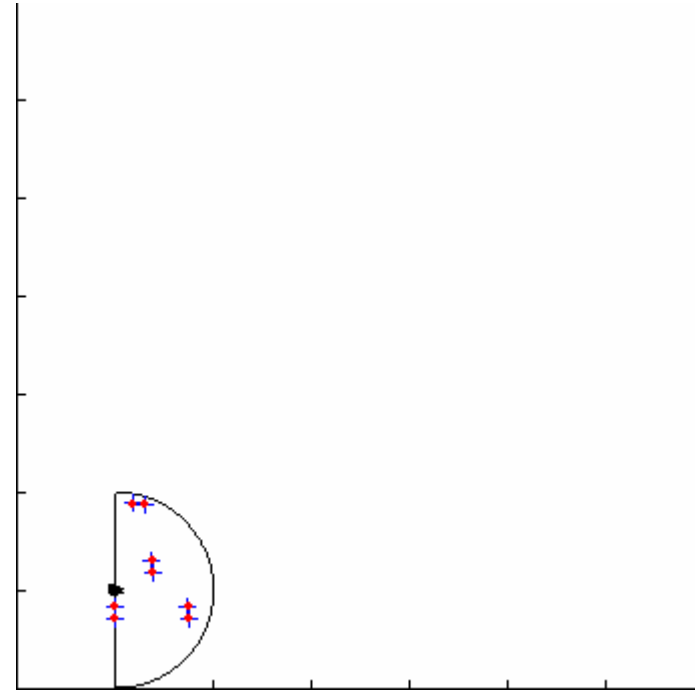
- Alta densidad de características



¿Porqué es importante?

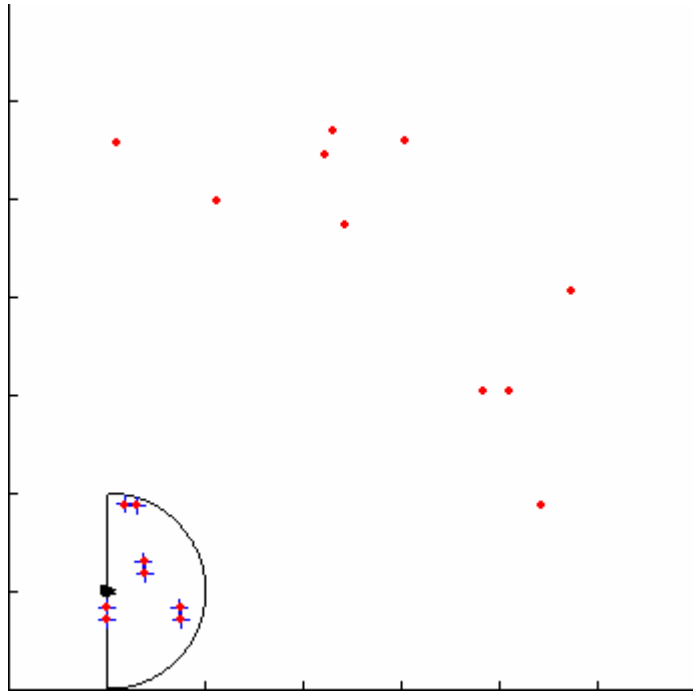


Un buen algoritmo

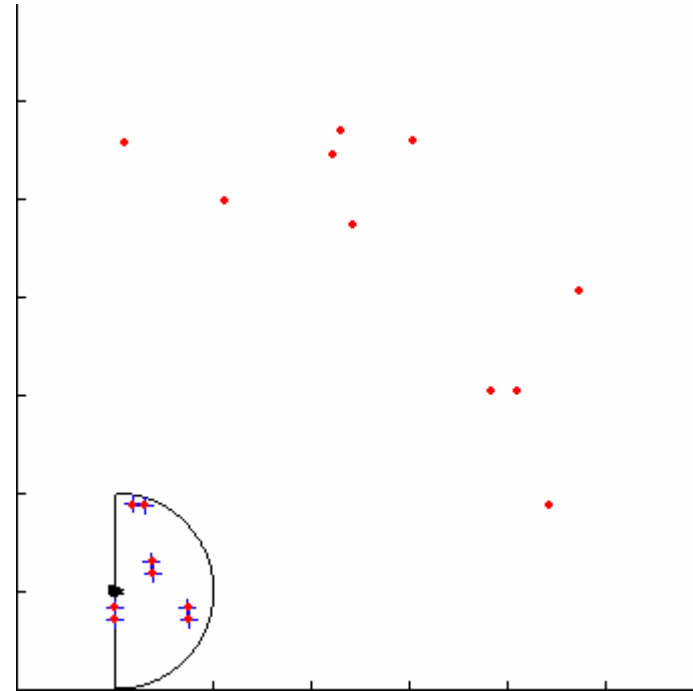


Un **mal** algoritmo

¿Porqué es difícil?

