Pure Visual SLAM

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Outline

1. Motivation

2. Monocular SLAM
    1. Feature representation
    2. Data association
    3. Hierarchical SLAM algorithm

3. SLAM using only stereo
    1. Feature representation
    2. D&C SLAM algorithm

4. Conclusions

Motivation

SLAM seeks to answer this question:

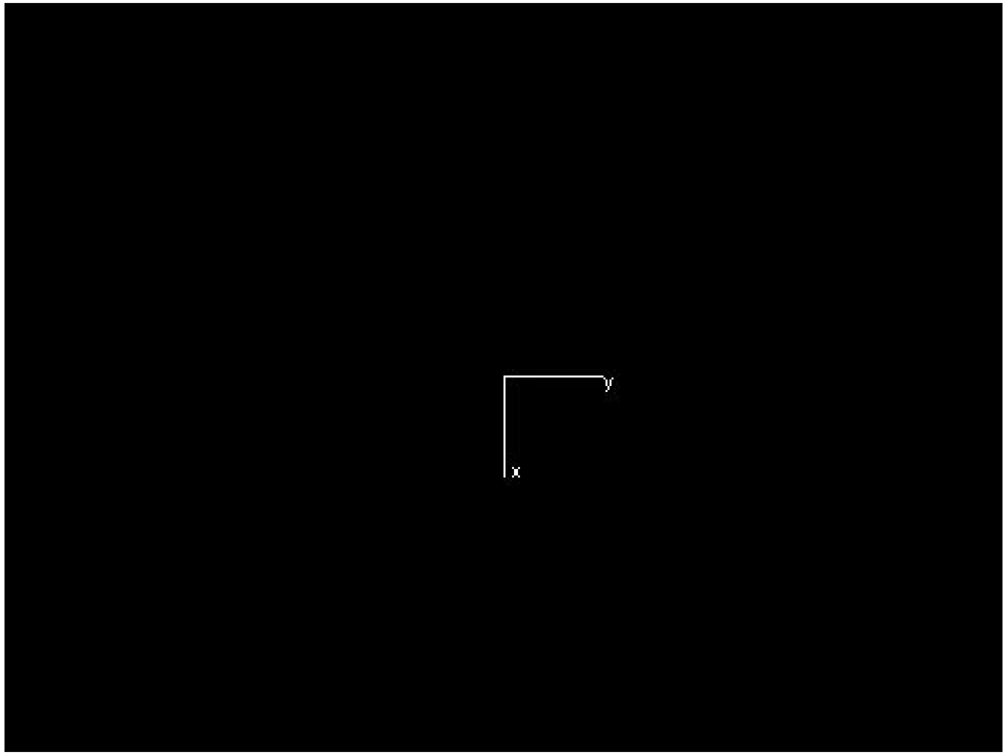
Is it possible to use a vehicle, starting at an

- **unknown initial location**, in an
- **unknown environment**, to
- **incrementally**

build a map of the environment,

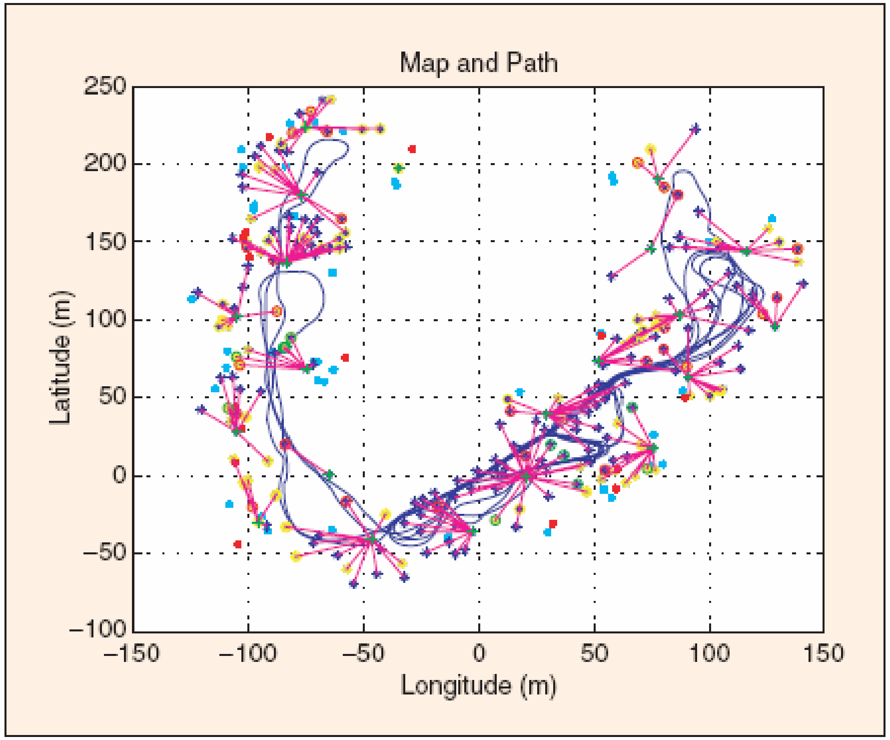
- and **at the same time**

use the map to determine the vehicle location?



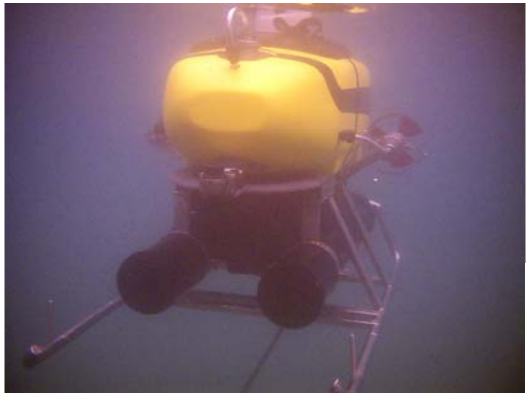
(video: Paul Newman)

Outdoor vehicles



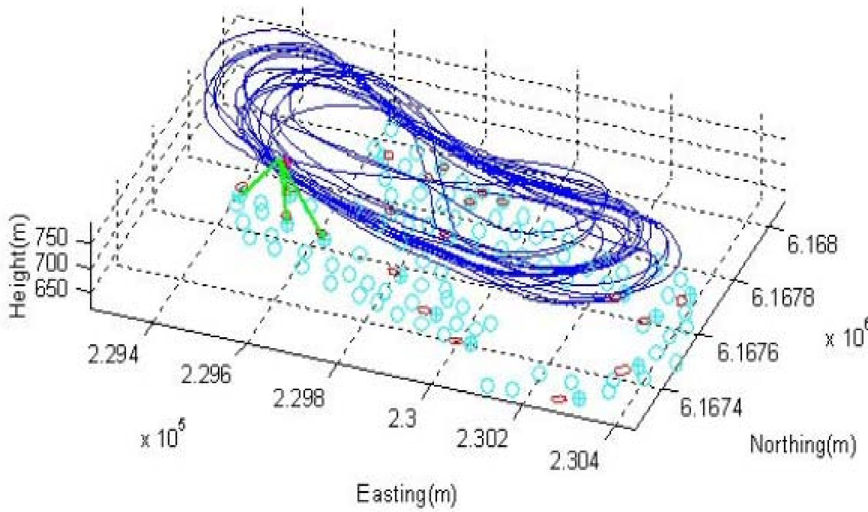
Victoria Park, Univ. Syndey

Underwater, Airborne



Garbi, Univ. Girona, Spain

Brumby, Univ. Syndey



Monocular SLAM

A Unibrain fire-I camera, a laptop and a firewire cable

290 m.

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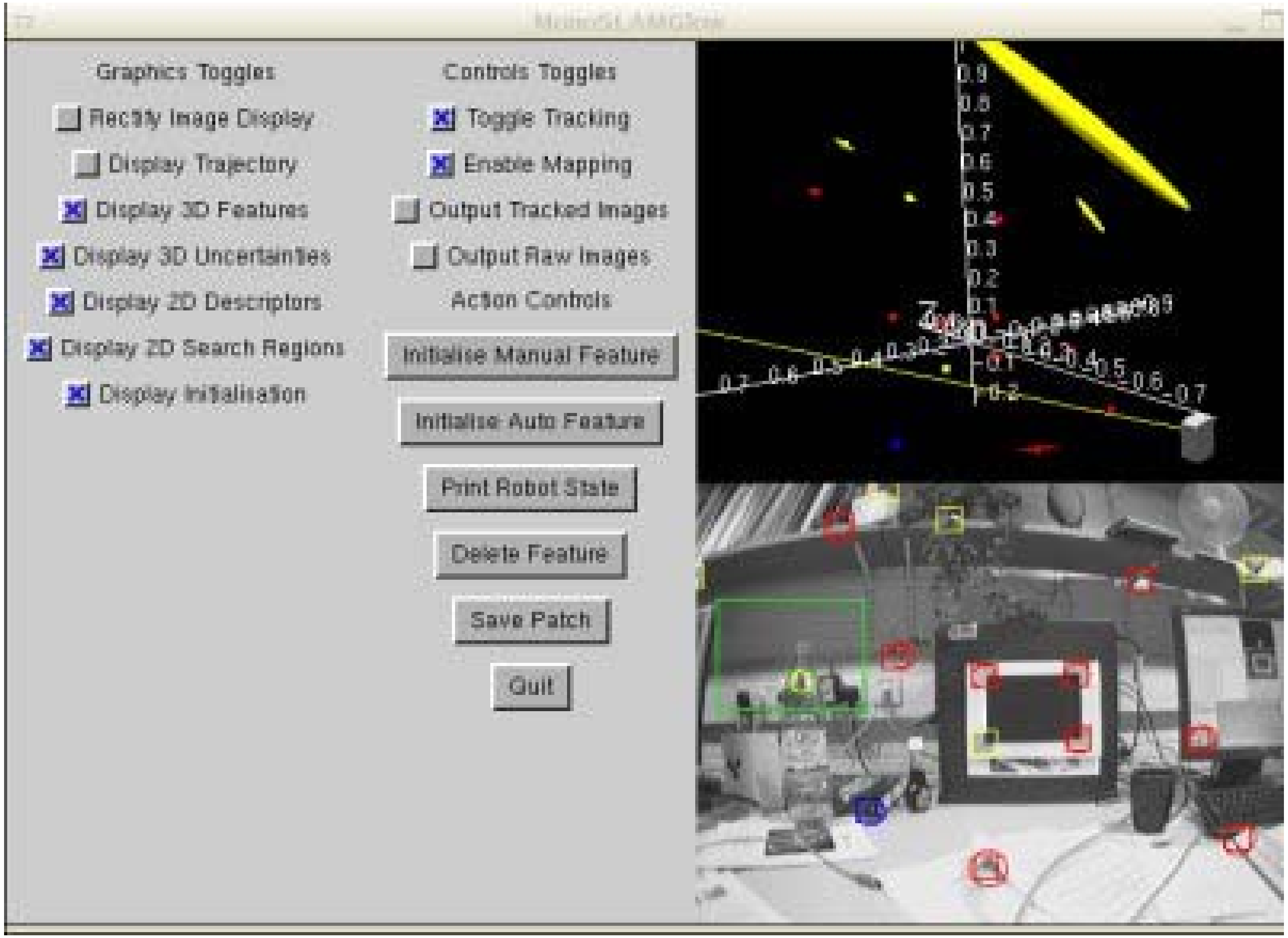
Monoslam (A. Davison)



Basic EKF SLAM

EKF state vector:

- Camera state
- Features state

Camera state:

- Position
- Orientation
- Linear Velocity
- Angular Velocity

$$\mathbf{x} = \begin{pmatrix} \mathbf{x}_c \\ \mathbf{y}_1 \\ \mathbf{y}_2 \\ \dots \\ \mathbf{y}_n \end{pmatrix} \qquad \mathbf{x}_c = \begin{pmatrix} \mathbf{r}^{BC} \\ \mathbf{\Psi}^{BC} \\ \mathbf{v}^{B} \\ \mathbf{w}^{C} \end{pmatrix}$$

3D features representation

3D points:

- \- Cartesian coordinates

$$\mathbf{y}_i = \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix}$$

Inverse depth points:

\- Camera position the first time the feature was seen

\- Azimuth

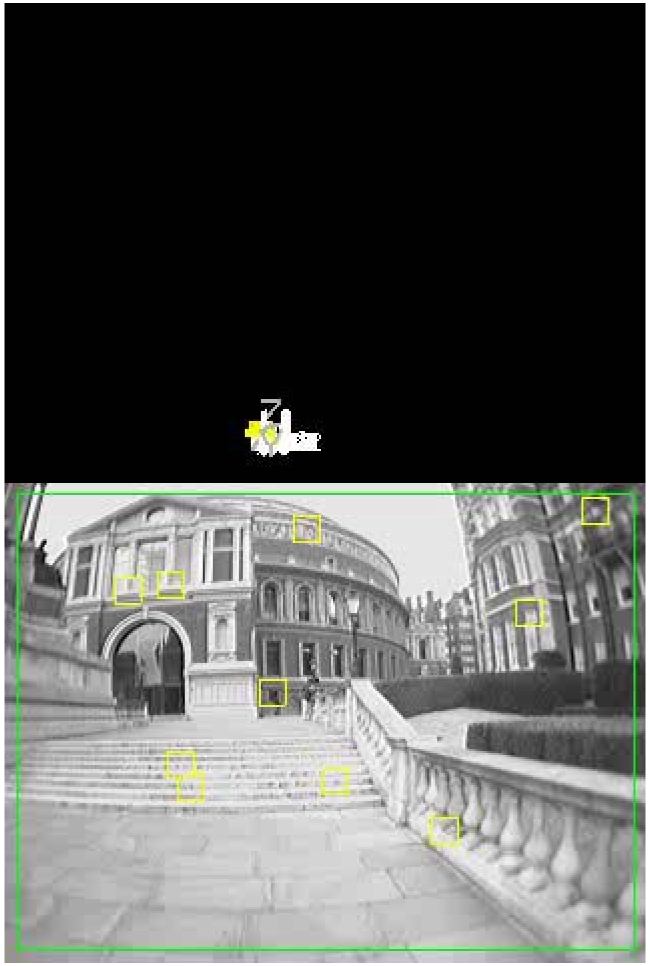
\- Elevation

\- Inverse depth

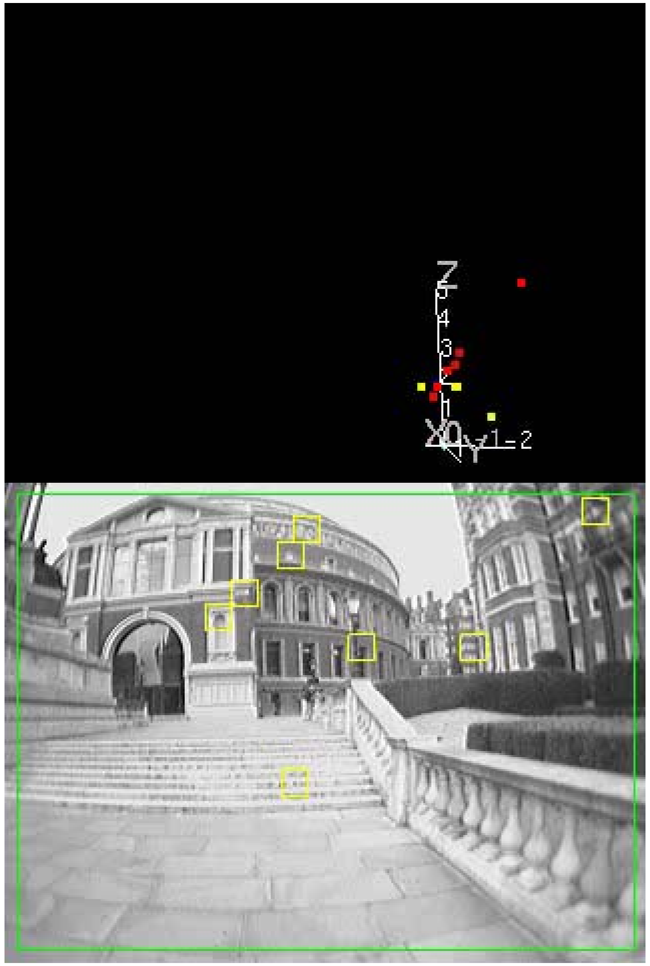
$$\mathbf{y}_i = \begin{pmatrix} x_i \\ y_i \\ z_i \\ \theta_i \\ \phi_i \\ \rho_i \end{pmatrix}$$

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

Data association

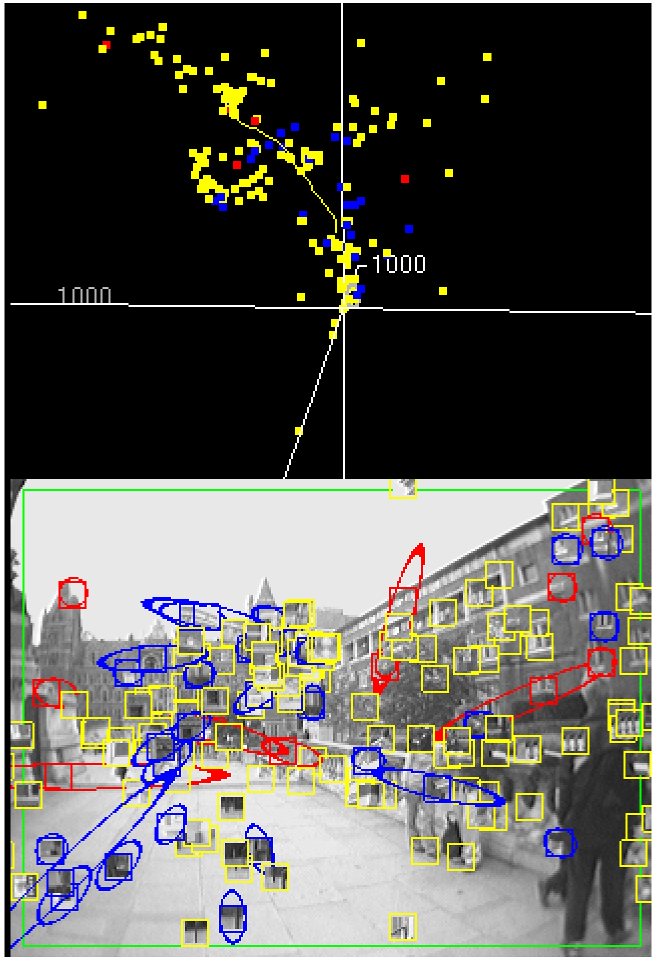


Individual tracks

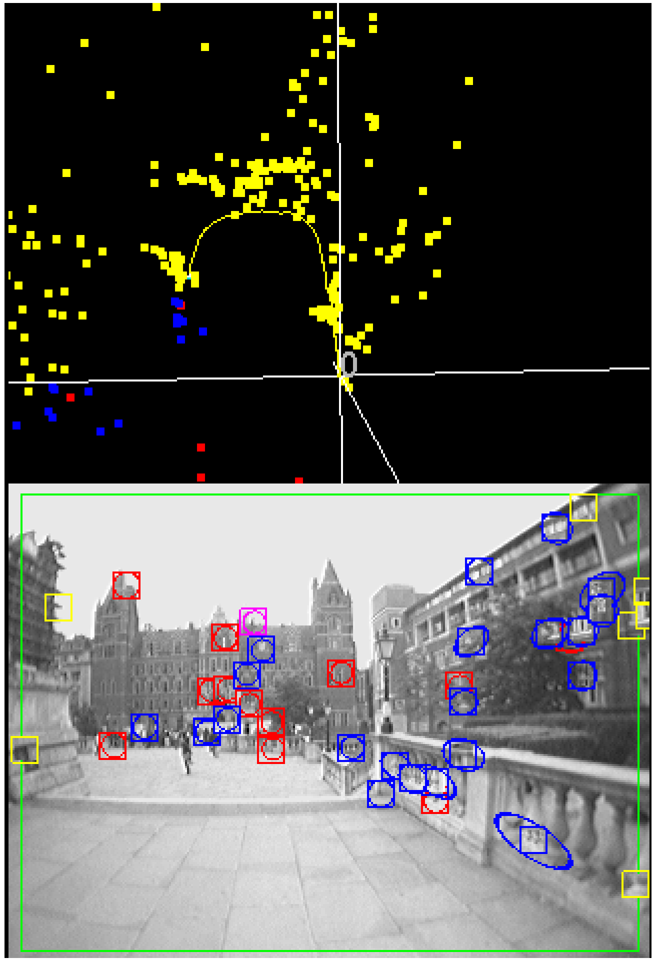


Jointly compatible tracks

Nearest neighbor .vs. Joint Compatibility



Individual Tracks



Jointly Compatible Tracks (cost: 2ms)

The EKF SLAM algorithm

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**

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

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

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

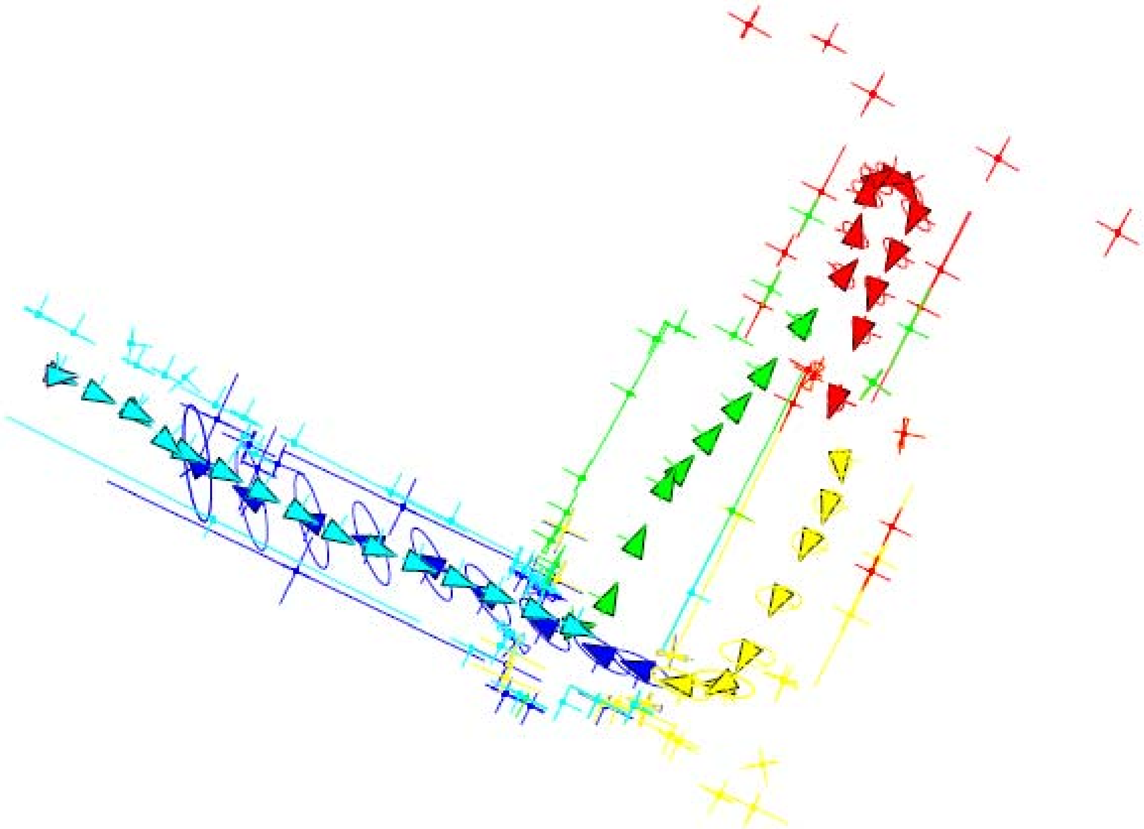
$\mathcal{H}_k = \text{data\_association}(\mathbf{x}_{k|k-1}^B, \mathbf{P}_{k|k-1}^B, \mathbf{z}_k, \mathbf{R}_k)$

$O(n^2)$ $[\mathbf{x}_k^B, \mathbf{P}_k^B] = \text{EKF\_update}(\mathbf{x}_{k|k-1}^B, \mathbf{P}_{k|k-1}^B, \mathbf{z}_k, \mathbf{R}_k, \mathcal{H}_k)$