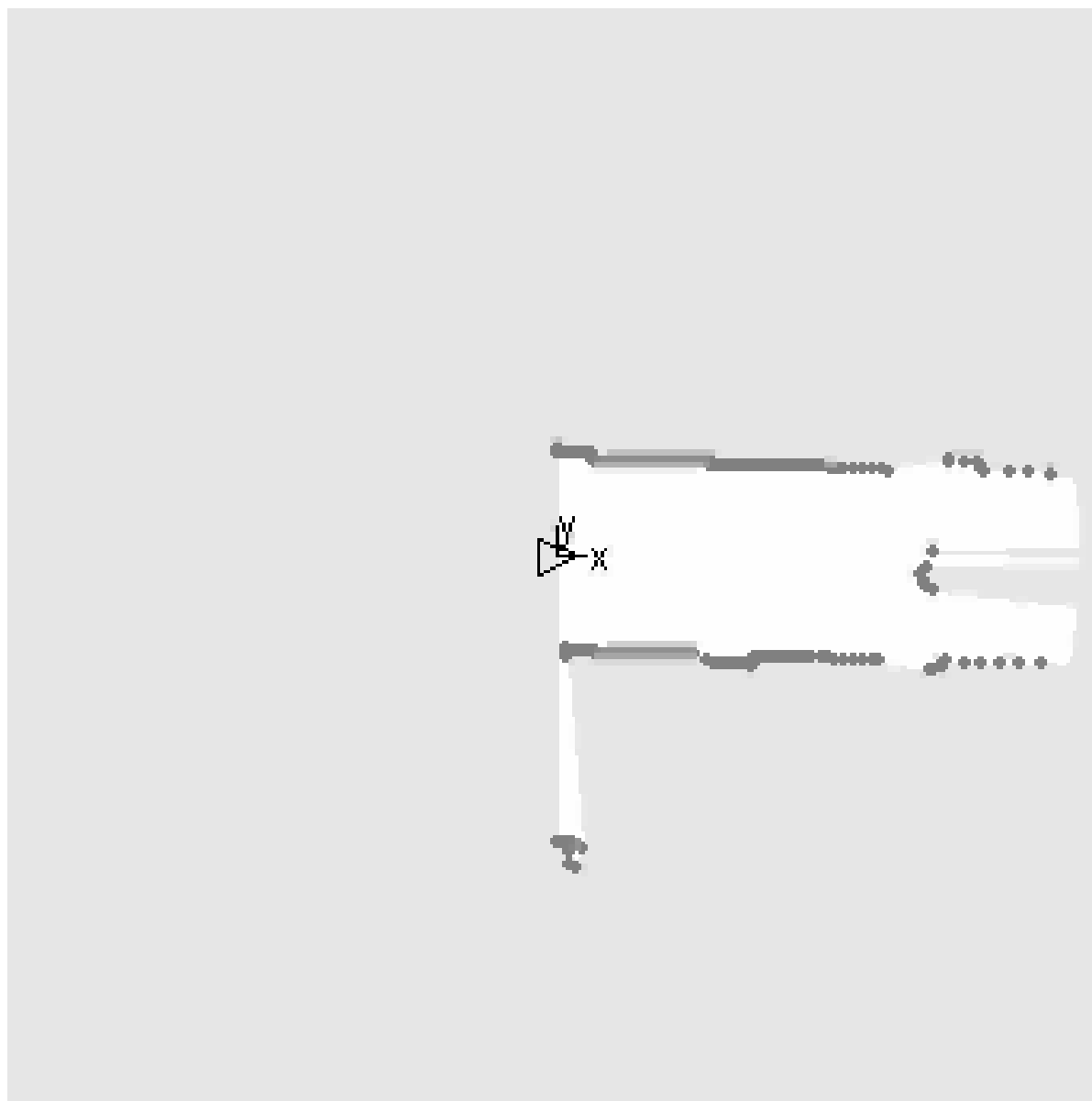


Un buen algoritmo

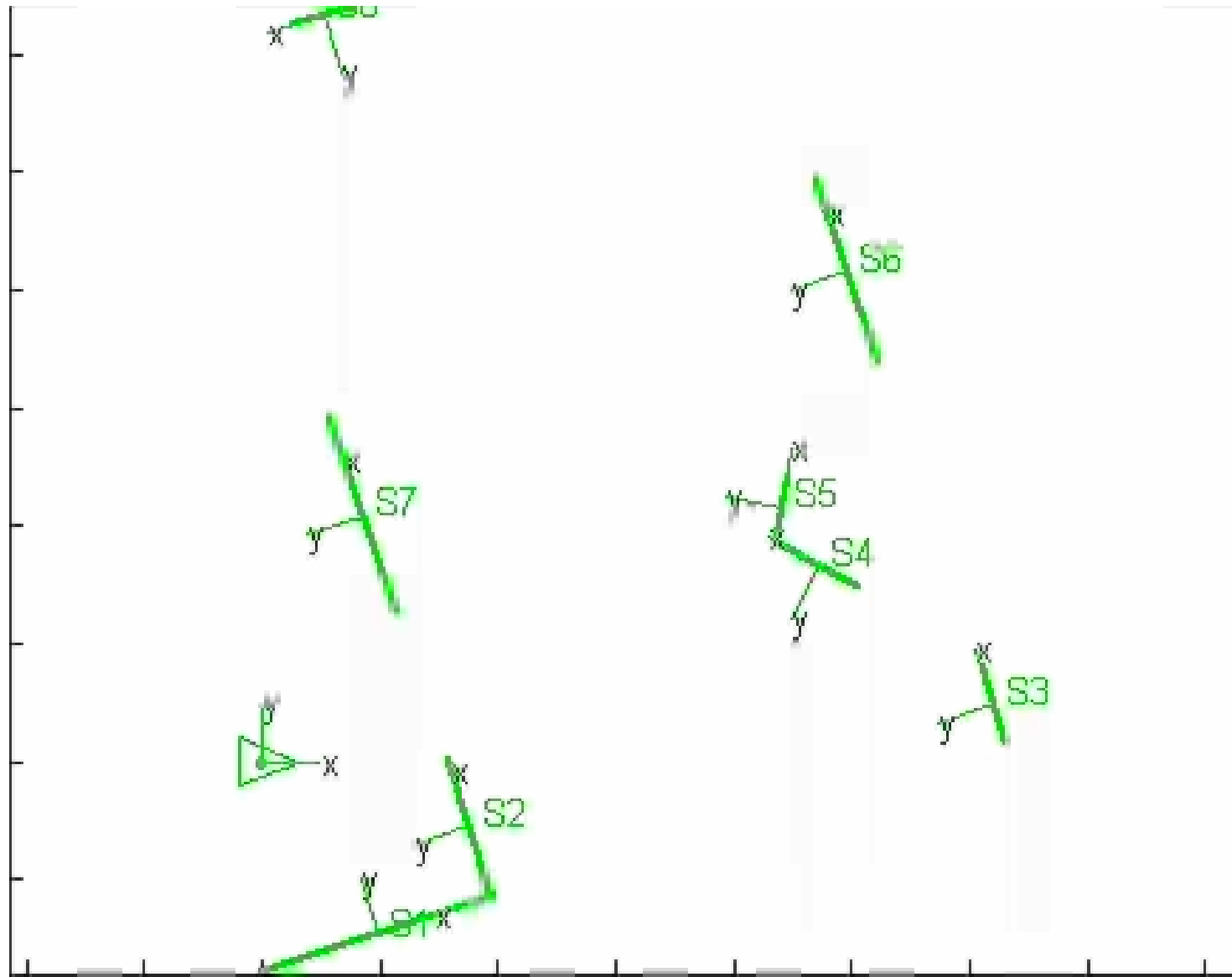


Un **mal** algoritmo

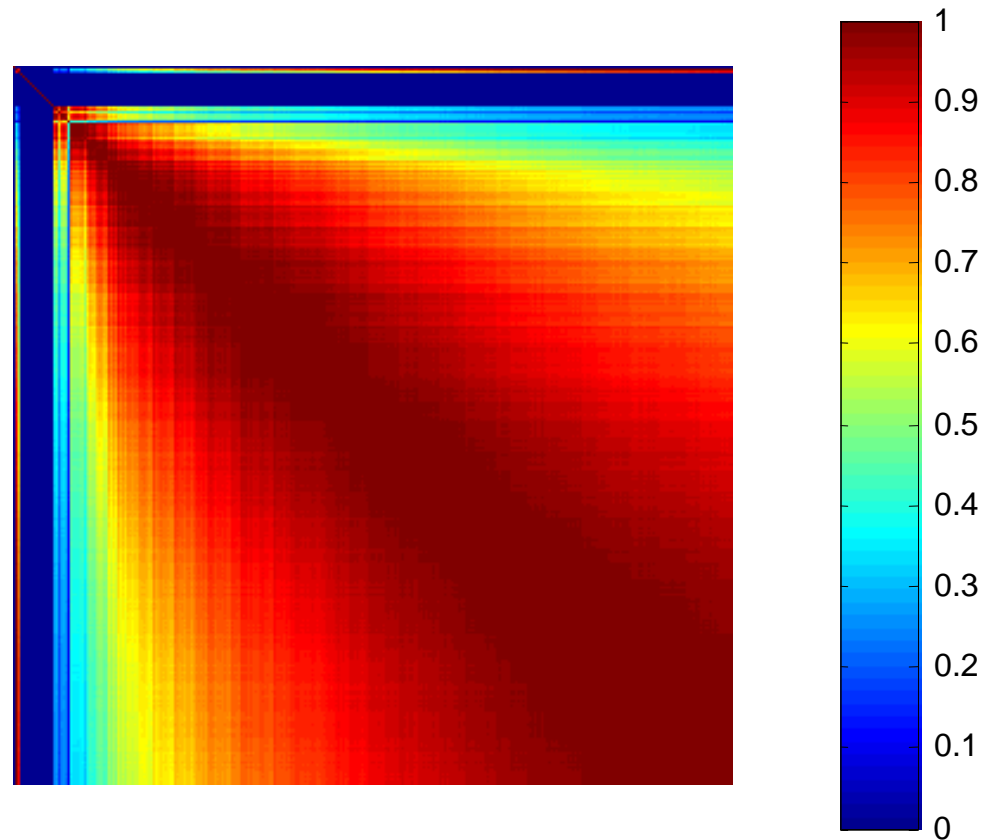
EKF SLAM con laser



EKF SLAM con láser



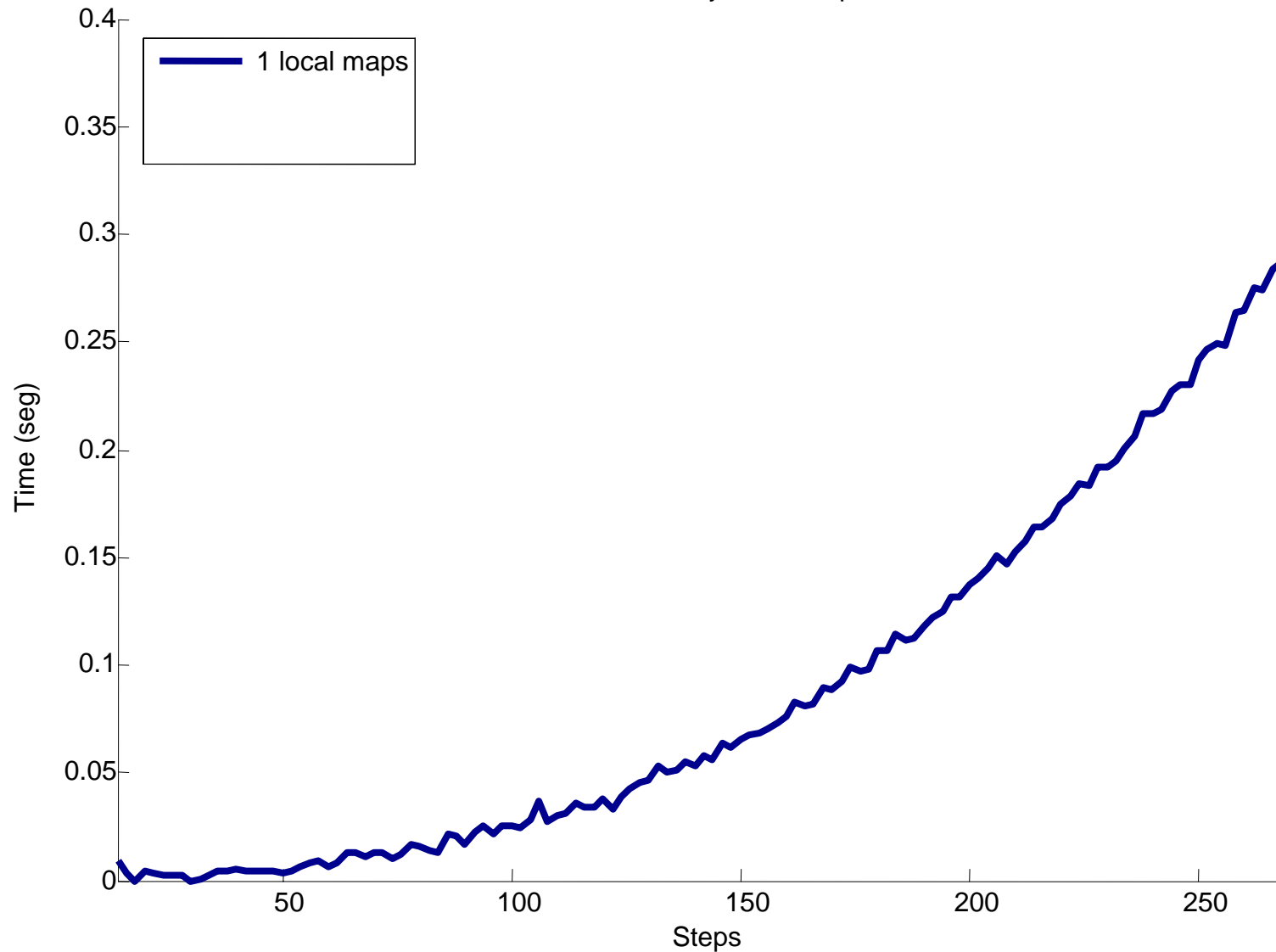
La 'bendición' de la Covarianza



- Permite hacer asociación de datos
- Pero la matriz de covarianza es llena

EKF-SLAM: las actualizaciones son $O(n^2)$

Mean Time by Local Maps



EKF SLAM: consistencia



EKF SLAM: consistencia



Indice

1. El problema de SLAM

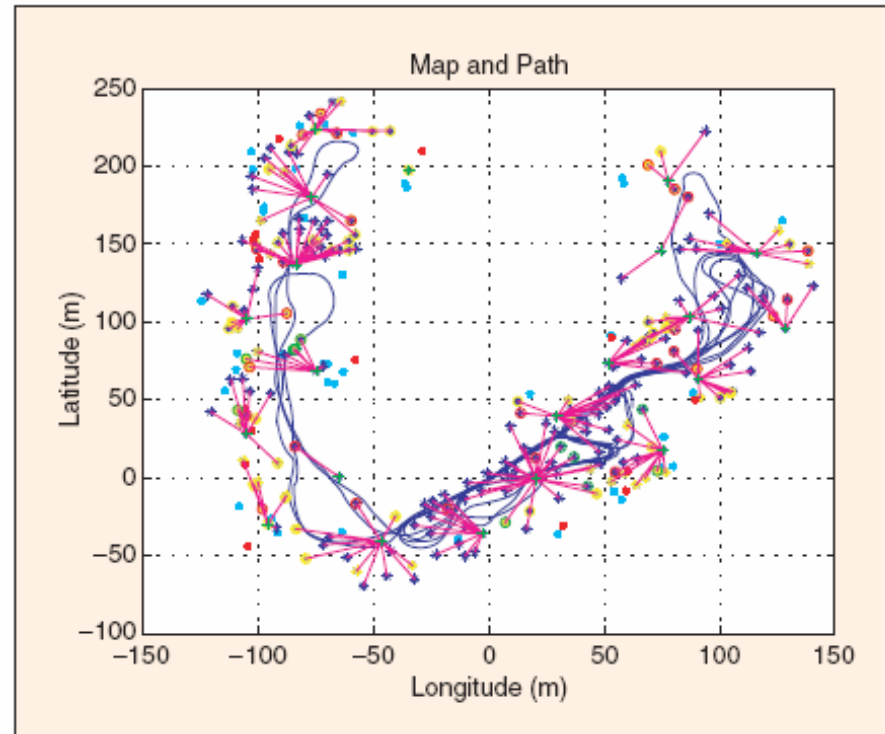
2. EKF SLAM

3. SLAM visual puro

- Monocular
- Estéreo

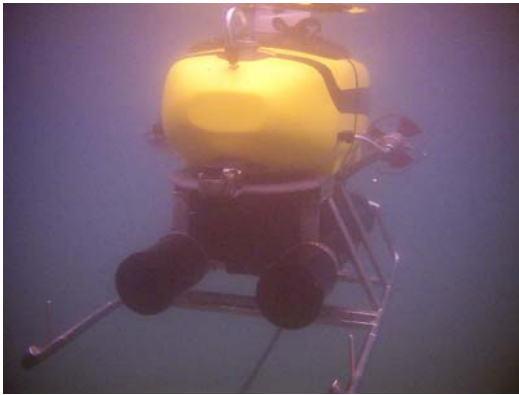
4. Perspectiva

SLAM en exteriores



Victoria Park, Univ. Sydney

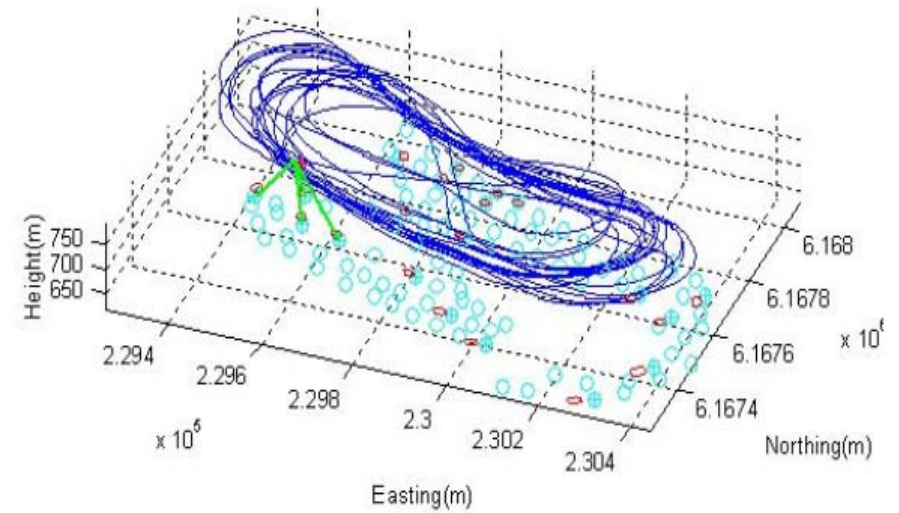
Subacuático, Aéreo



Garbi, Univ. Girona, Spain



Brumby, Univ. Sydney



Sensores móviles



SLAM Visual Puro



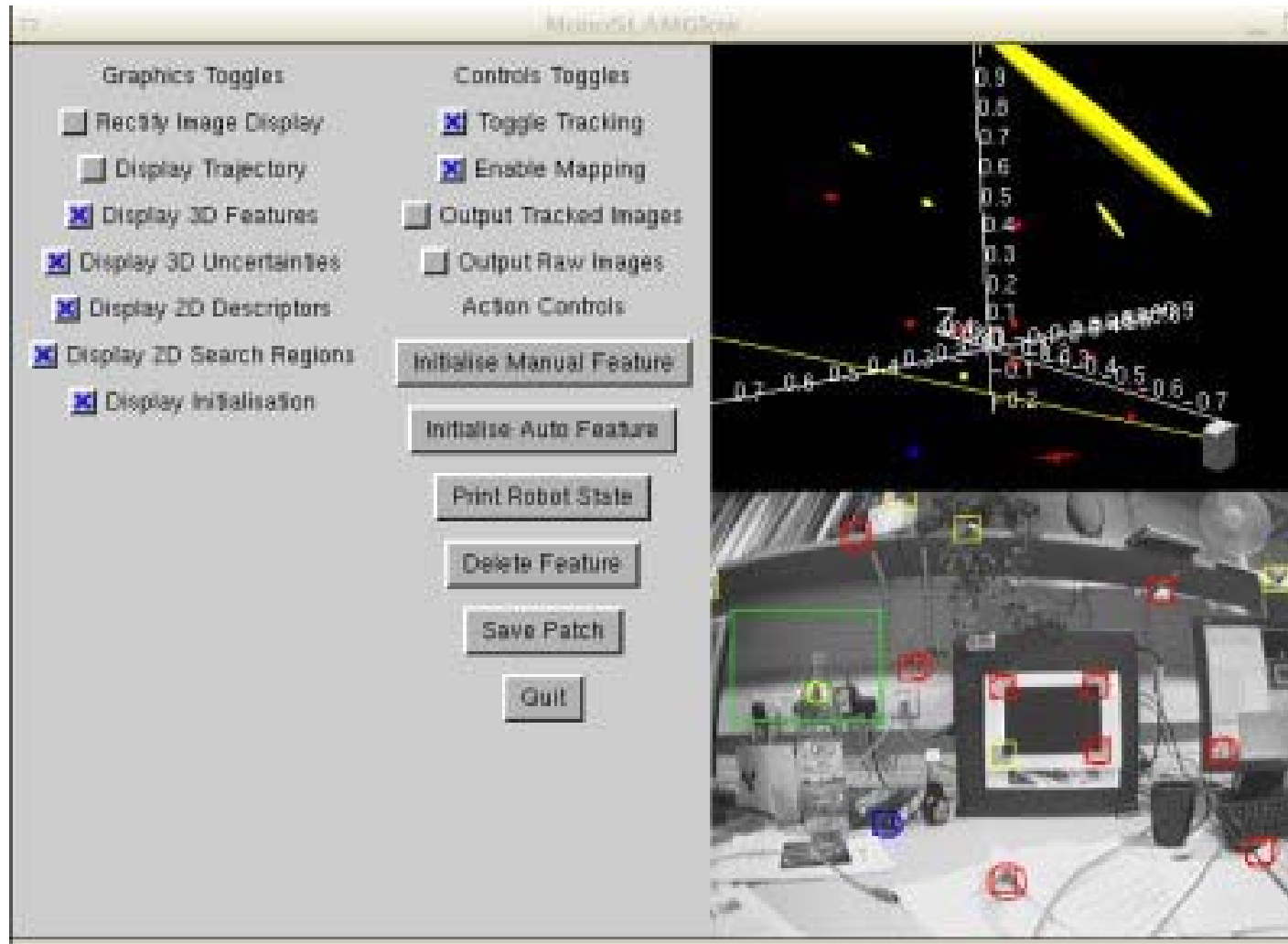
**Una cámara Unibrain
fire-I , un laptop y un
cable firewire**

Jornadas Argentinas de Robótica 2008

290 m.



Monoslam (A. Davison)



EKF SLAM básico

Vector de estado:

- Cámara
- Características

$$\mathbf{x} = \begin{pmatrix} \mathbf{x}_c \\ y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix}$$

Cámara:

- Posición
- Orientación
- Velocidad lineal
- Velocidad angular

$$\mathbf{x}_c = \begin{pmatrix} \mathbf{r}^{BC} \\ \Psi^{BC} \\ \mathbf{v}^B \\ \mathbf{w}^C \end{pmatrix}$$

Representación de característica 3D

Puntos 3D:

- Coordenadas cartesianas

$$y_i = \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix}$$

Puntos de profundidad inversa:

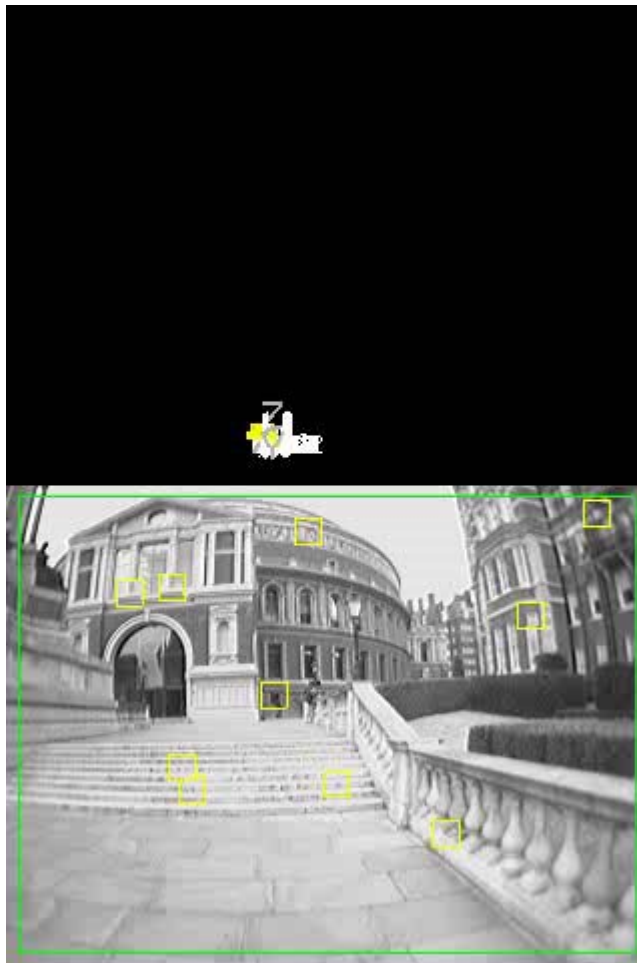
- Posición de la cámara al verlo por primera vez

$$y_i = \begin{pmatrix} x_i \\ y_i \\ z_i \\ \theta_i \\ \phi_i \\ \rho_i \end{pmatrix}$$

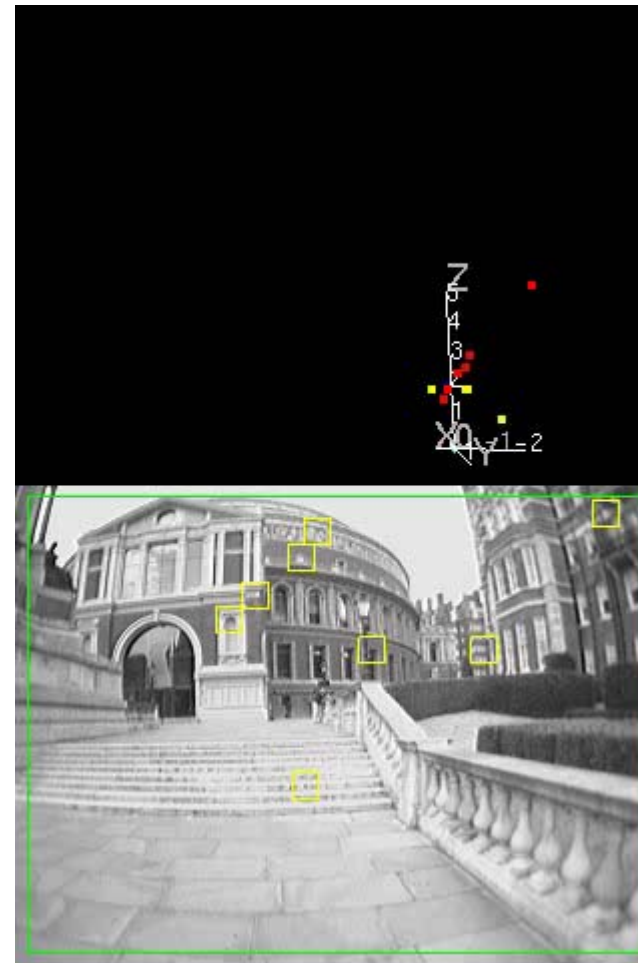
- Azimut
- Elevación
- Profundidad inversa

J.M.M. Montiel, J. Civera, A.J. Davison: **Unified inverse depth parametrization for monocular SLAM**. IEEE Transactions on Robotics, 2008.

Asociación de datos

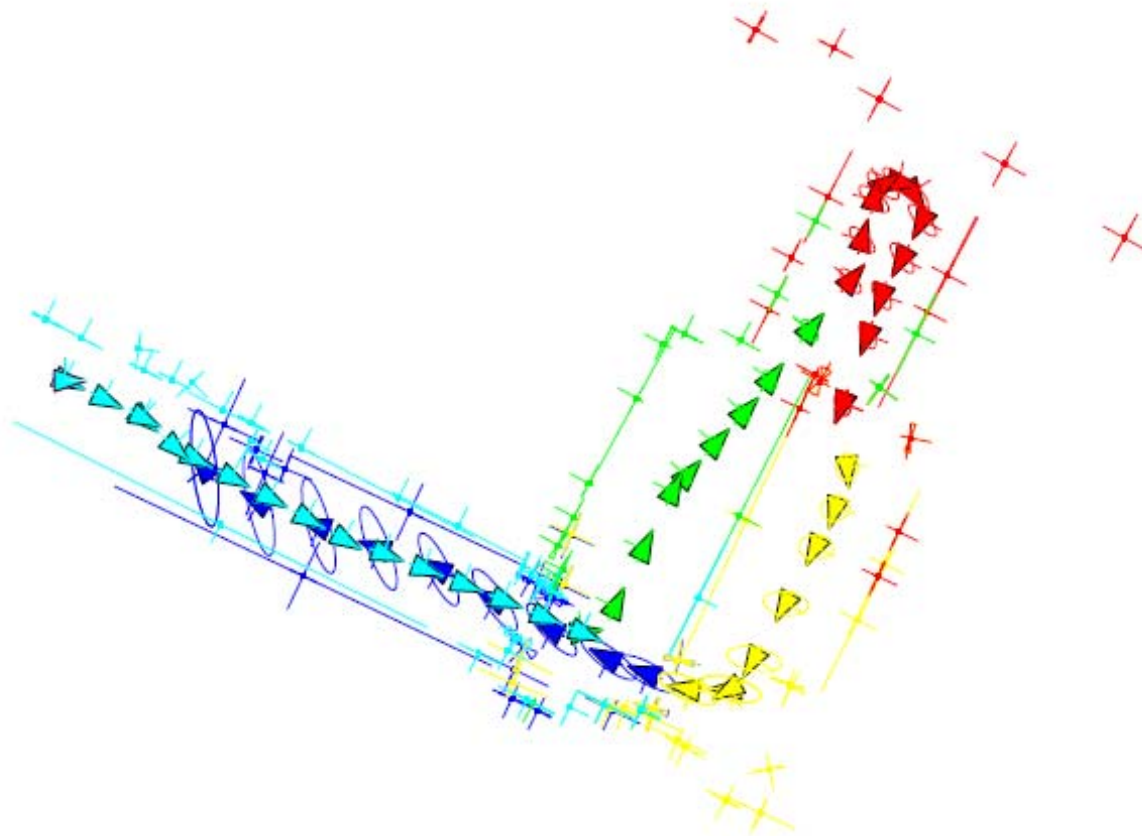


Tracks individuales



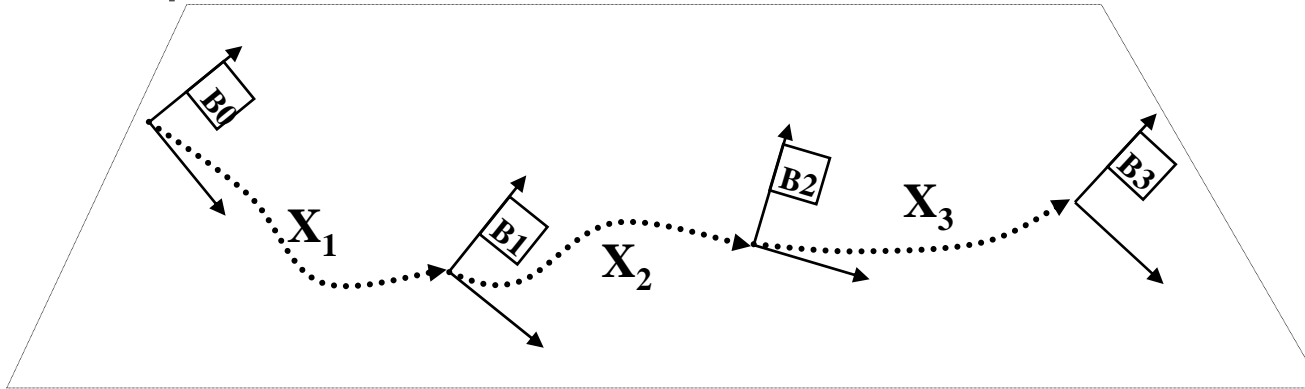
Conjuntamente compatibles

EKF SLAM escalable: Mapas locales independientes

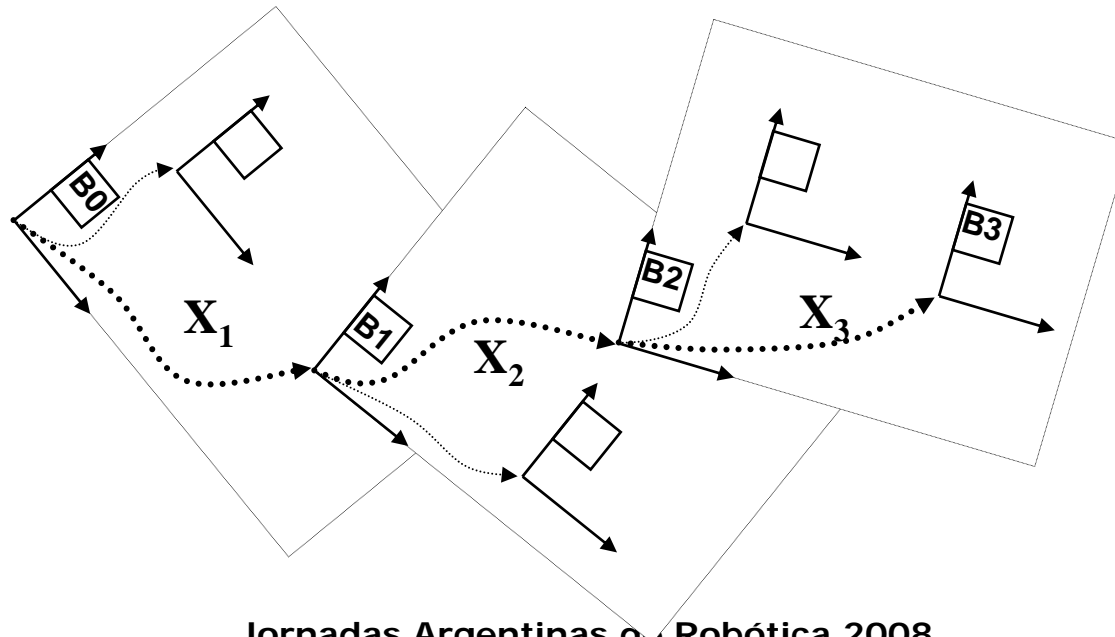


SLAM jerárquico

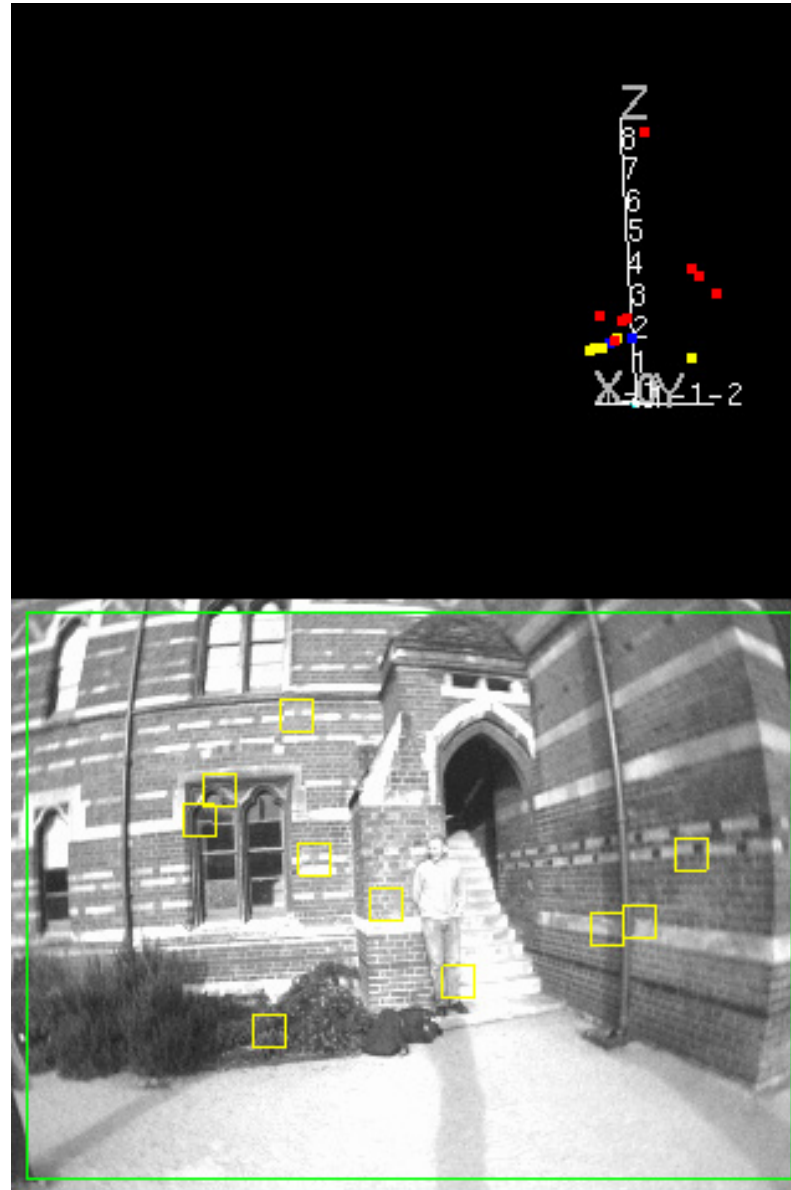
- Nivel global: grafo de localizaciones relativas entre mapas



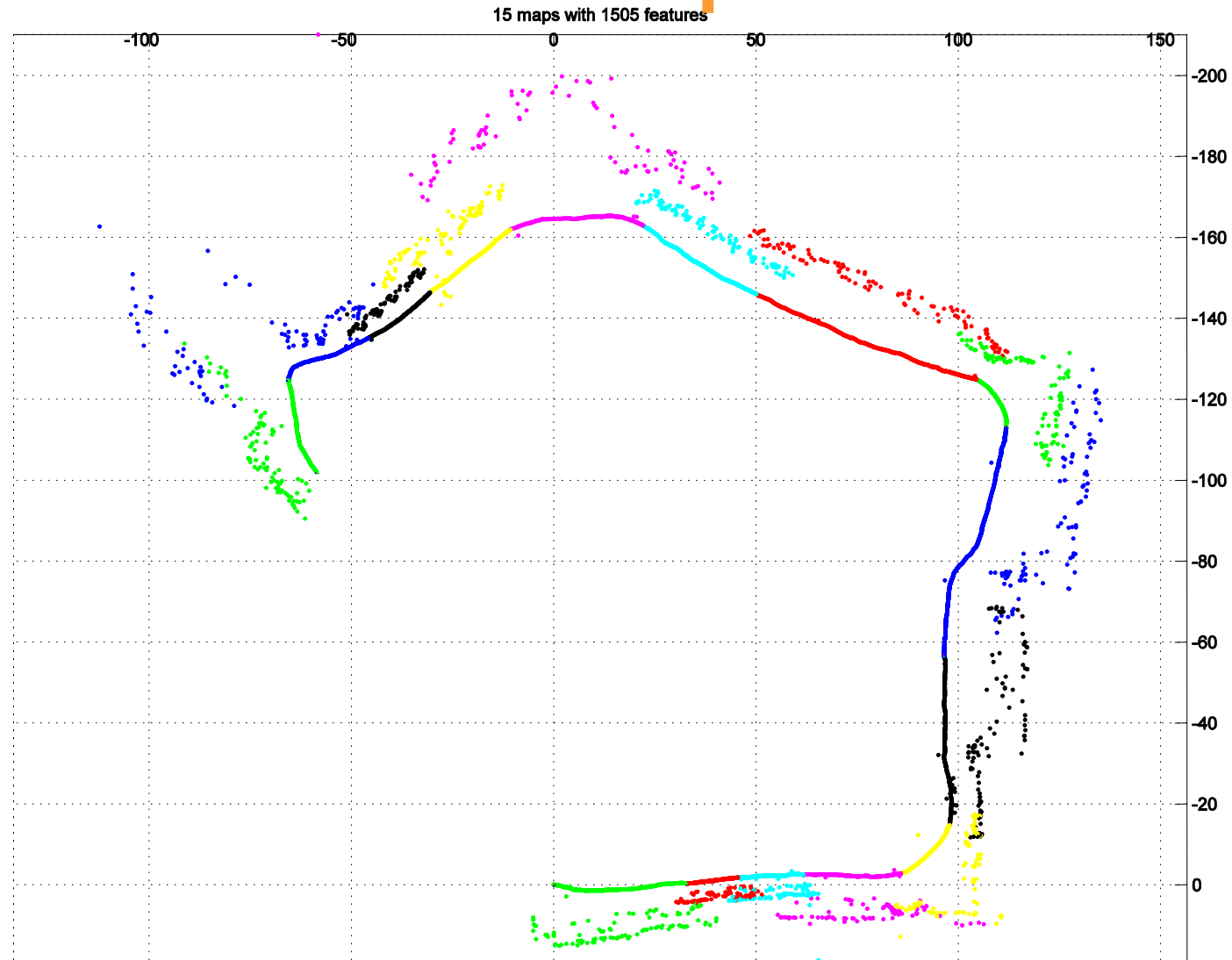
- Nivel local: mapas estocásticos independientes