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

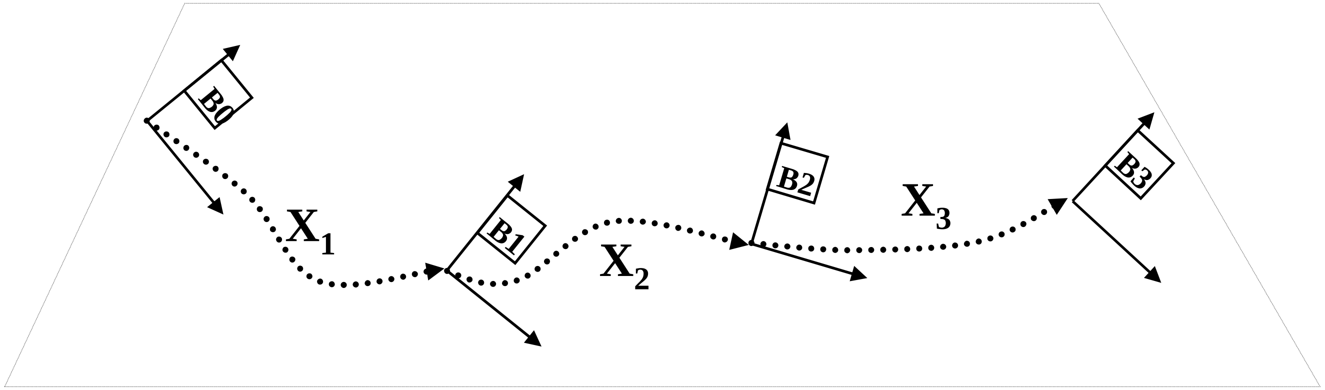
end for

Scalable EKF SLAM: Independent Local Maps

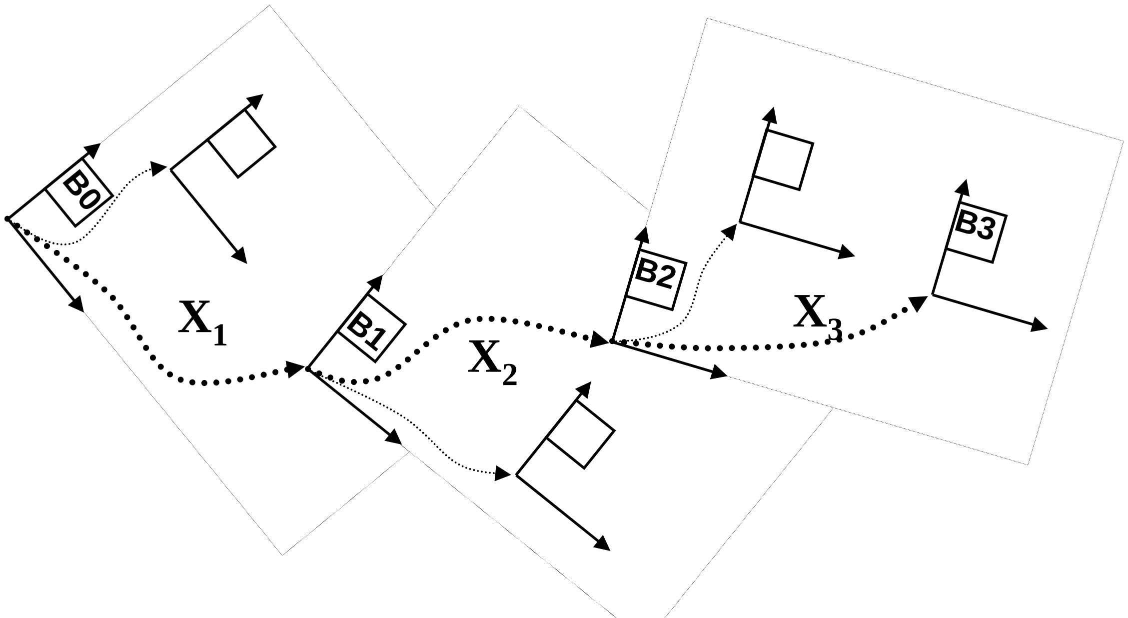


Hierarchical SLAM

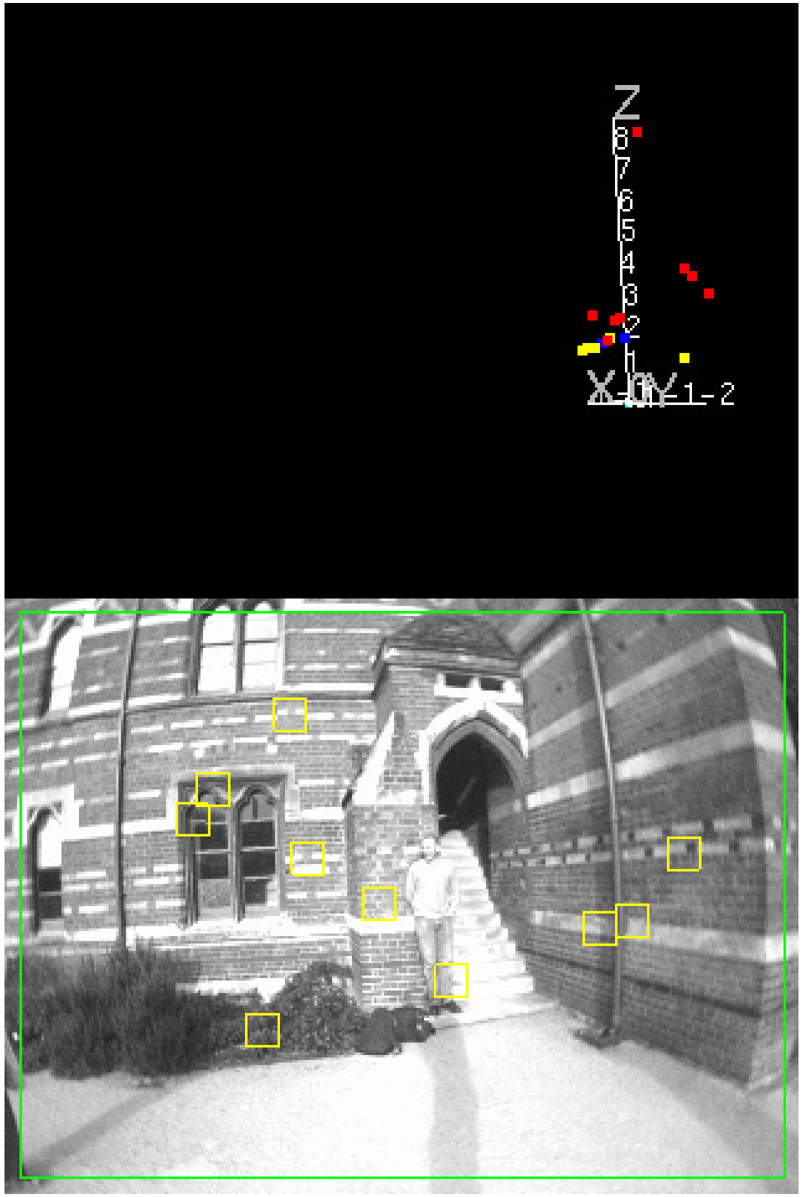
- Global level: adjacency graph and relative stochastic map



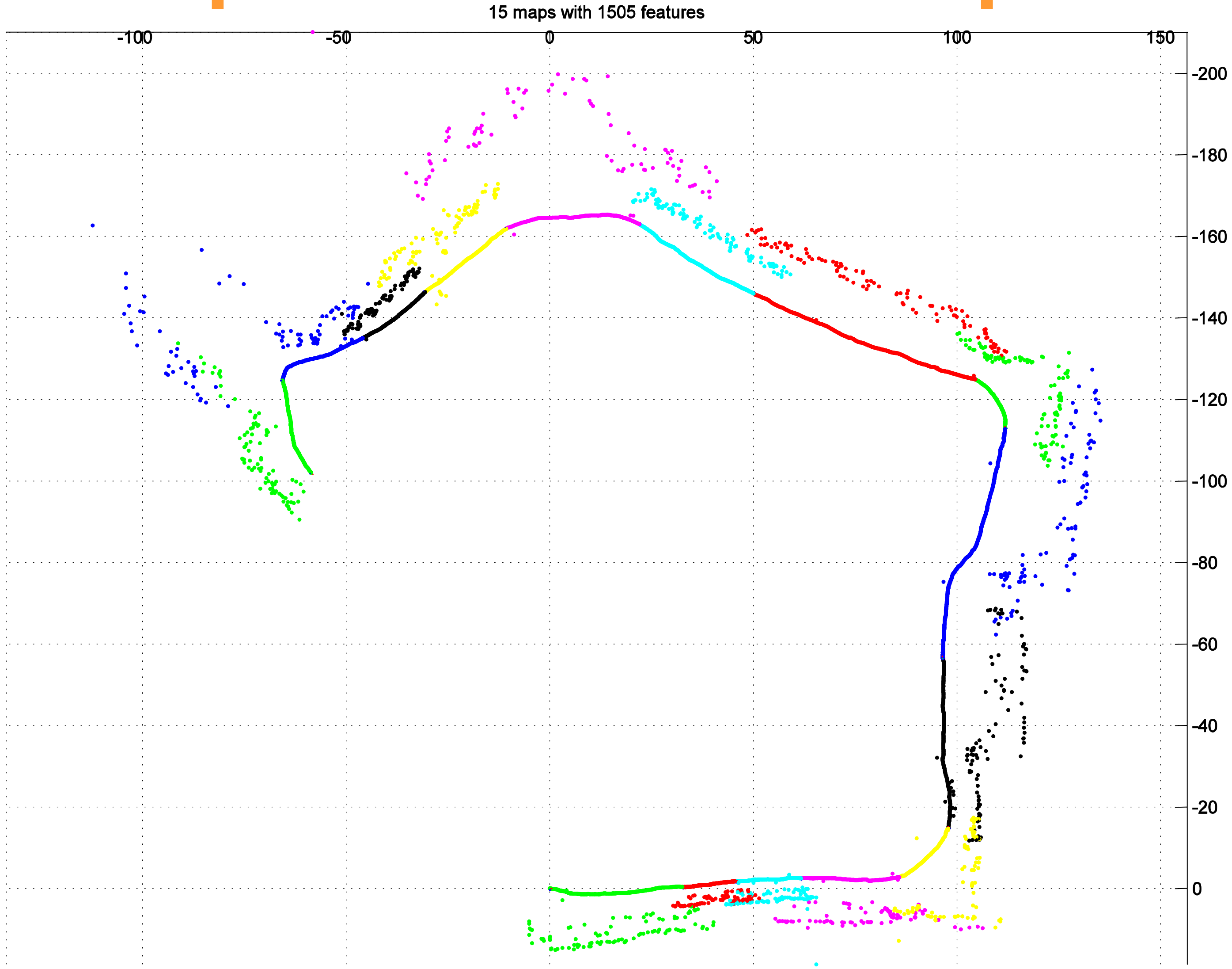
- Local level: statistically independent local maps