Keble College, Oxford

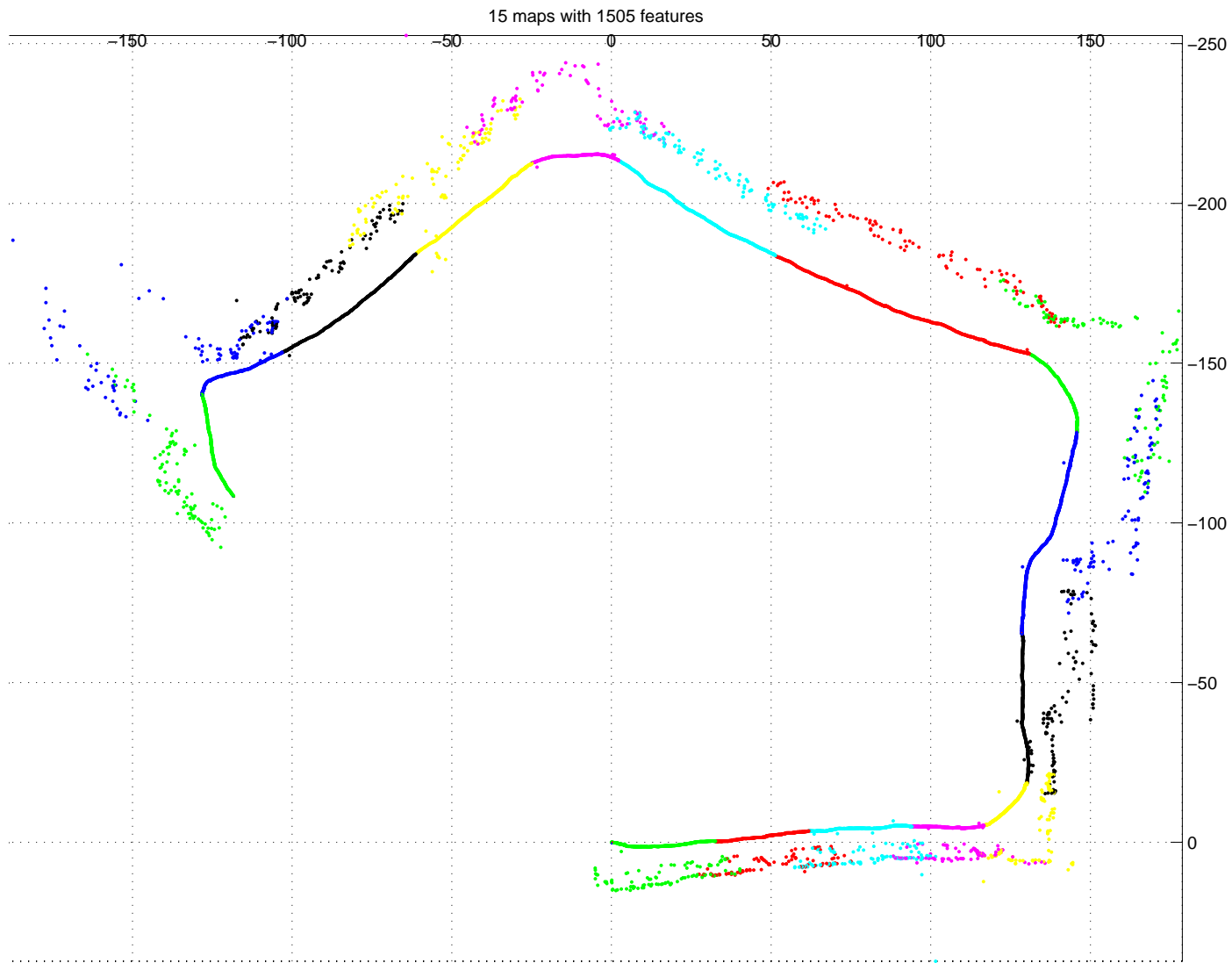


Secuencia de mapas locales



Escala arbitraria (no observable)

Compensación de escala



Optimización no lineal

- Minimizar las correcciones al mapa global, sujeto a la restricción del bucle:

$$\min_{\mathbf{x}} \frac{1}{2}(\mathbf{x} - \hat{\mathbf{x}})^T \mathbf{P}^{-1}(\mathbf{x} - \hat{\mathbf{x}})$$
$$\mathbf{h}(\mathbf{x}) = 0$$

- Sequential Quadratic Programming (SQP) :

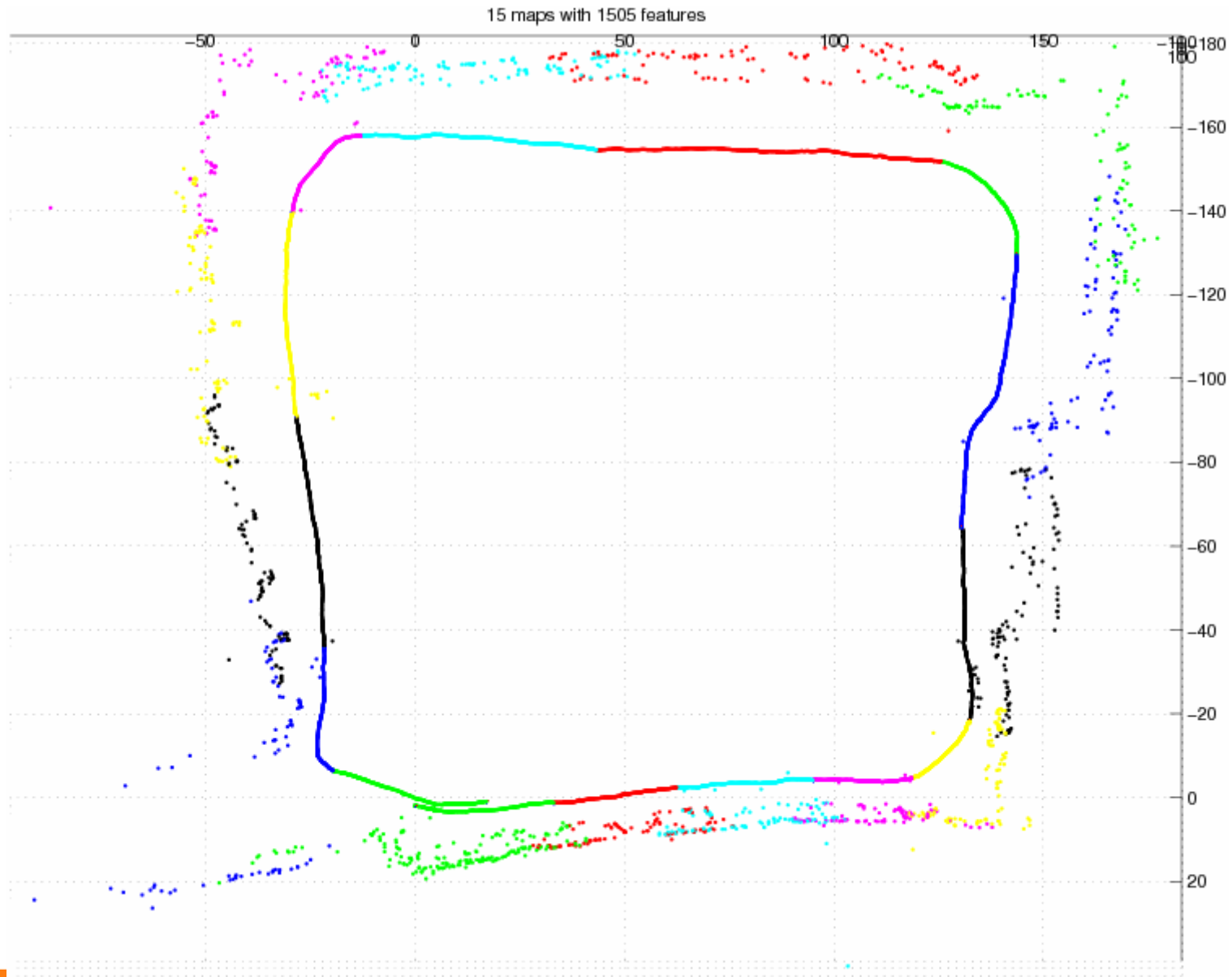
$$\mathbf{H}_i = \left[\begin{array}{cccc} \frac{\partial \mathbf{h}}{\partial \mathbf{x}_1} \Big|_{\hat{\mathbf{x}}_i} & \frac{\partial \mathbf{h}}{\partial \mathbf{x}_2} \Big|_{\hat{\mathbf{x}}_i} & \cdots & \frac{\partial \mathbf{h}}{\partial \mathbf{x}_{n-1}} \Big|_{\hat{\mathbf{x}}_i} \\ & & & \frac{\partial \mathbf{h}}{\partial \mathbf{x}_n} \Big|_{\hat{\mathbf{x}}_i} \end{array} \right]$$

$$\mathbf{P}_i = \mathbf{P}_0 - \mathbf{P}_0 \mathbf{H}_i^T \left(\mathbf{H}_i \mathbf{P}_0 \mathbf{H}_i^T \right)^{-1} \mathbf{H}_i \mathbf{P}_0$$

$$\hat{\mathbf{x}}_{i+1} = \hat{\mathbf{x}}_i - \mathbf{P}_i \mathbf{P}_0^{-1} (\hat{\mathbf{x}}_i - \hat{\mathbf{x}}_0) - \mathbf{P}_0 \mathbf{H}_i^T \left(\mathbf{H}_i \mathbf{P}_0 \mathbf{H}_i^T \right)^{-1} \hat{\mathbf{h}}_i$$

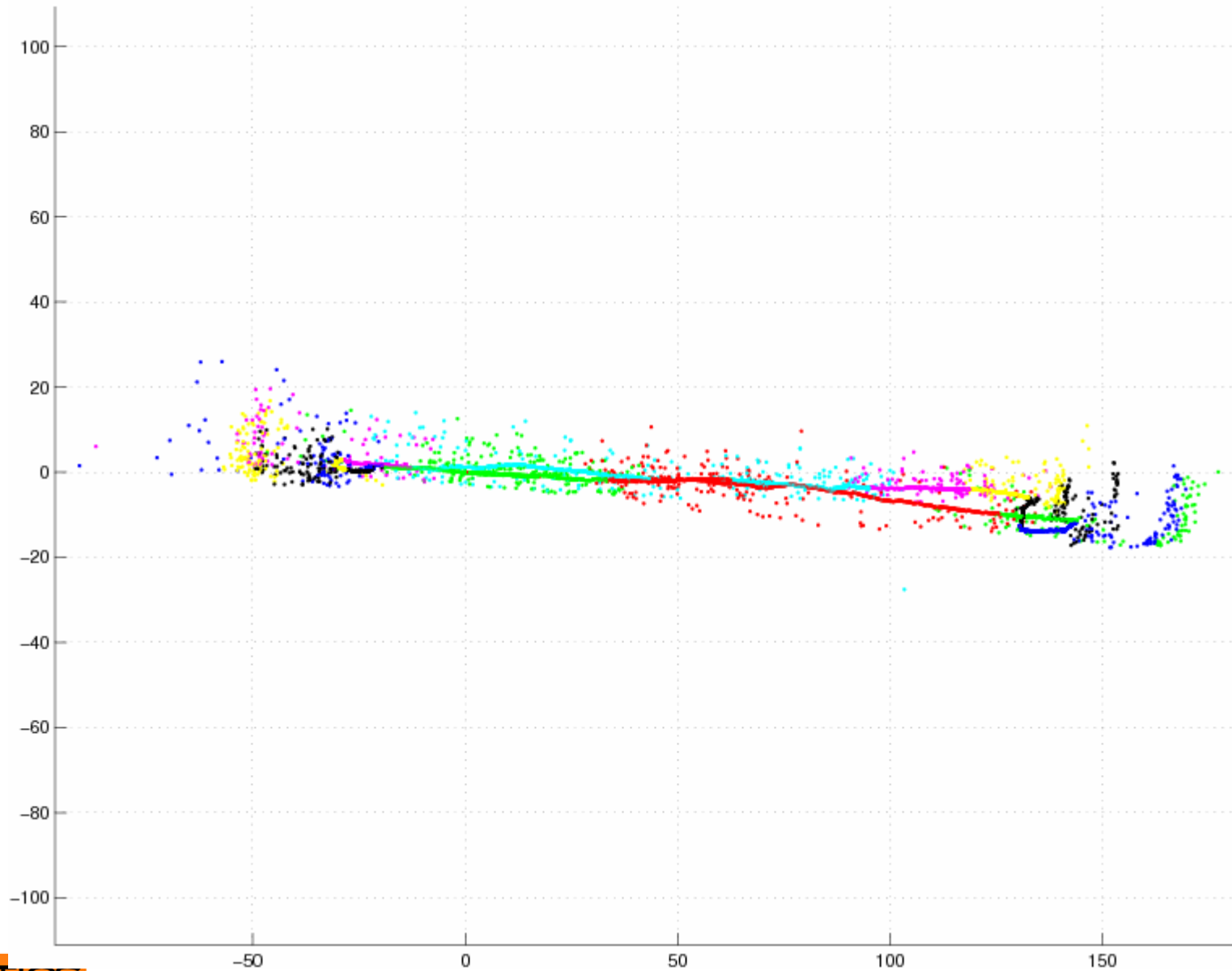
» Se itera hasta lograr convergencia

Cerrado de bucle



Cerrado de bucle

15 maps with 1505 features



Keble College, Oxford (290m)



Resultados

- Mapas locales en tiempo real @30Hz
 - 60 características por mapa
- Cerrado de bucle en 1s (in Matlab)
- Optimización del bucle en 800ms (6 iteraciones)
- **Deriva de la escala a lo largo del mapa**

L. Clemente, A. Davison, I. Reid, J. Neira and J.D. Tardós **Mapping Large Loops with a Single Hand-Held Camera**. Robotics: Science and Systems, 2007.