Keble College, Oxford

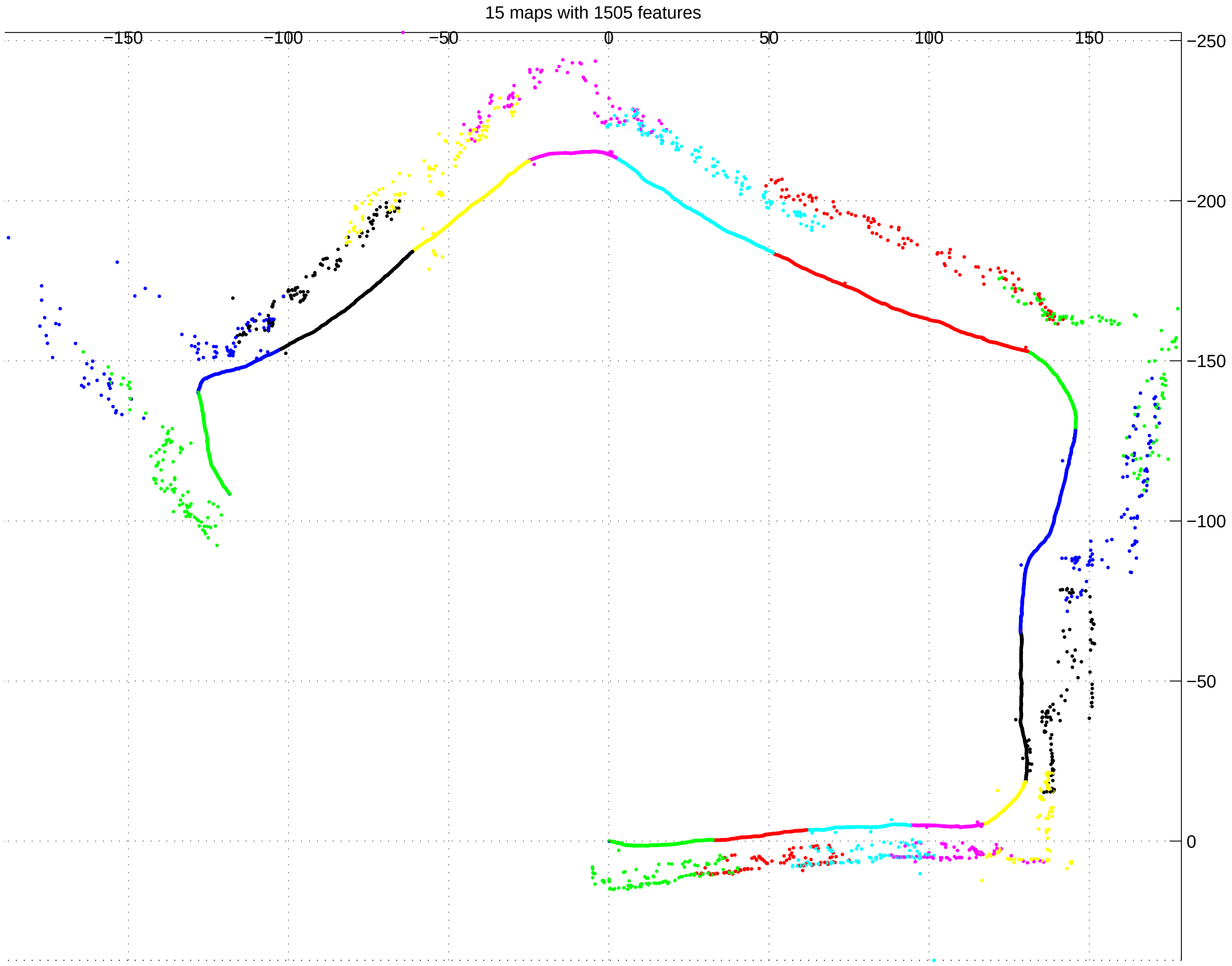


Sequence of local maps



The scale is arbitrary (not observable)

With scale compensation



Map Matching

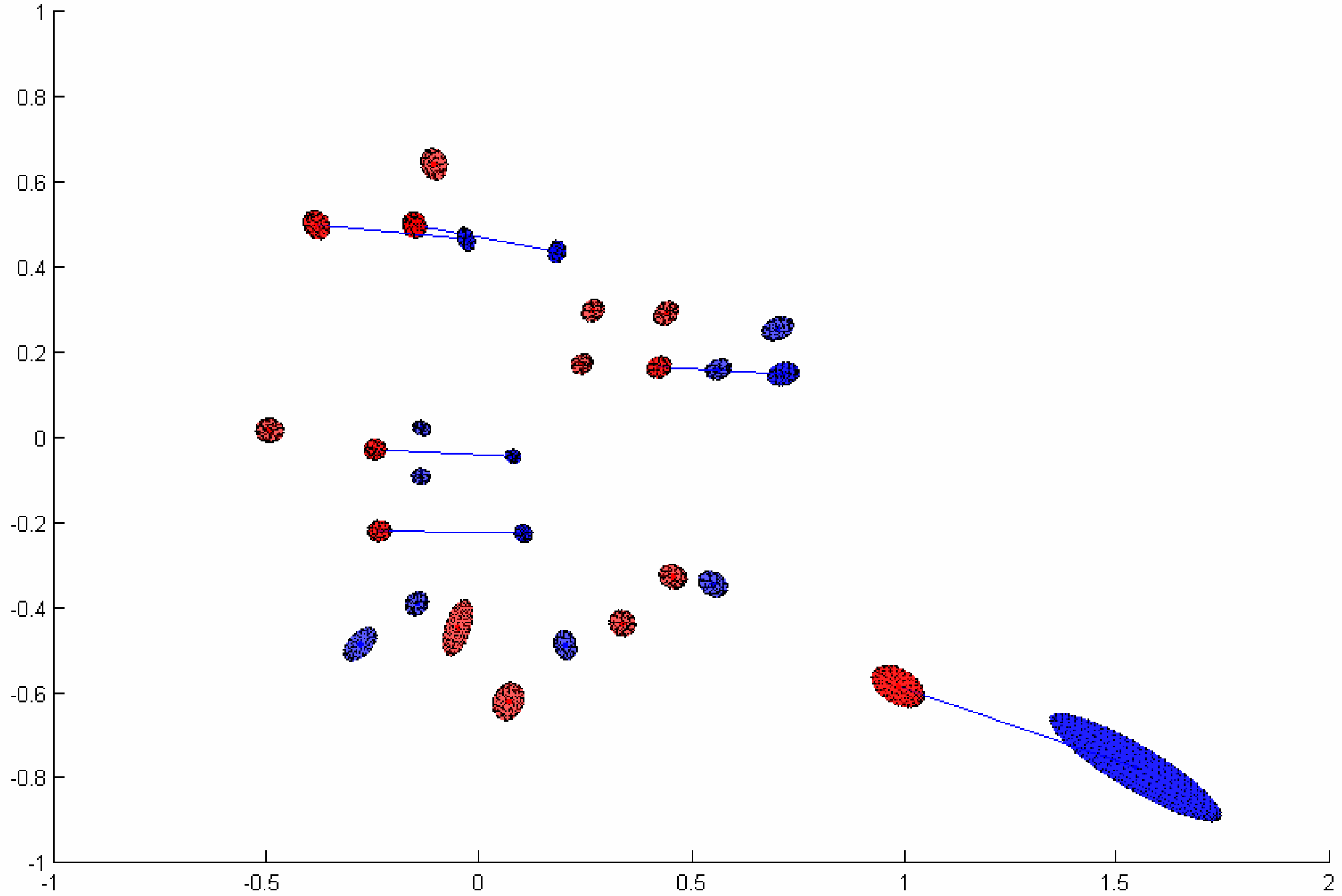
Unary Constraints

Cloud 1

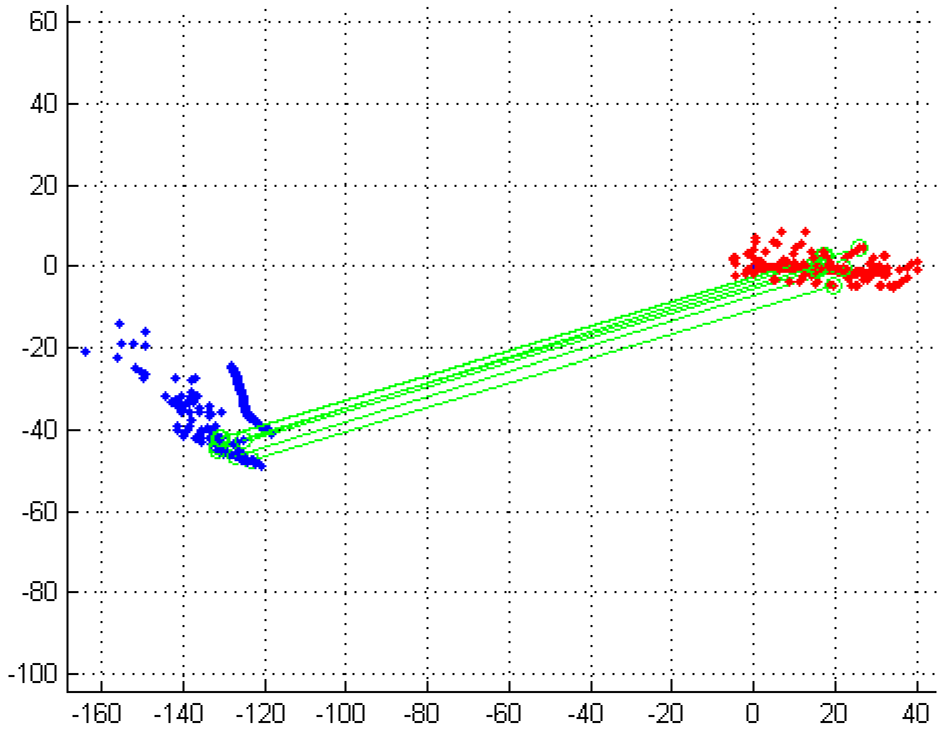
Cloud 2

Map Matching

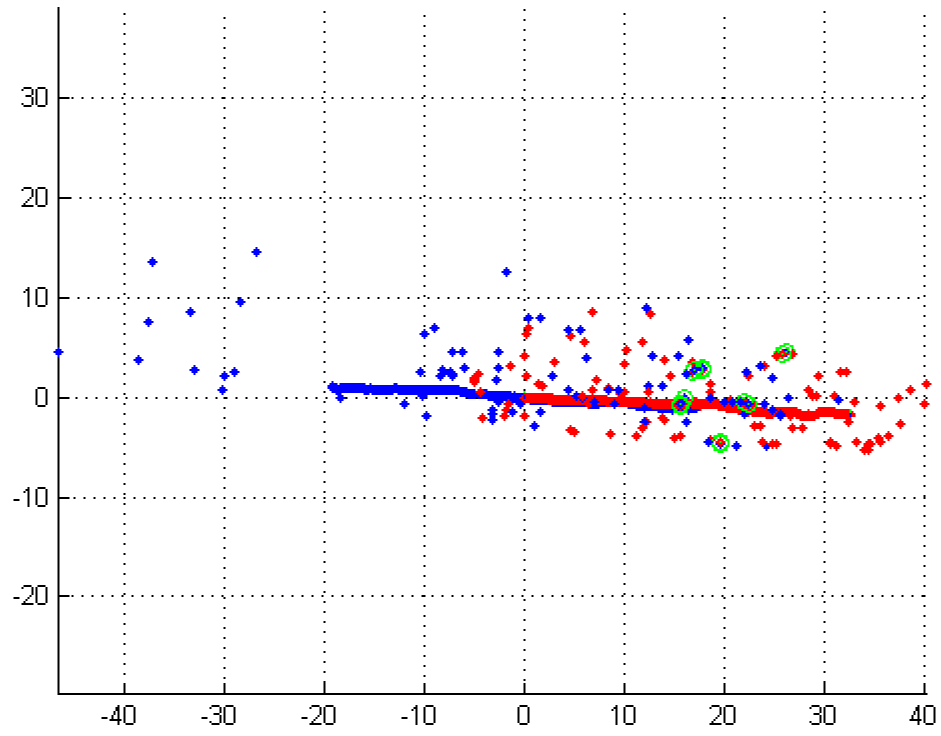
Binary Constraints



Map-to-Map Matching



Matchings found



Aligned Submaps

Nonlinear constrained optimization

- Minimize corrections to the global map, subject to the loop constraint:

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

$$\mathbf{h}(\mathbf{x}) = \mathbf{0}$$

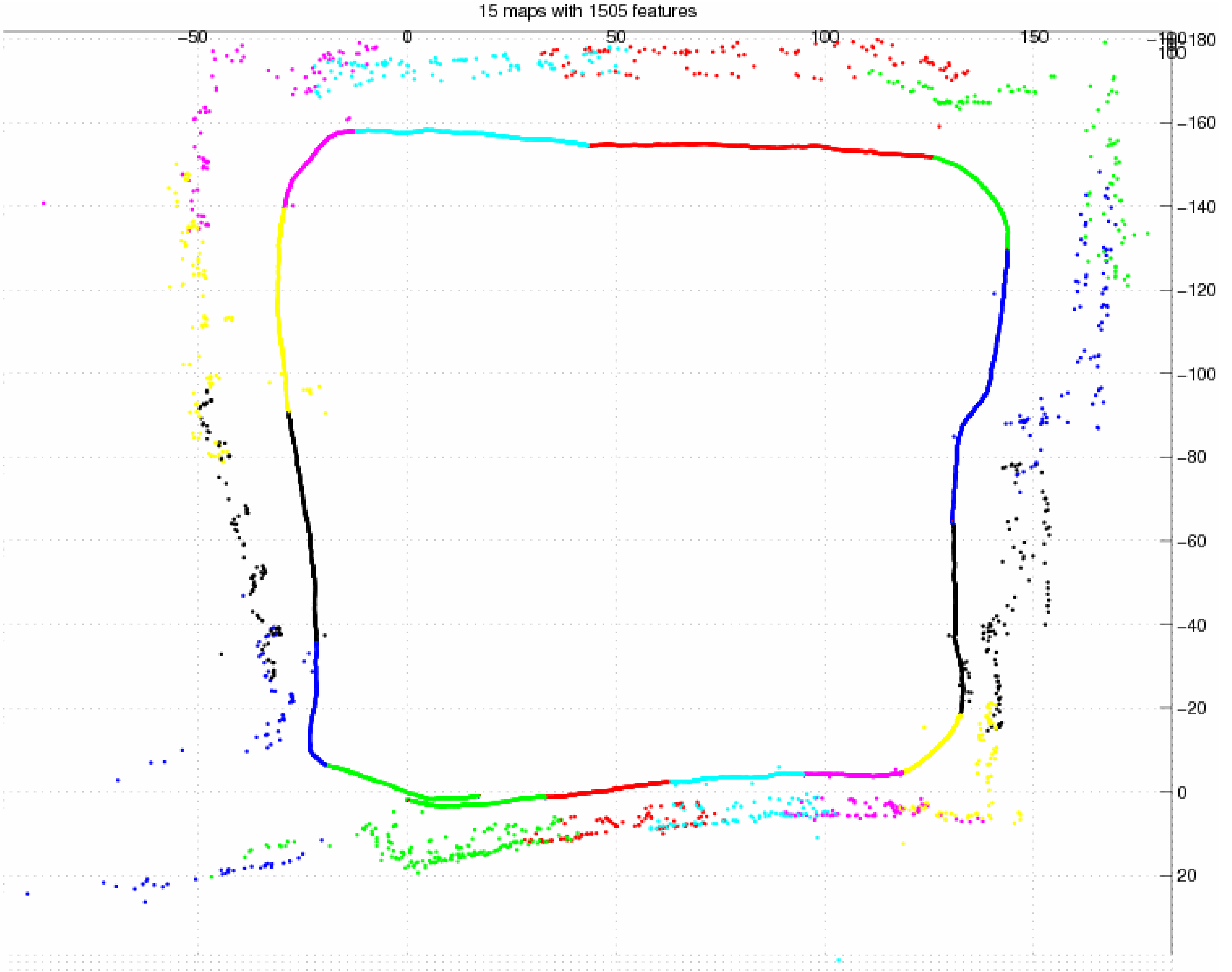
- Sequential Quadratic Programming (SQP) :

$$\mathbf{H}_i = \left[\left.\frac{\partial \mathbf{h}}{\partial \mathbf{x}_1}\right|_{\hat{\mathbf{x}}_i} \left.\frac{\partial \mathbf{h}}{\partial \mathbf{x}_2}\right|_{\hat{\mathbf{x}}_i} \cdots \left.\frac{\partial \mathbf{h}}{\partial \mathbf{x}_{n-1}}\right|_{\hat{\mathbf{x}}_i} \left.\frac{\partial \mathbf{h}}{\partial \mathbf{x}_n}\right|_{\hat{\mathbf{x}}_i} \right]$$

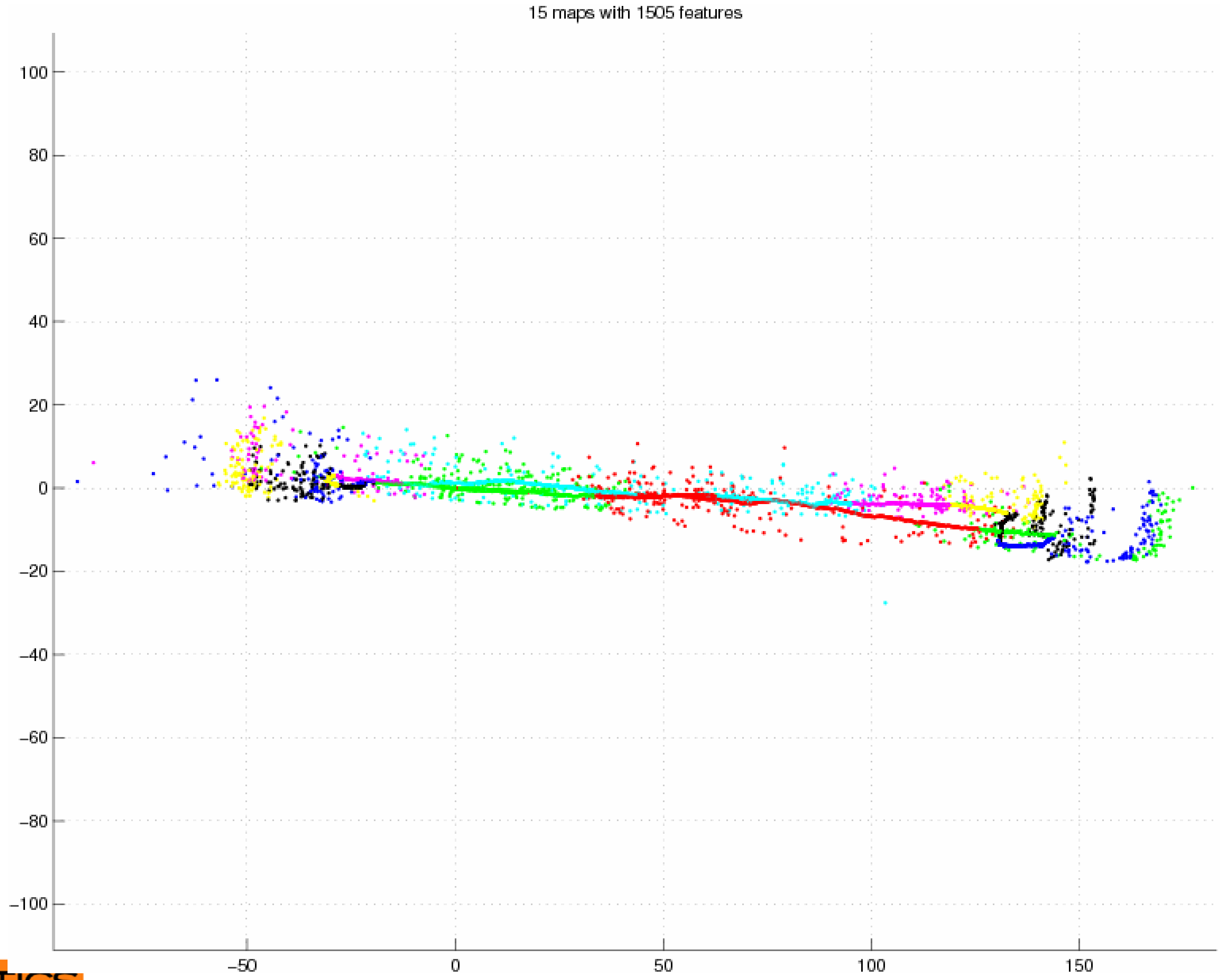
$$\begin{aligned} \mathbf{P}_i &= \mathbf{P}_0 - \mathbf{P}_0\mathbf{H}_i^T \left(\mathbf{H}_i\mathbf{P}_0\mathbf{H}_i^T\right)^{-1} \mathbf{H}_i\mathbf{P}_0 \\ \hat{\mathbf{x}}_{i+1} &= \hat{\mathbf{x}}_i - \mathbf{P}_i\mathbf{P}_0^{-1}(\hat{\mathbf{x}}_i - \hat{\mathbf{x}}_0) - \mathbf{P}_0\mathbf{H}_i^T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

  » Iterate until convergence

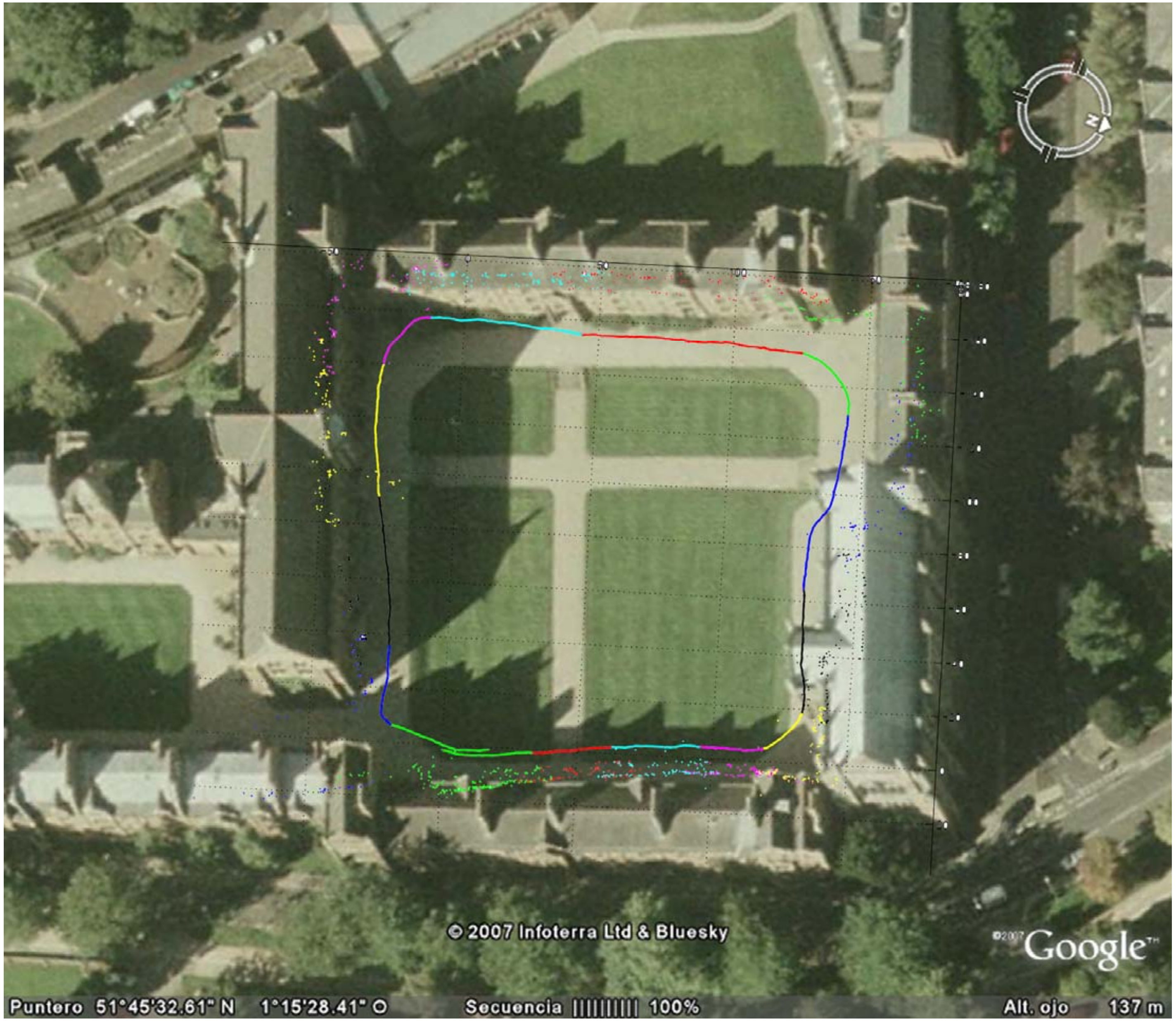
Loop closing



Loop closing (lateral view)



Keble College, Oxford (290m)



Results

- Local Map building in real-time @30Hz
  - 60 features per map using inverse depth
  - Bigger maps if converted to (x,y,z)
- Joint Compatibility search adds only 2ms in the worst case
- Map-to-map matching in 1s (in Matlab)
  - With a new algorithm based on graph theory
- Loop optimization takes 800ms (6 iterations)
- **The scale drifts along the map**

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.

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SLAM using only stereo

- Experimental setup

A bumblebee, a laptop and a firewire cable

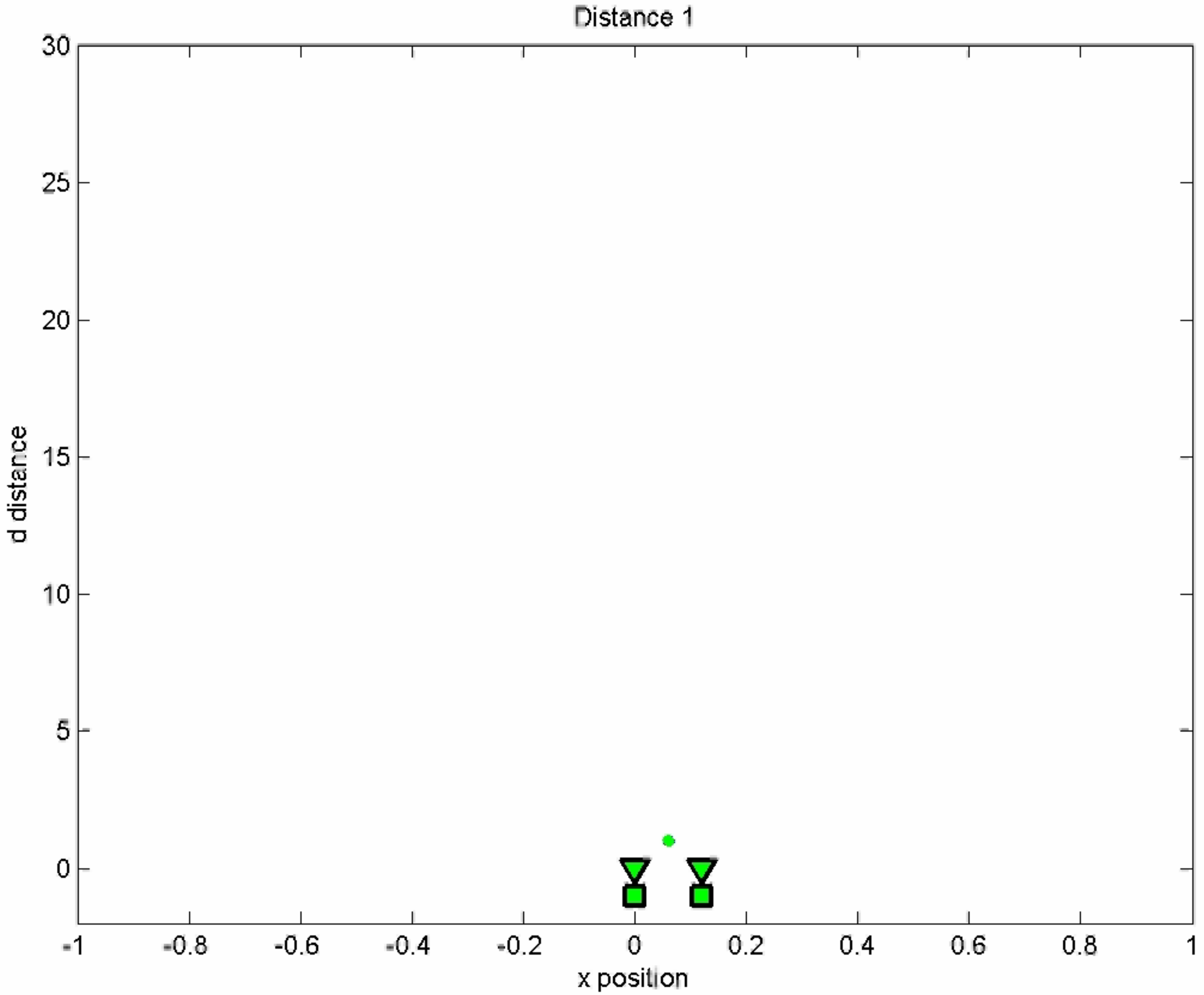
Pure Stereo SLAM

180m indoor loop, CPS, Zaragoza

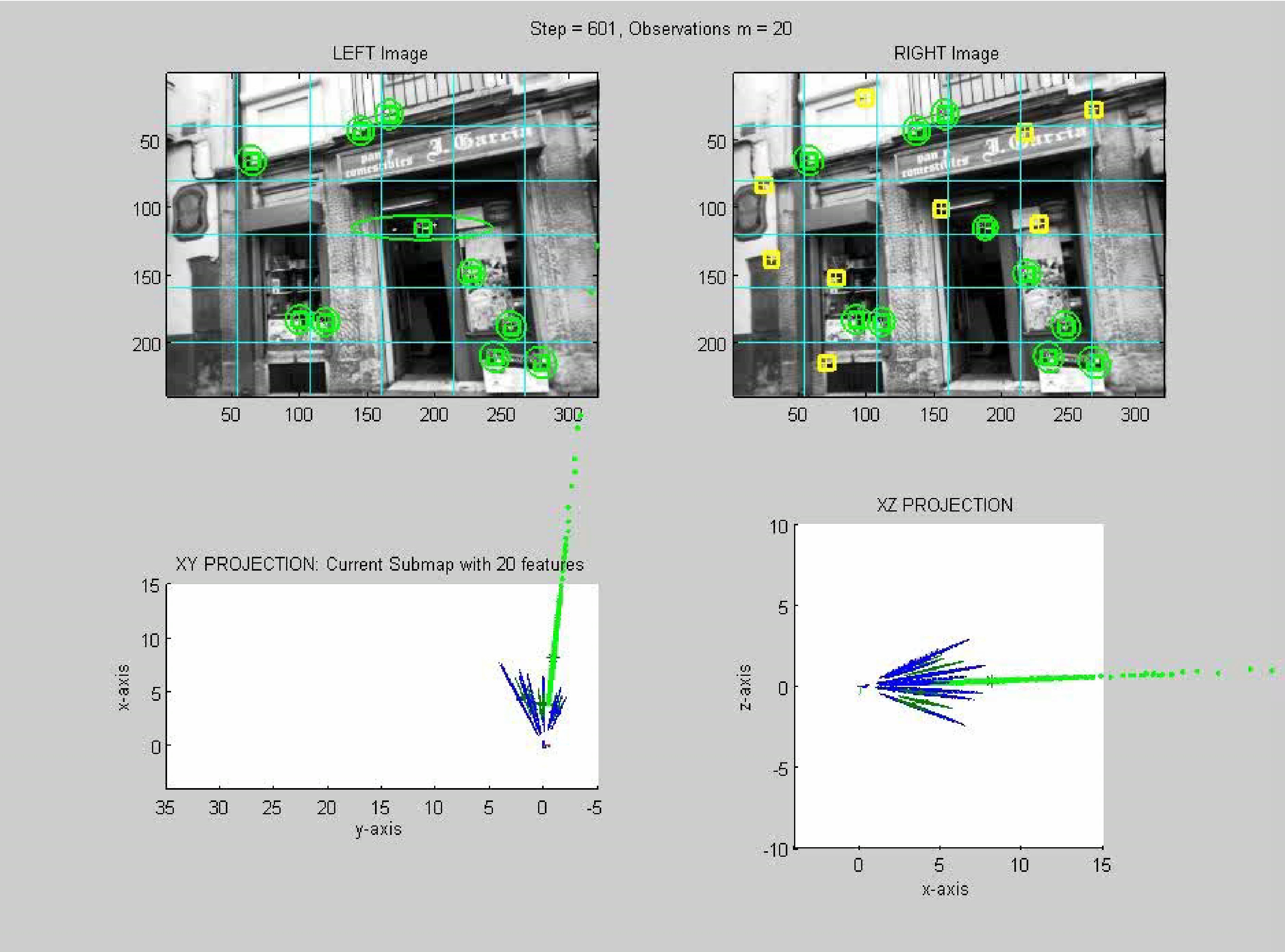
Pure Stereo SLAM

150m outdoor loop, public square, Zaragoza

Depth .vs. Inverse Depth

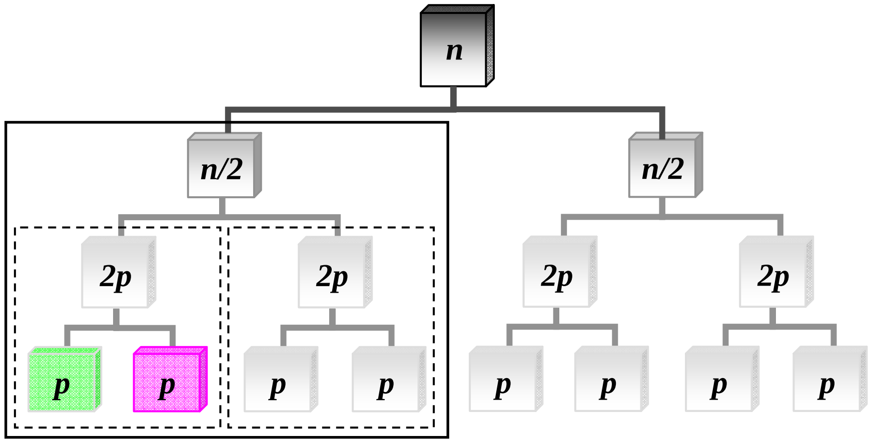


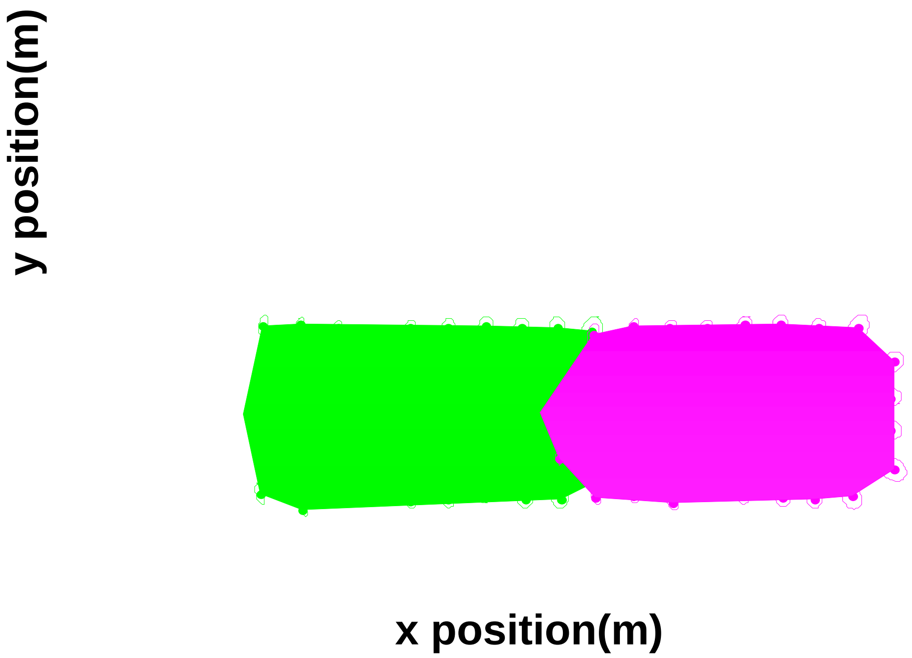
Basic EKF SLAM