SLAM utilizando estéreo



**Cámara bumblebee,
portátil y cable firewire**

SLAM estéreo puro



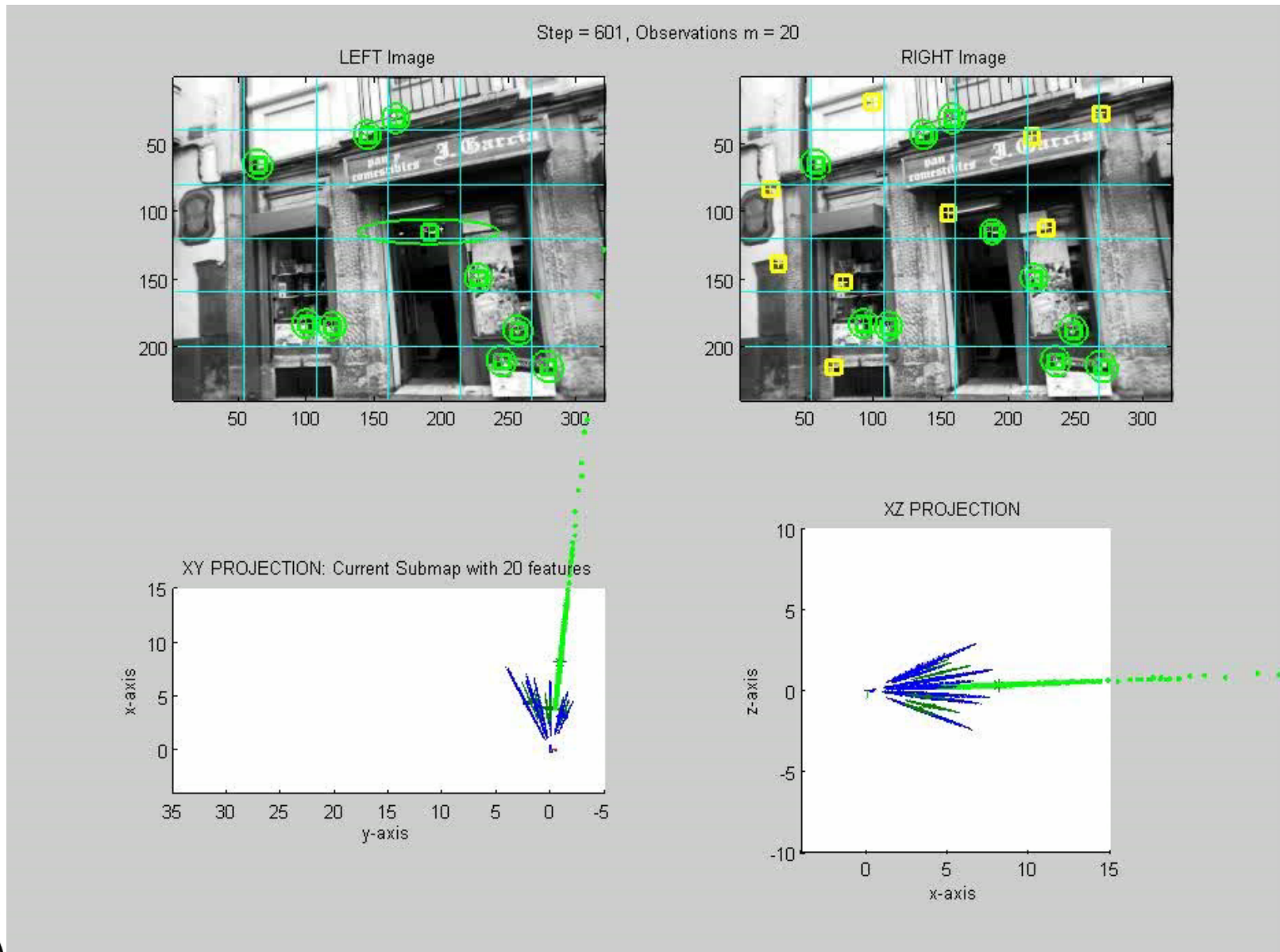
Bucle 210m, CPS, Zaragoza

SLAM estéreo puro



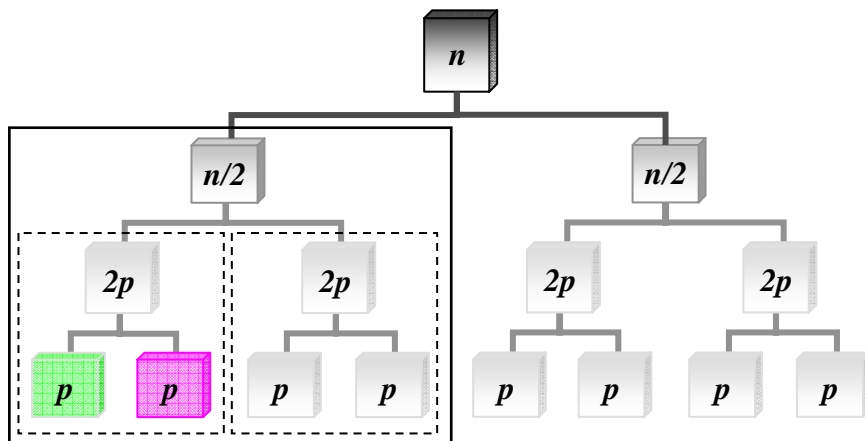
Bucle de 150m, plaza en Zaragoza

EKF SLAM básico

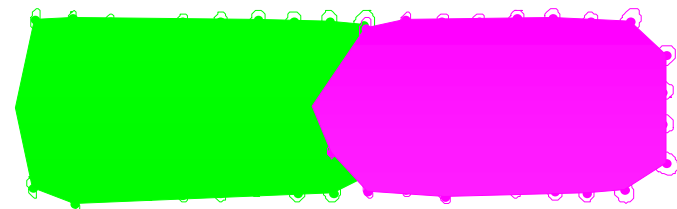


SLAM divide y vencerás

Number of Maps : 2



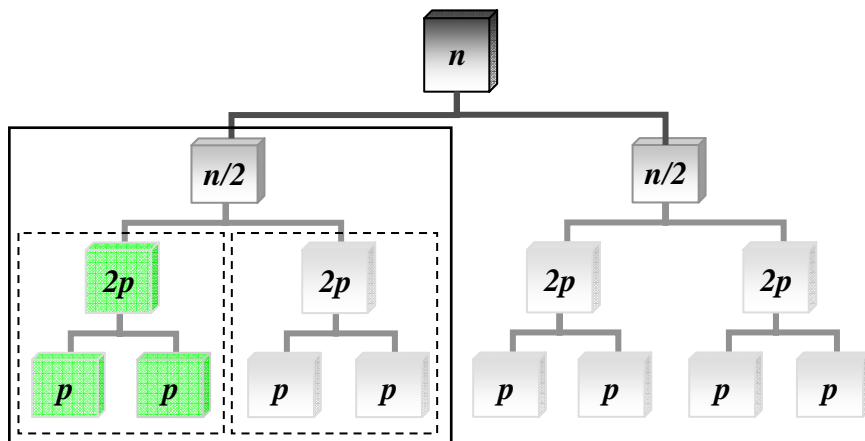
y position(m)



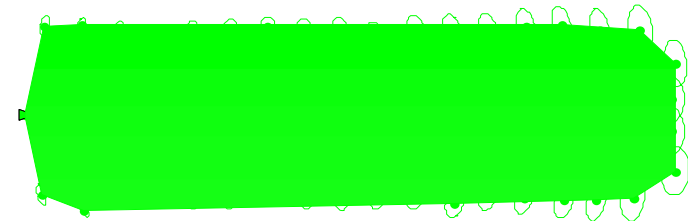
x position(m)

SLAM divide y vencerás

Number of Maps : 1



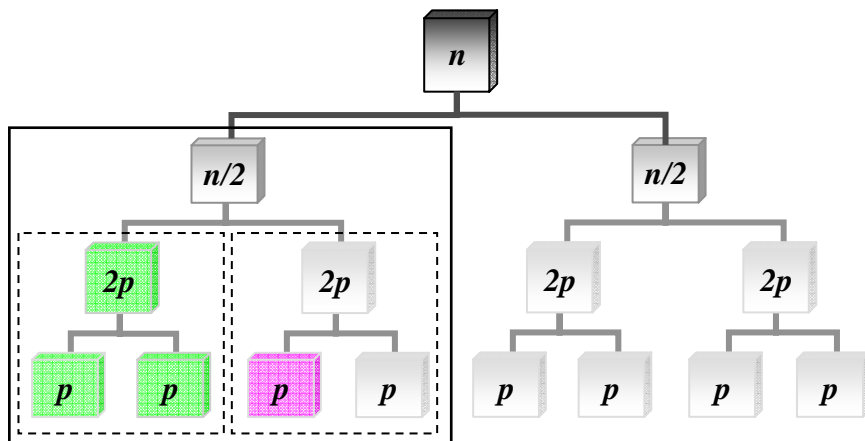
y position(m)



x position(m)

SLAM divide y vencerás

Number of Maps : 2



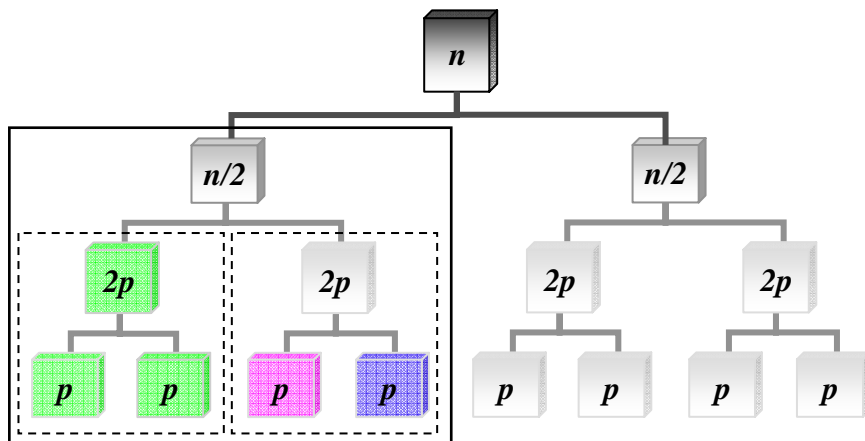
y position(m)



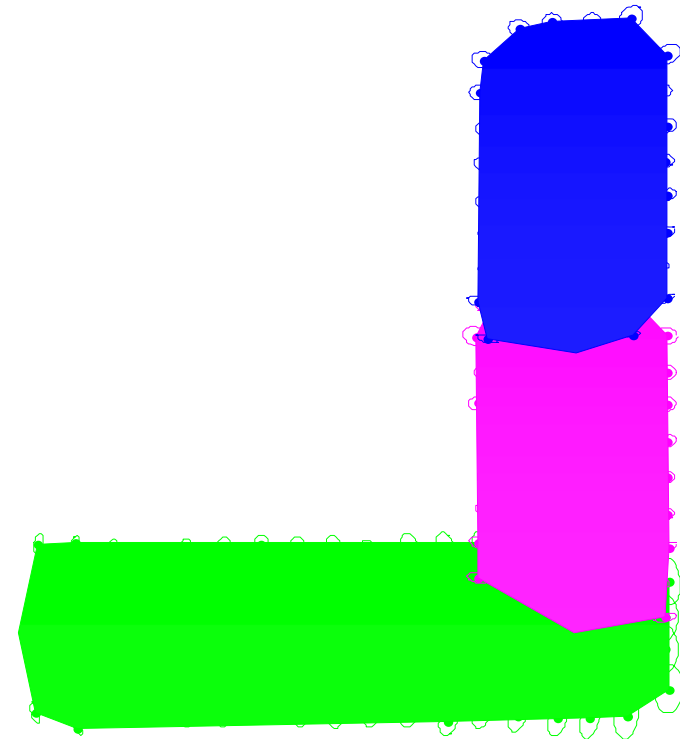
x position(m)

SLAM divide y vencerás

Number of Maps : 3



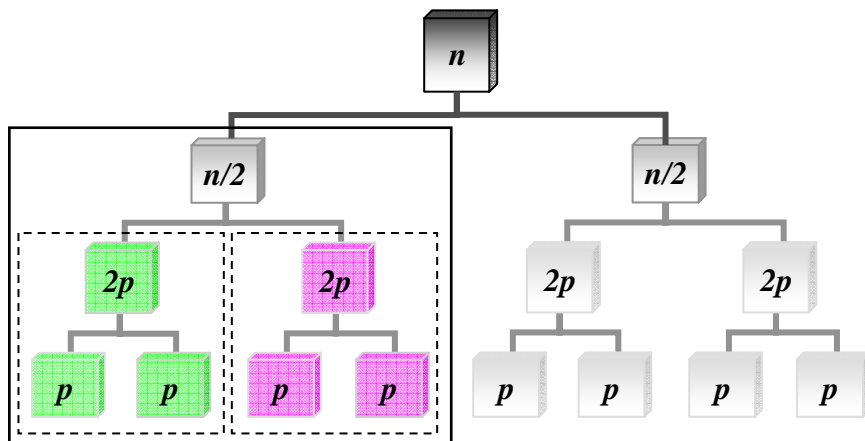
y position(m)



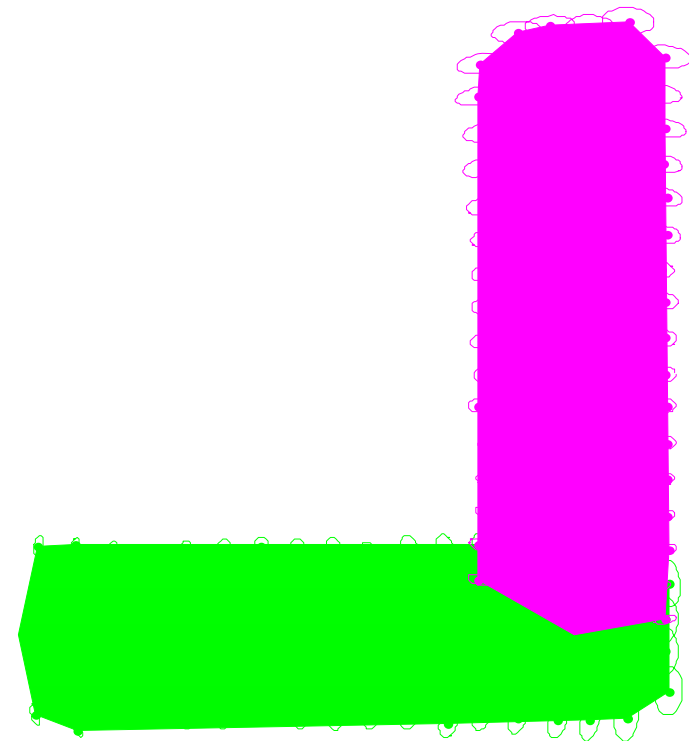
x position(m)

SLAM divide y vencerás

Number of Maps : 2



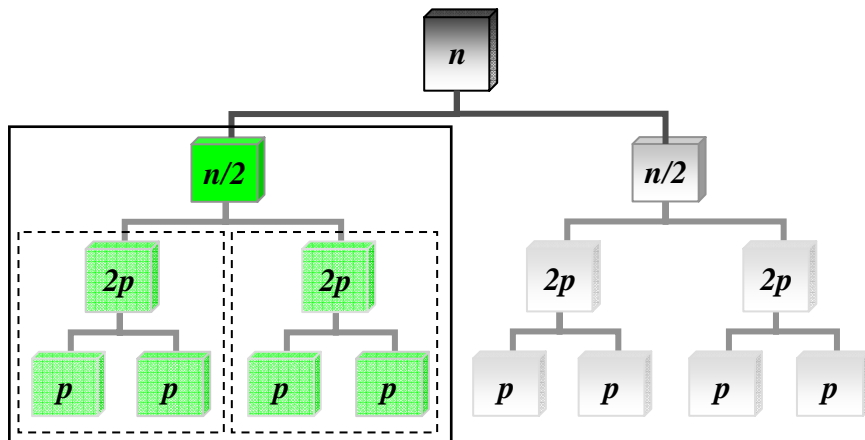
y position(m)



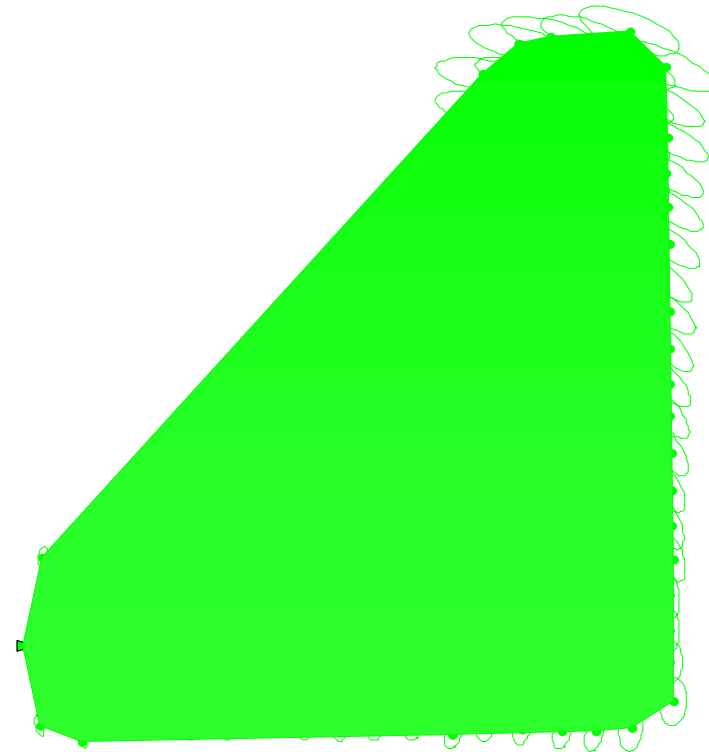
x position(m)