Divide & Conquer SLAM

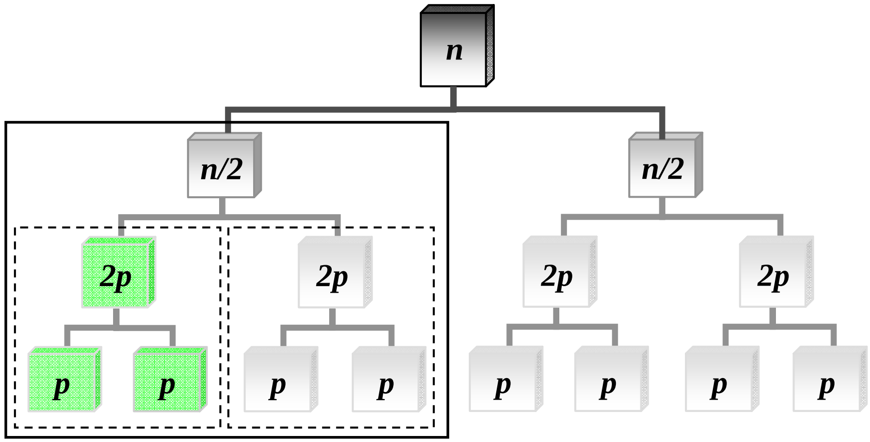
Number of Maps : 2

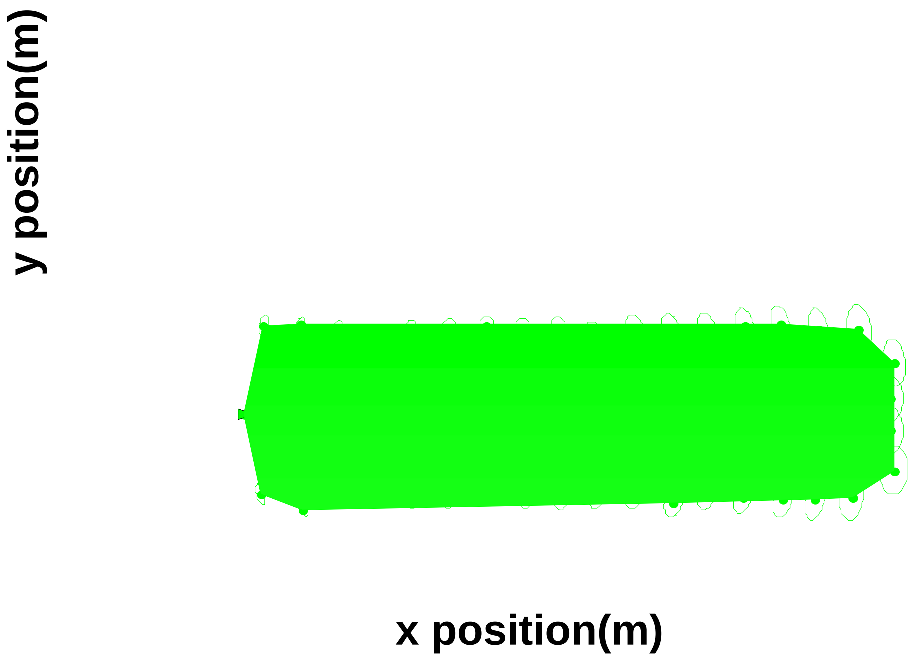




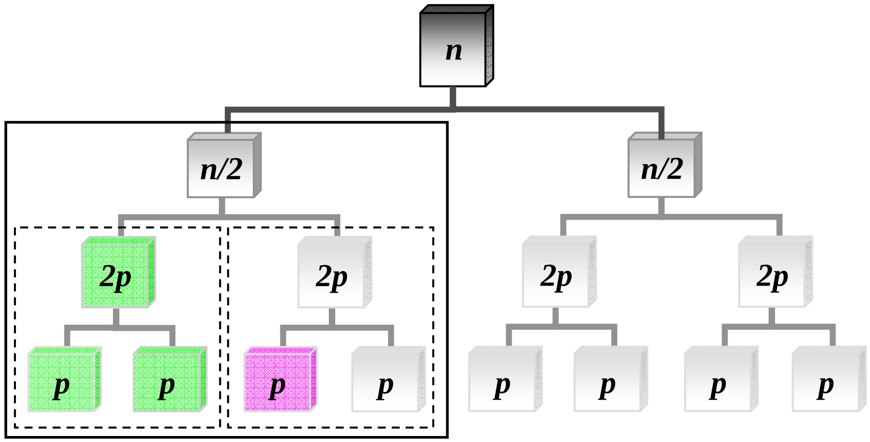
Divide & Conquer SLAM

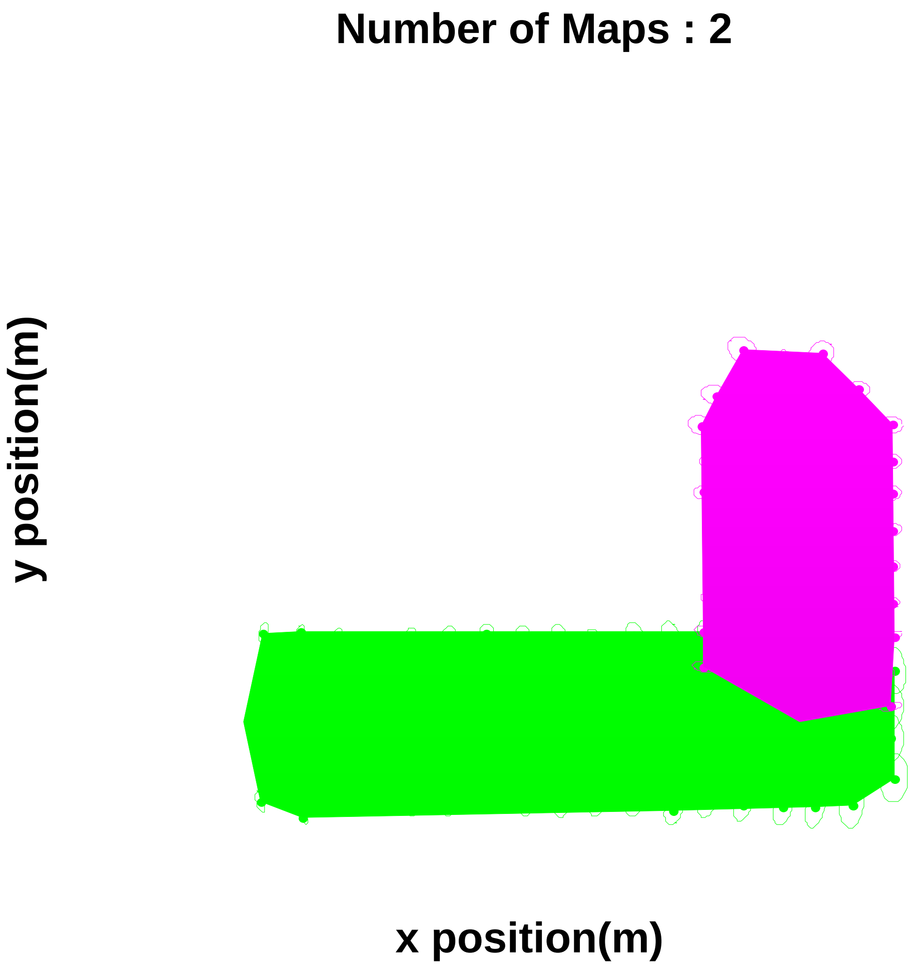
Number of Maps : 1



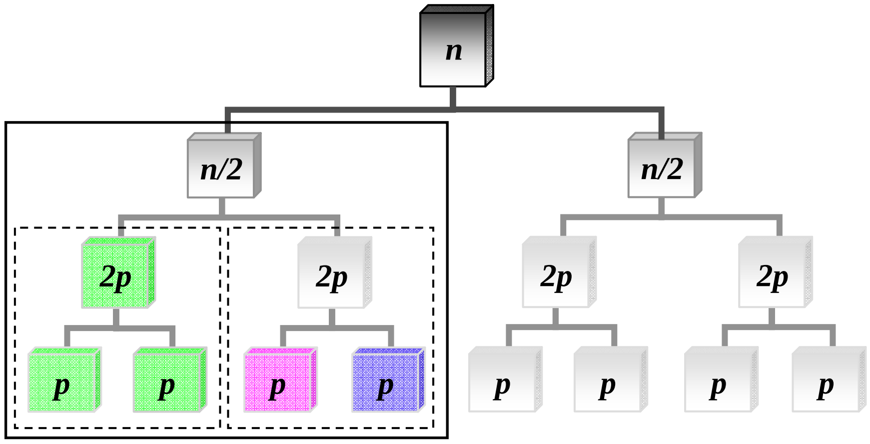


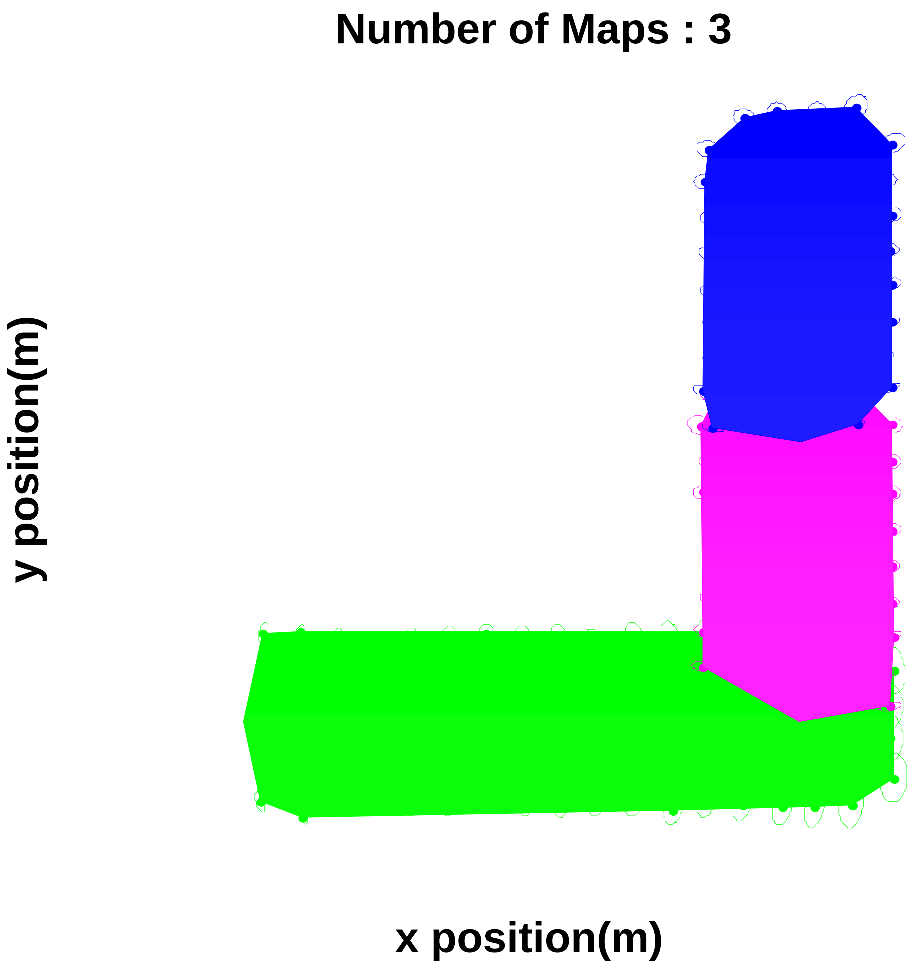
Divide & Conquer SLAM





Divide & Conquer SLAM





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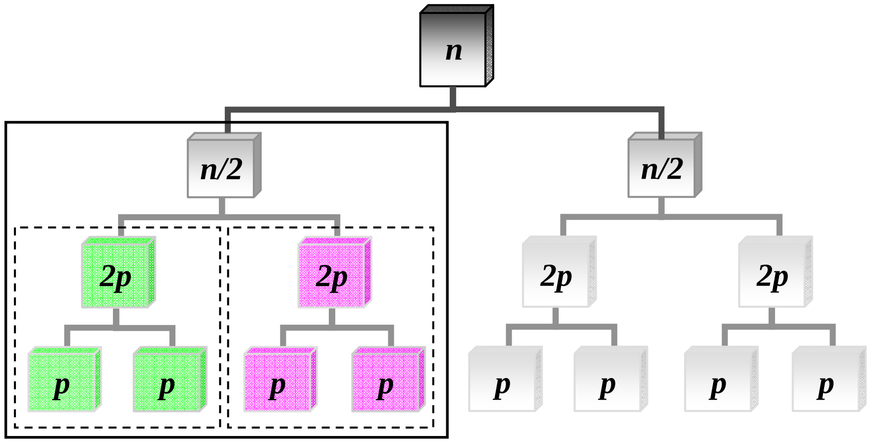