SLAM divide y vencerás

Number of Maps : 1



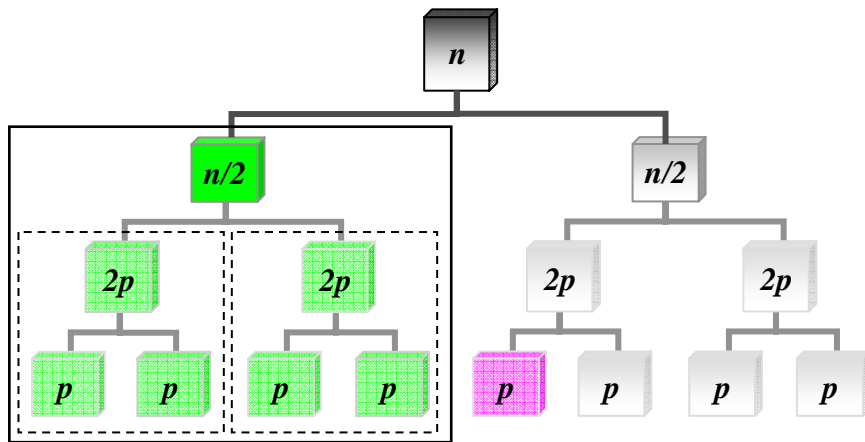
y position(m)



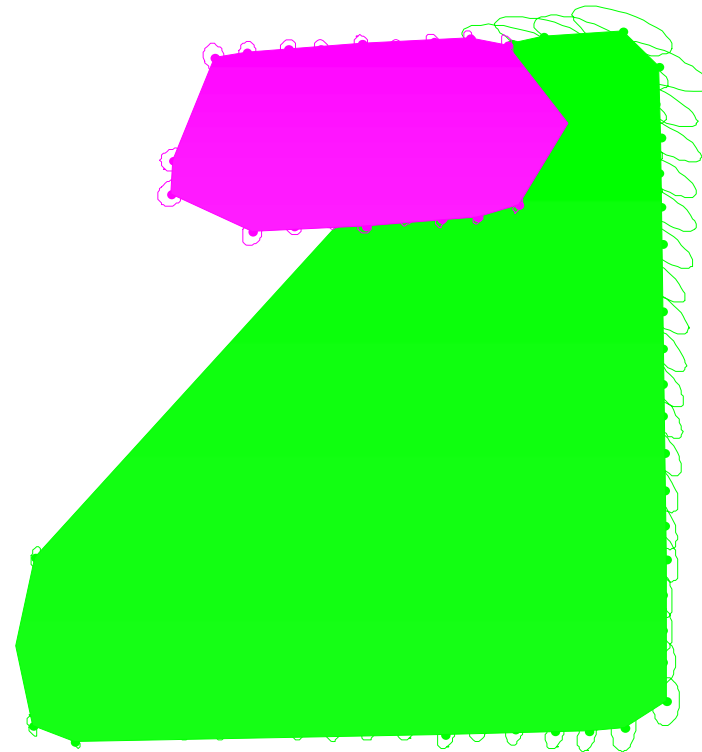
x position(m)

SLAM divide y vencerás

Number of Maps : 2



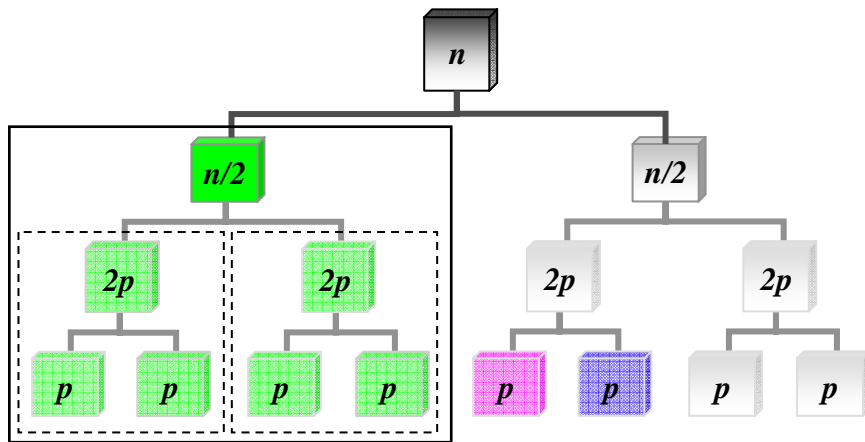
y position(m)



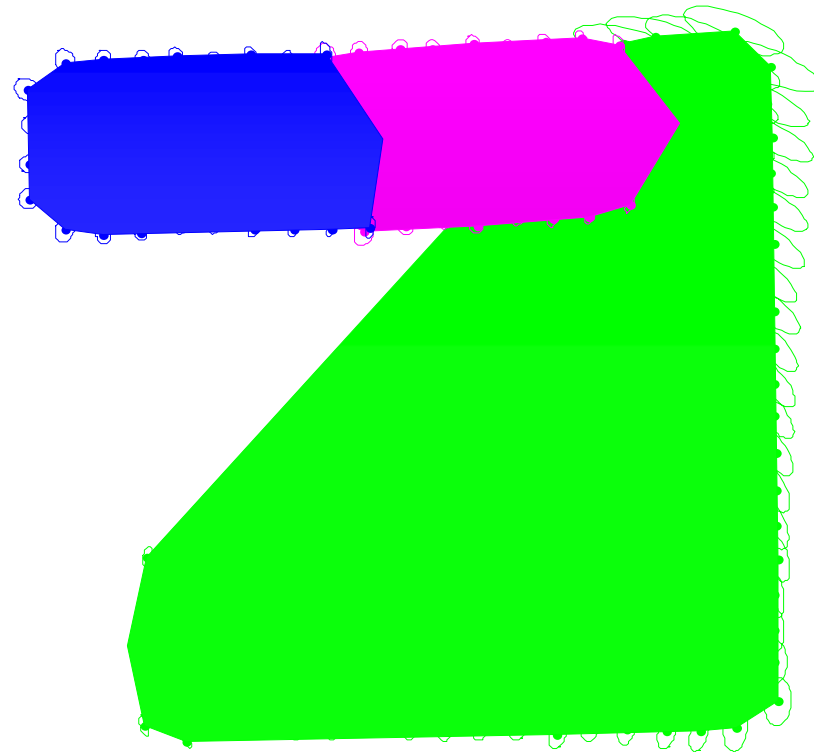
x position(m)

SLAM divide y vencerás

Number of Maps : 3



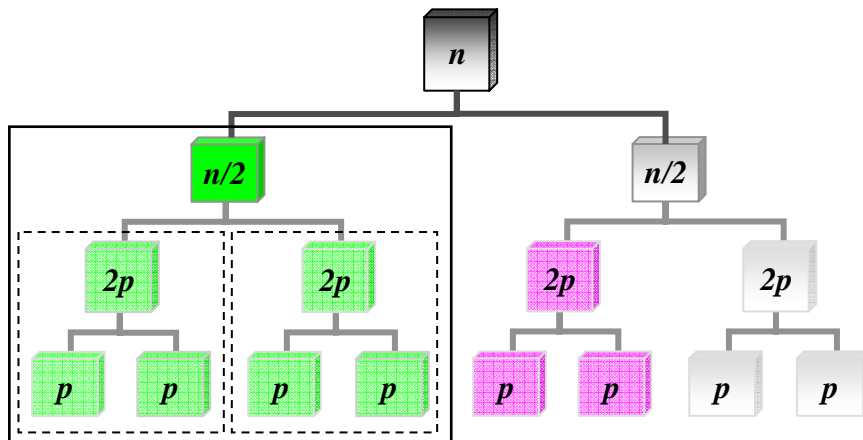
y position(m)



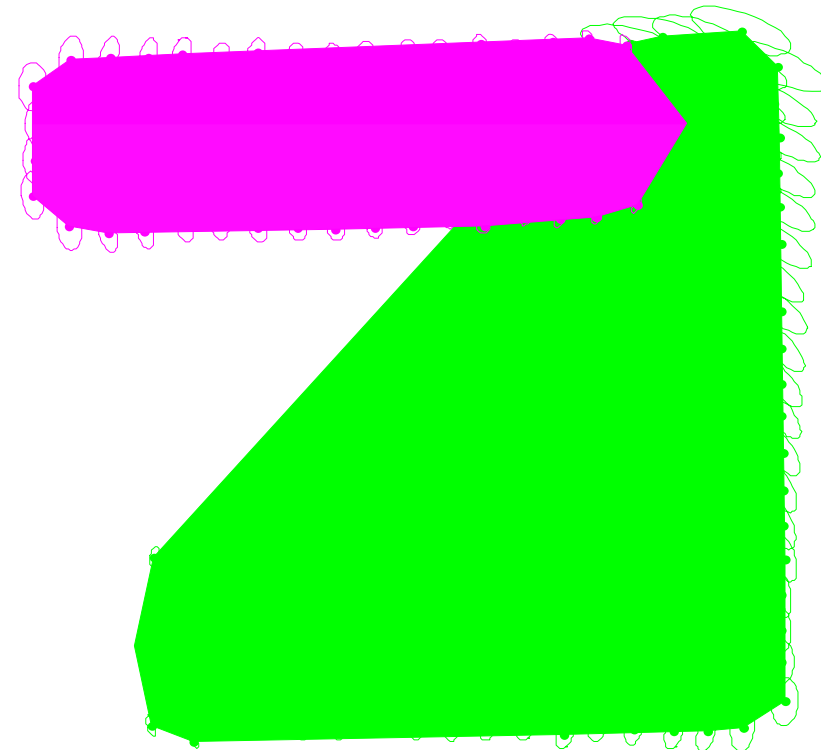
x position(m)

SLAM divide y vencerás

Number of Maps : 2

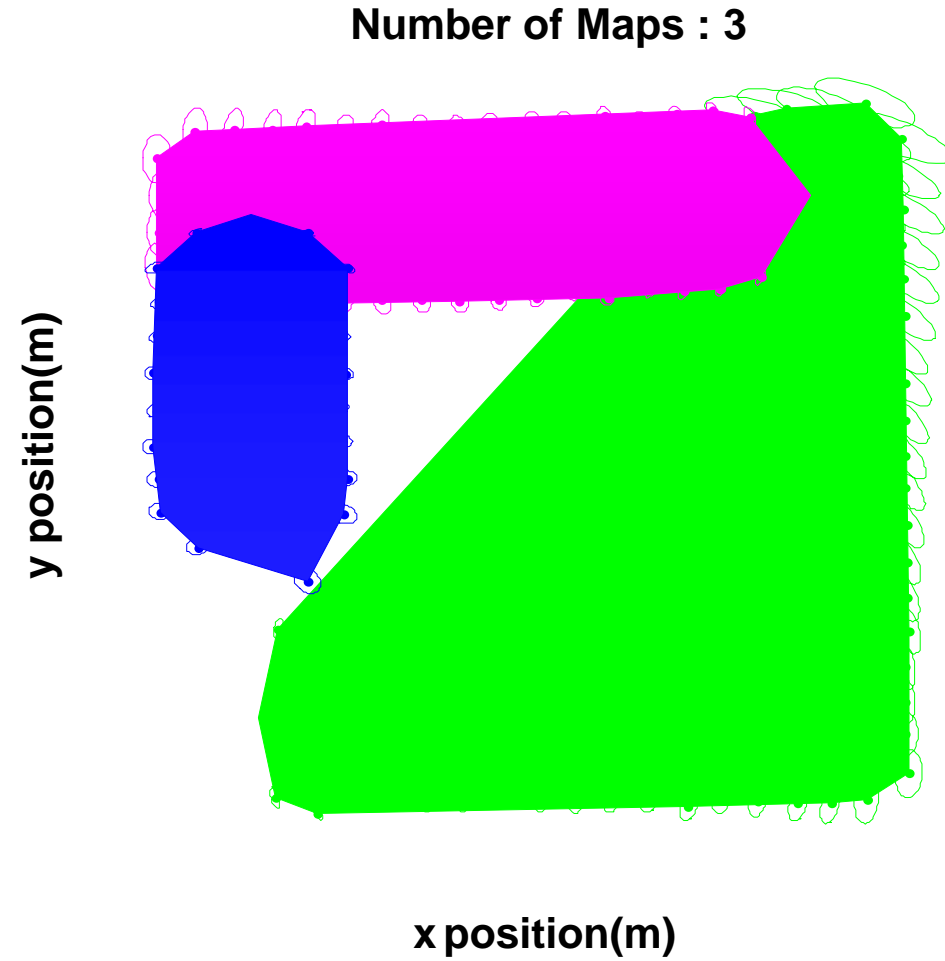
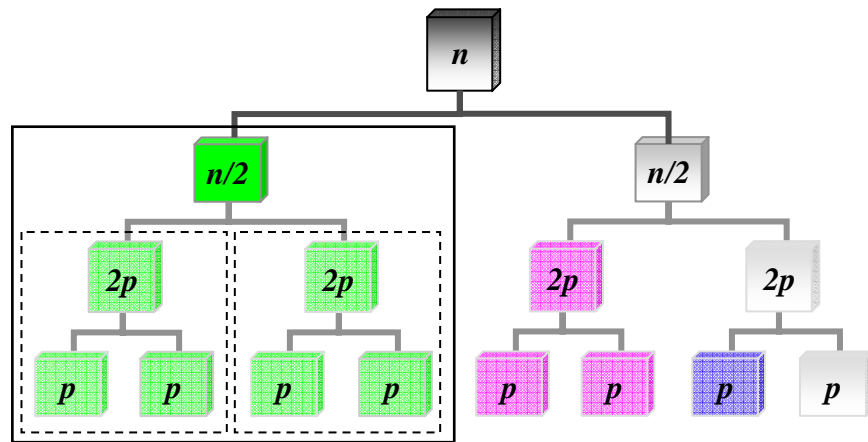


y position(m)

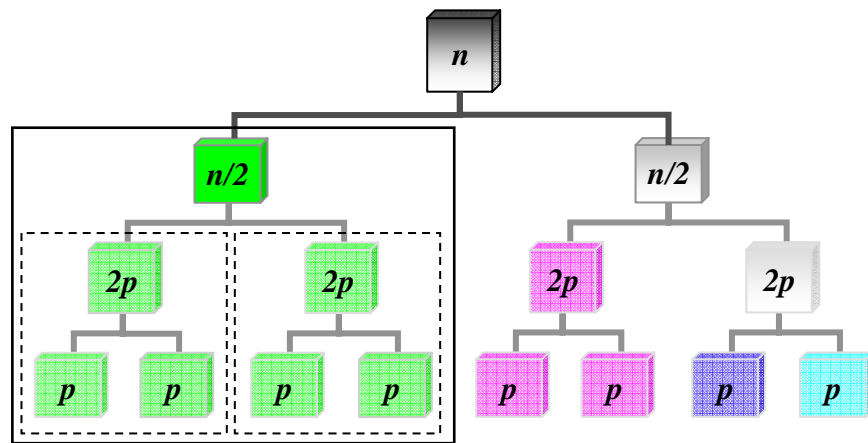


x position(m)

SLAM divide y vencerás

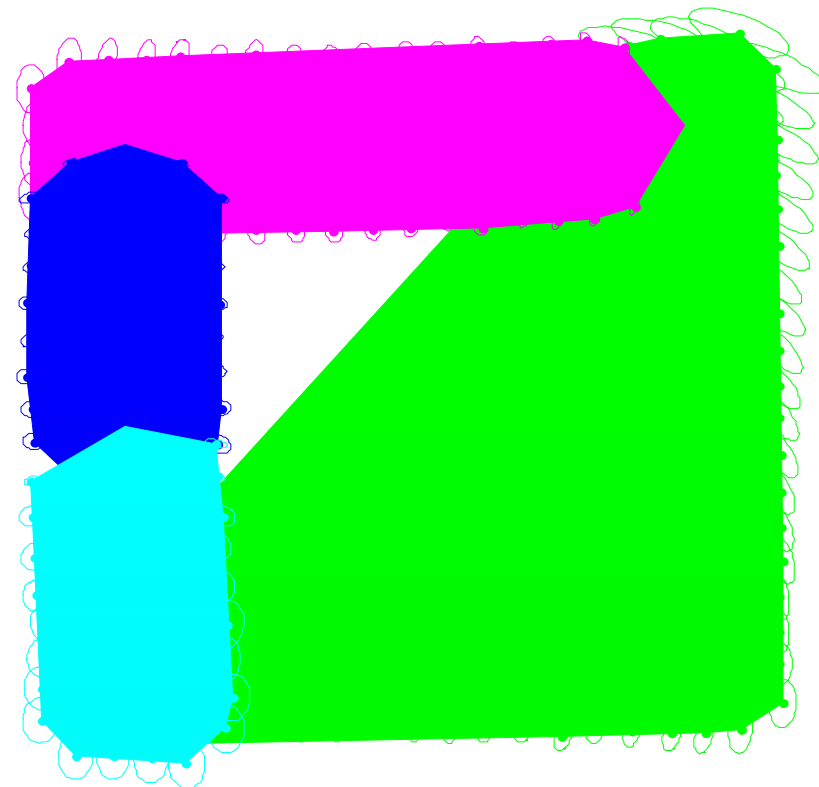


SLAM divide y vencerás



y position(m)

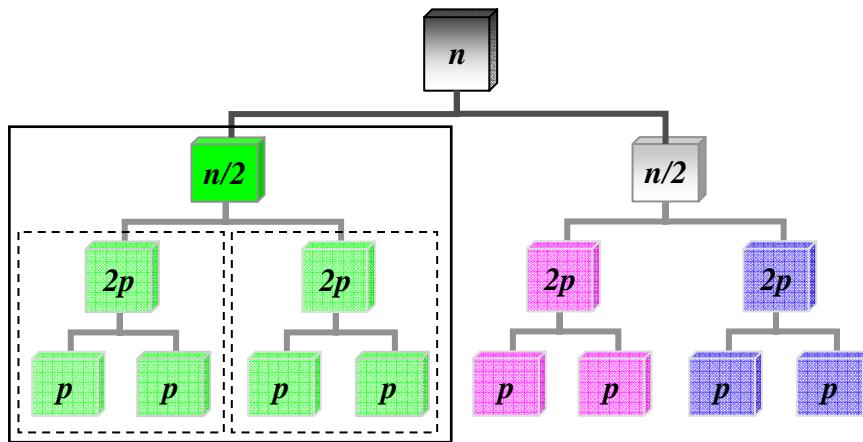
Number of Maps : 4



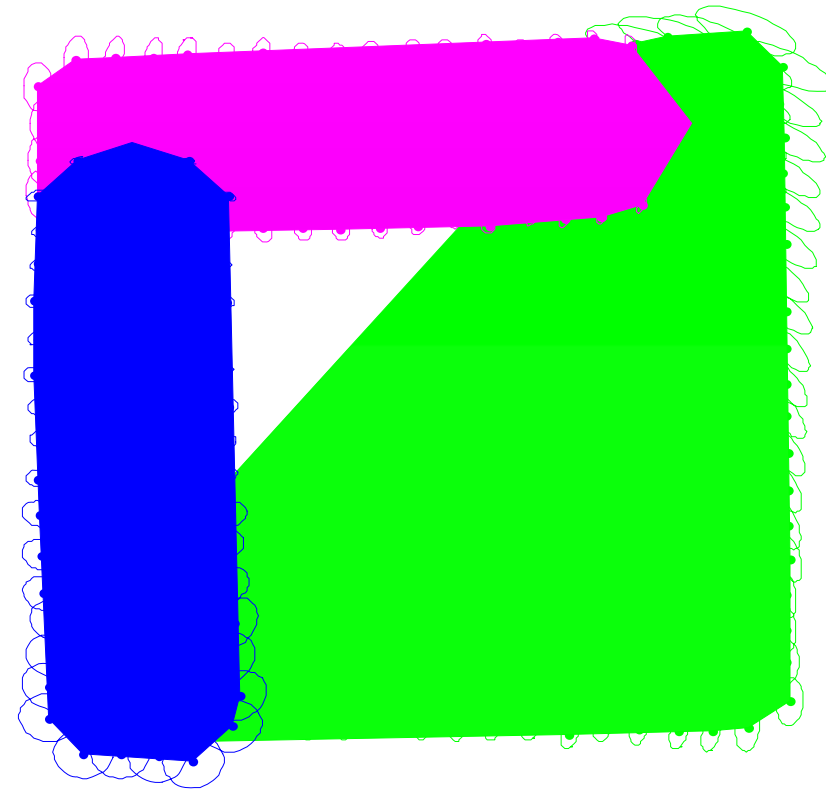
x position(m)

SLAM divide y vencerás

Number of Maps : 3



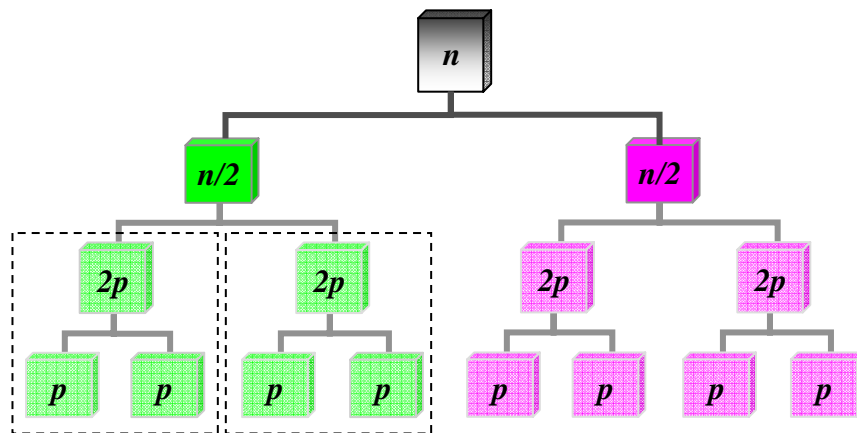
y position(m)



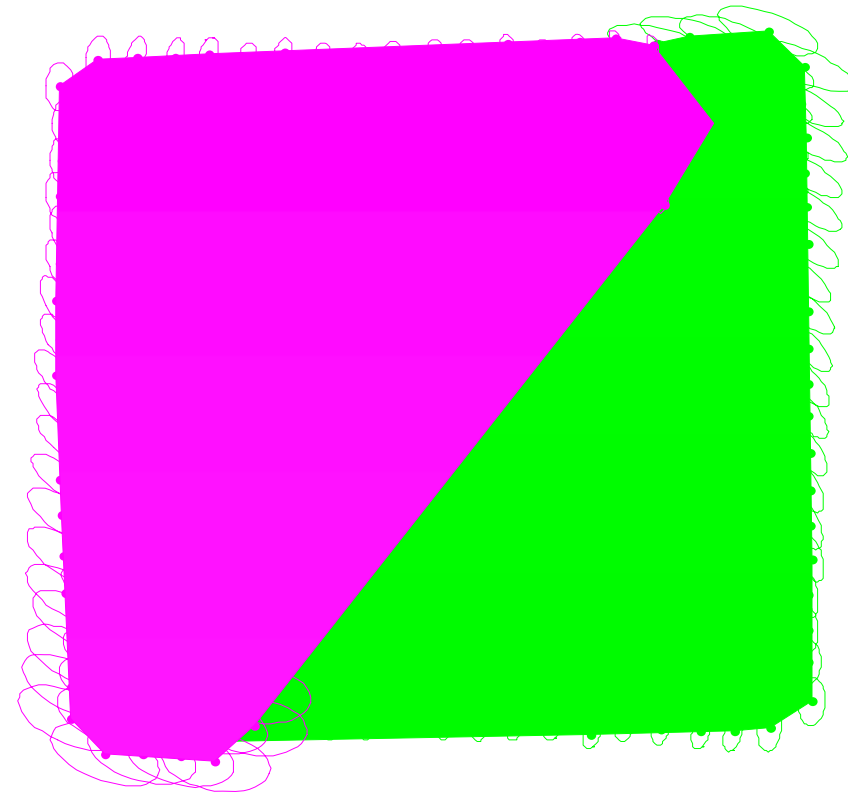
x position(m)

SLAM divide y vencerás

Number of Maps : 2



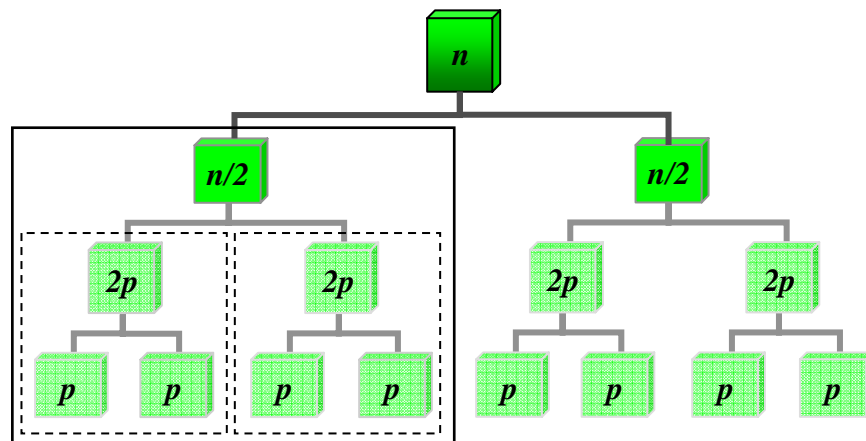
y position(m)



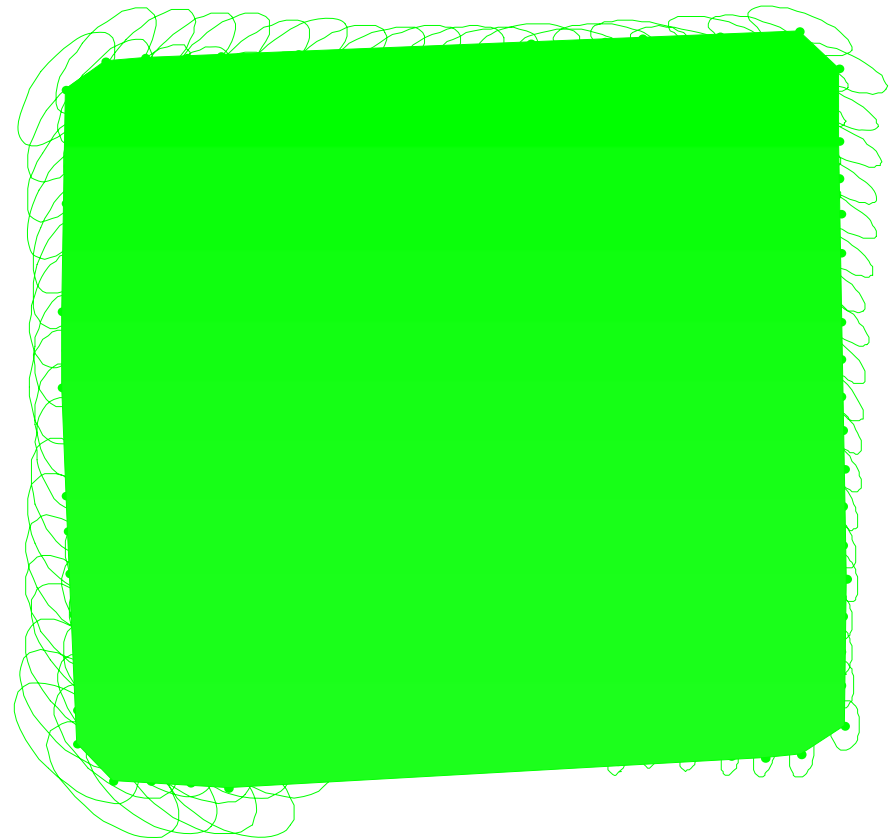
x position(m)

SLAM divide y vencerás

Number of Maps : 1



y position(m)



x position(m)

L.M. Paz, P. Jensfelt, J.D. Tardós and J. Neira. **EKF SLAM updates in $O(n)$ with Divide and Conquer SLAM** 2007 IEEE Int. Conf. Robotics and Automation, April 10-14, Rome, Italy

D&C SLAM



L. Paz, J. Neira and J.D. Tardós **Divide and Conquer: EKF SLAM in $O(n)$** . Conditionally accepted, IEEE Transactions on Robotics, 2008.

Lawn mower Trajectory



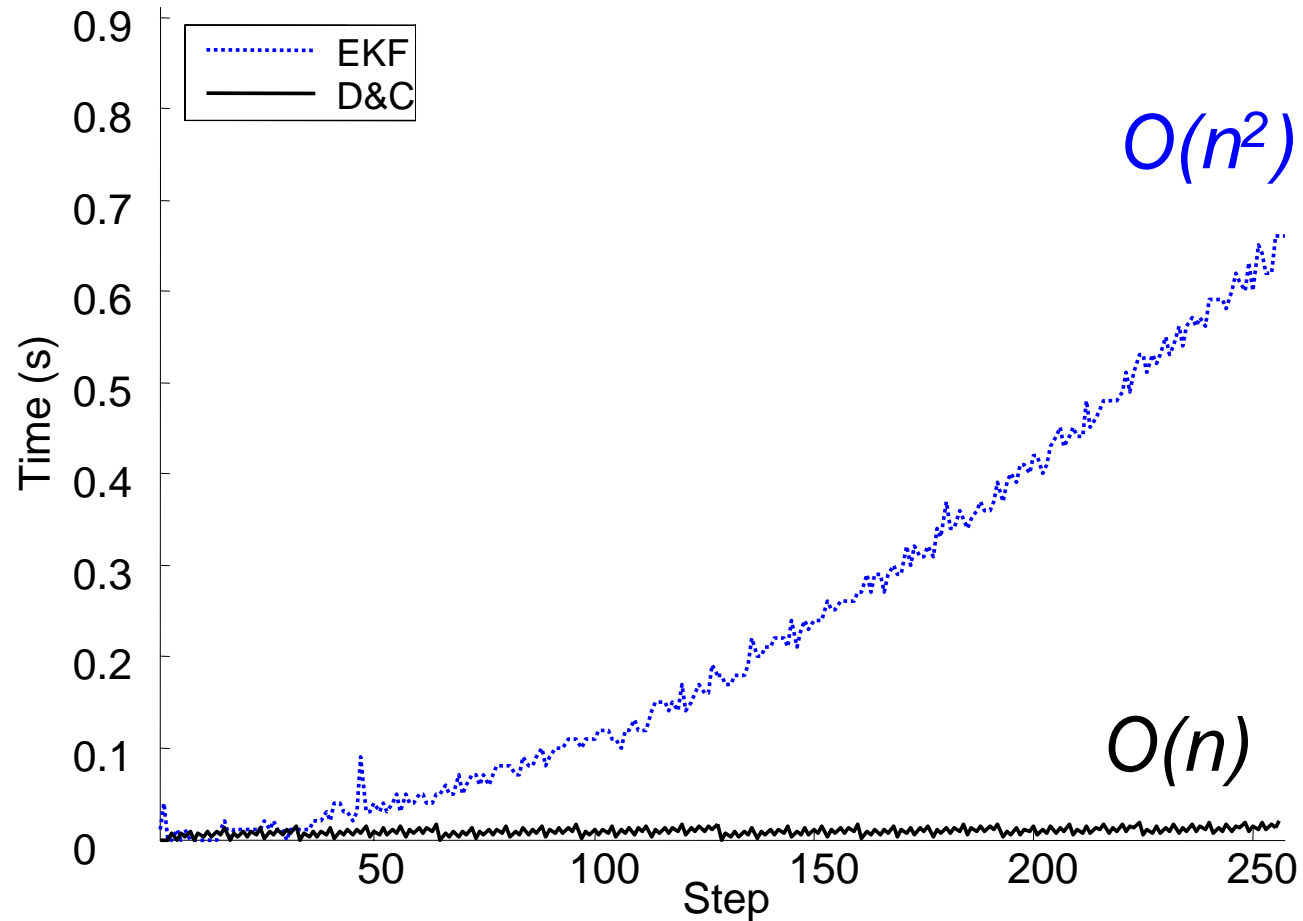
D&C is $\sim 1/5$ of EKF total time

Snail Trajectory



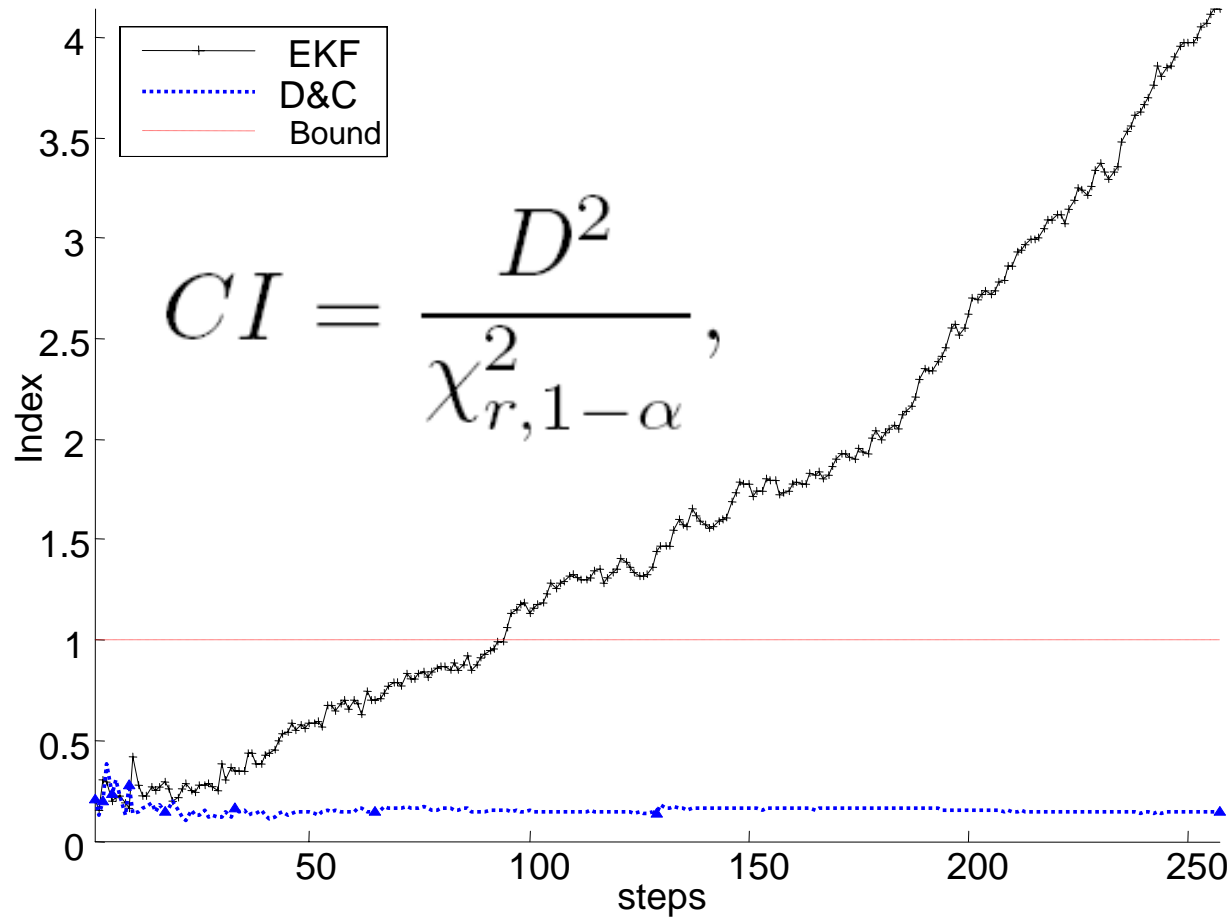
D&C is $\sim 1/3$ of EKF total time

Costo amortizado por paso



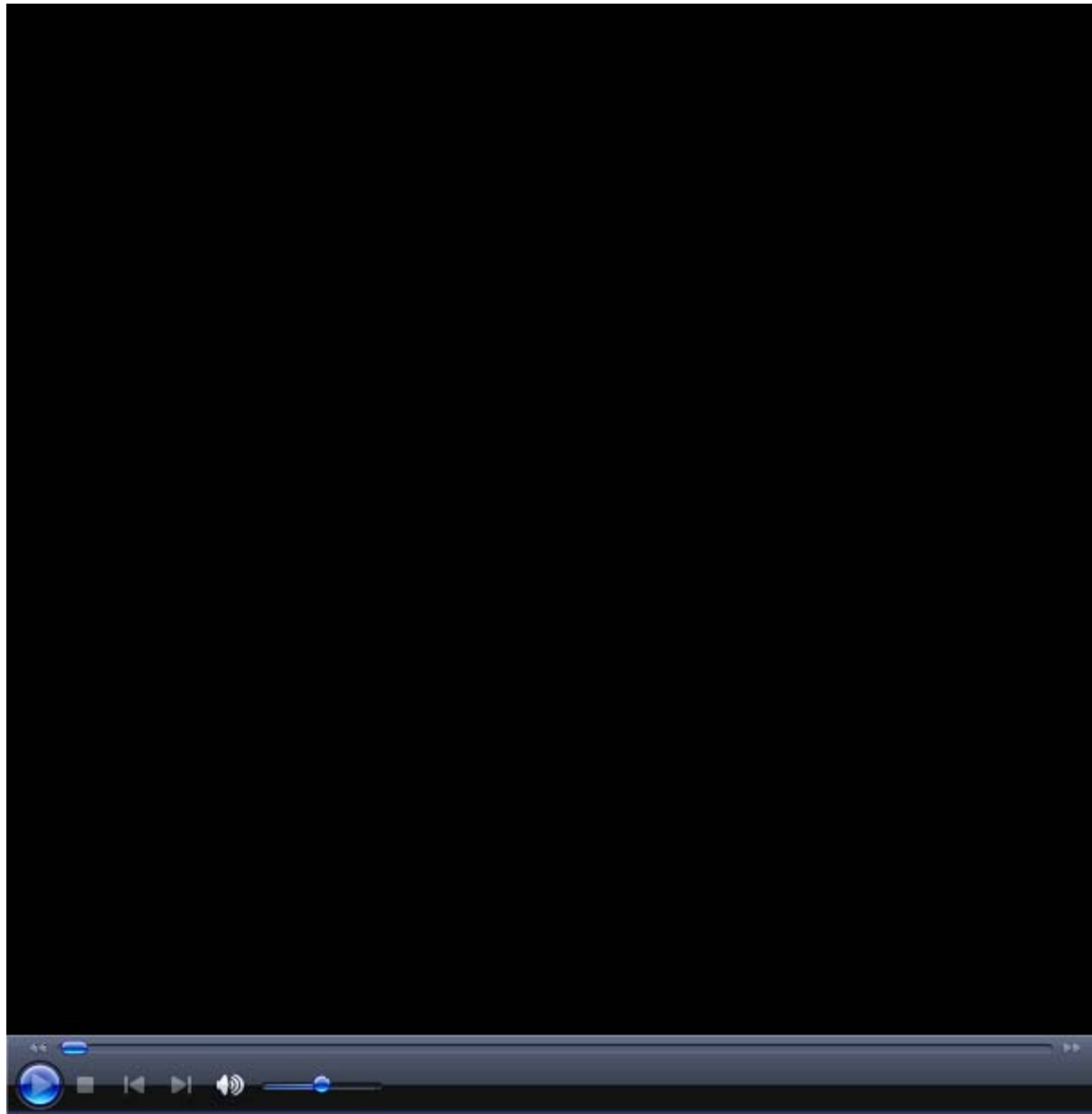
D&C es $O(n)$ por paso

Mejora de la consistencia con respecto a EKF SLAM

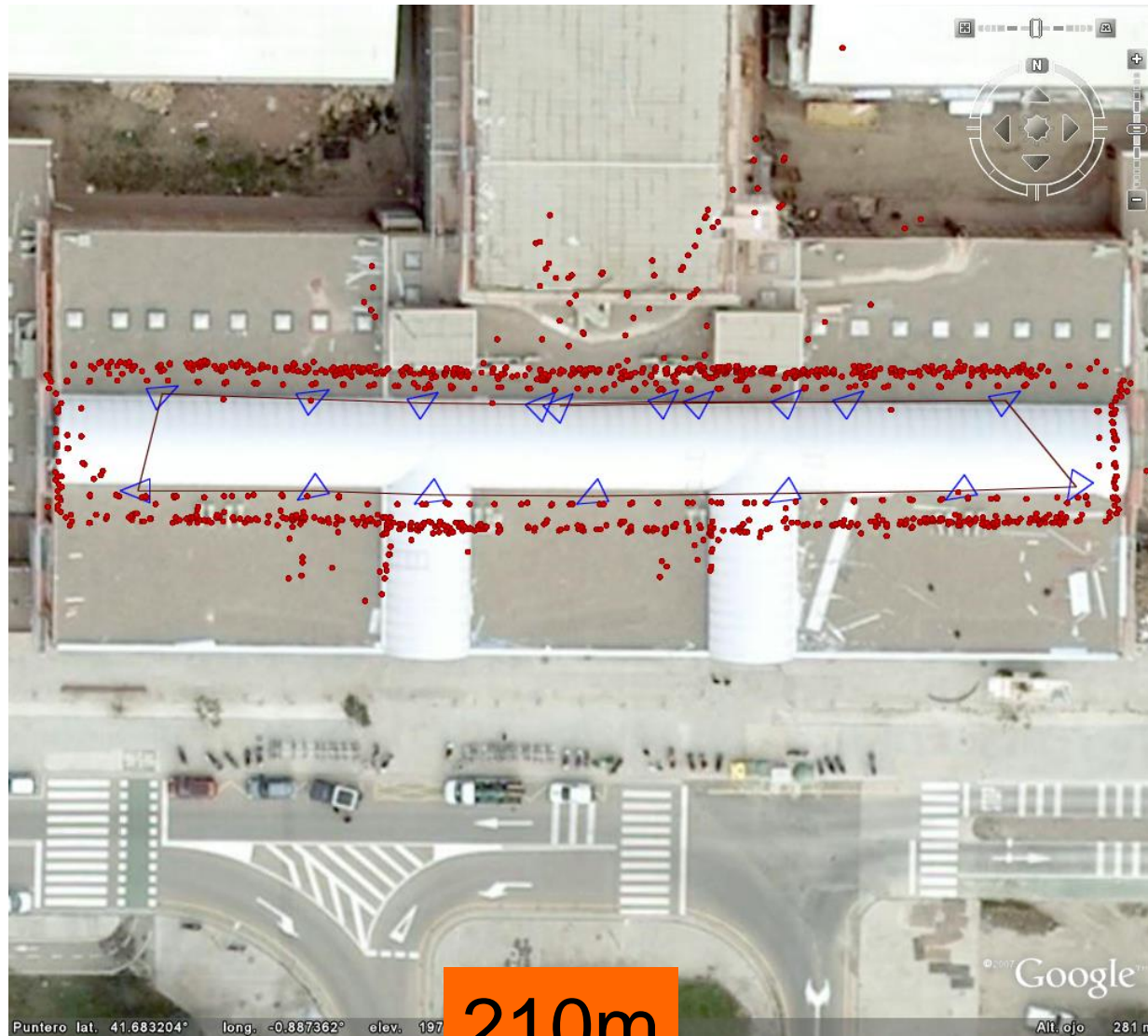


D&C SLAM siempre es más consistente

Experimento en interiores: 210 m



SLAM estéreo, interiores



Experimento en exteriores



L. Paz, P. Pinies, J. Neira and J.D. Tardós **Large Scale 6DOF SLAM with Stereo-in-Hand**. Conditionally accepted, IEE Transactions on Robotics, 2008.

Exteriores



Perspectiva

- ¿Complejidad $< O(n)$?
- Bucles más grandes y trayectorias más complejas.
- Entornos altamente dinámicos

INFORMACION

1st Summer School 2002, Stockholm

<http://www.cas.kth.se/SLAM/>

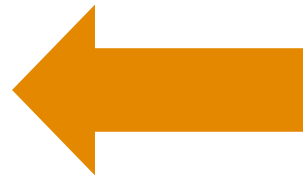
2nd Summer School 2004, Toulouse

<http://www2.laas.fr/SLAM/>

3rd Summer School 2006, Oxford

<http://www.robots.ox.ac.uk/~SSS06/>

4th Summer School 2009, Sydney



<http://www.acfr.usyd.edu.au/education/summerschool.shtml>

Lecturas recomendadas

- **Guest Editorial, Special Issue on Visual SLAM**, J. Neira, AJ Davison, J. Leonard, IEEE Transactions on Robotics Vol 24, Number 5, pp 929-931, October 2008
- **Large Scale 6DOF SLAM with Stereo-in-Hand**, L.M. Paz, P. Pinies, J.D. Tardós, J. Neira, IEEE Transactions on Robotics Vol 24, Number 5, pp 946-957, October 2008
- **Divide and Conquer: EKF SLAM in $O(n)$** , L.M. Paz, J.D. Tardós, J. Neira, IEEE Transactions on Robotics Vol 24, Number 5, pp 1107-1120, October 2008
- **Robocentric Map Joining: Improving the Consistency of EKF-SLAM**, J.A. Castellanos, R. Martinez-Cantin, J.D. Tardós and J. Neira, Robotics and Autonomous Systems (Elsevier), Volume 55, Issue 1, Pages 21-2, 31 January 2007
- **Hierarchical SLAM: real-time accurate mapping of large environments**, C. Estrada, J. Neira, J.D. Tardós, IEEE Transactions on Robotics, Vol: 21, Issue: , pages: 588- 596, August 2005
- **Robust Mapping and Localization in Indoor Environments using Sonar Data**, J.D. Tardós, J. Neira, P. Newman, and J. Leonard. The International Journal of Robotics Research, Vol. 21, No. 4, April, 2002, pp 311 –330
- **Data Association in Stochastic Mapping using the Joint Compatibility Test**, J. Neira and Juan D. Tardós, IEEE Transactions on Robotics and Automation Vol. 17, No. 6, Dec 2001, pp 890 –897
- **Multisensor Fusion for Simultaneous Localization and Map Building**, J.A. Castellanos, J. Neira and J.D. Tardós, IEEE Transactions on Robotics and Automation Vol. 17, No. 6, Dec 2001, pp 908 –911
- **The SPmap: A Probabilistic Framework for Simultaneous Localization and Map Building**, J.A. Castellanos, J.M.M. Montiel, J. Neira and J.D. Tardós. IEEE Transactions on Robotics and Automation Vol. 15, No. 5, Oct 1999, pp 948-953.
- **Fusing Range and Intensity Images for Mobile Robot Localization**, Neira J., Horn J., Tardós J.D. and Schmidt G. IEEE Transactions on Robotics and Automation, Vol. 15, No. 1, Feb 1999, pp 76-84.

BIBLIOGRAFIA