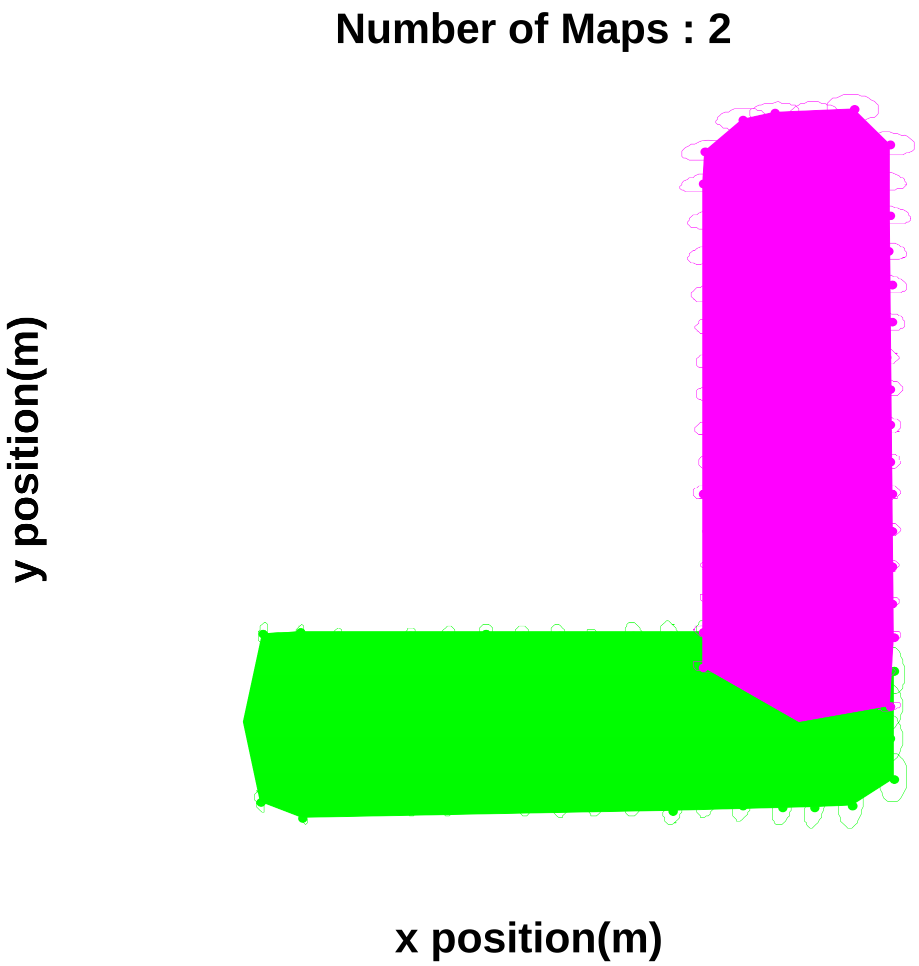

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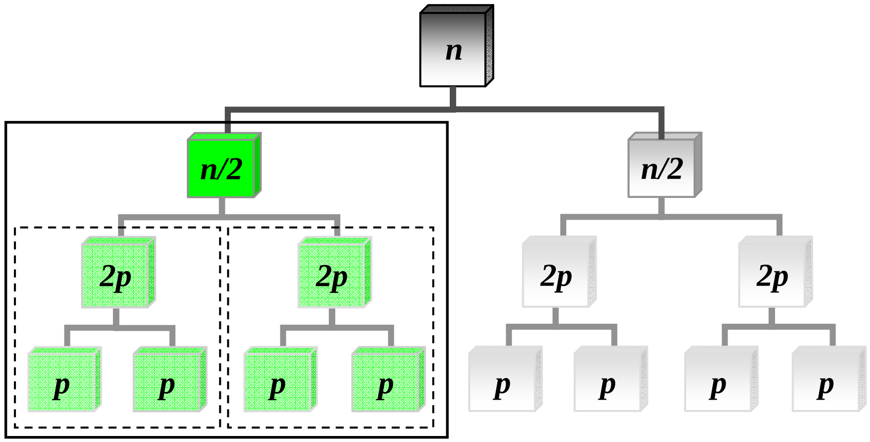

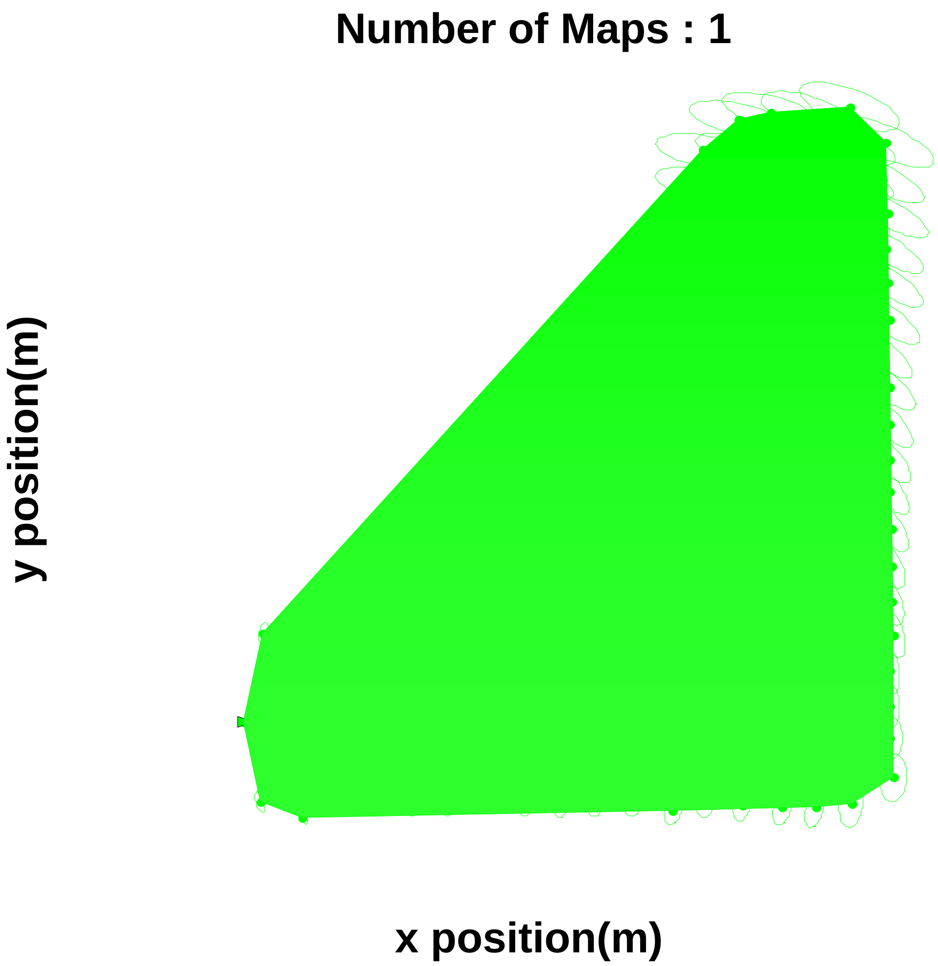

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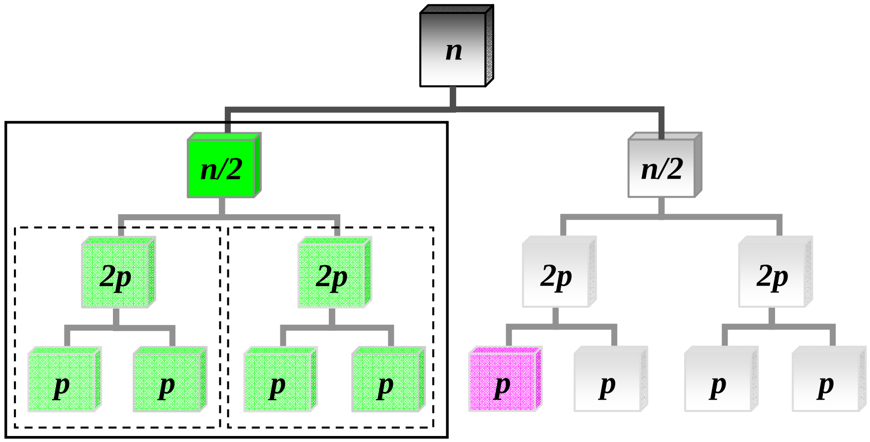

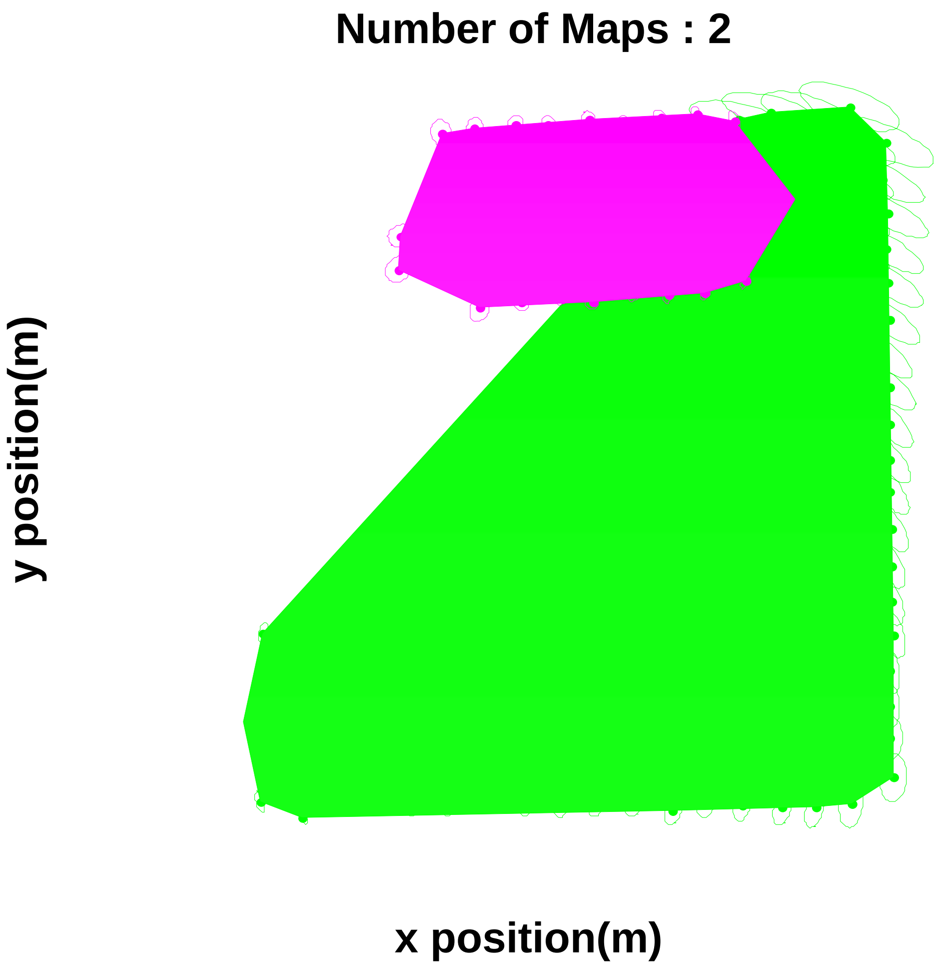

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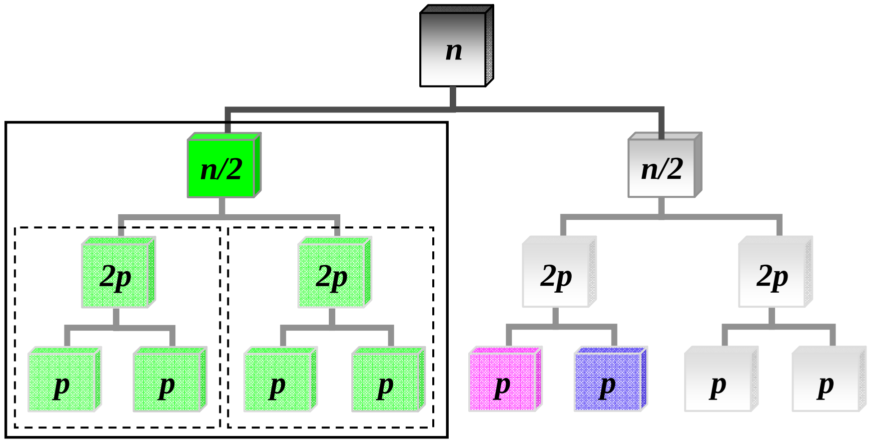

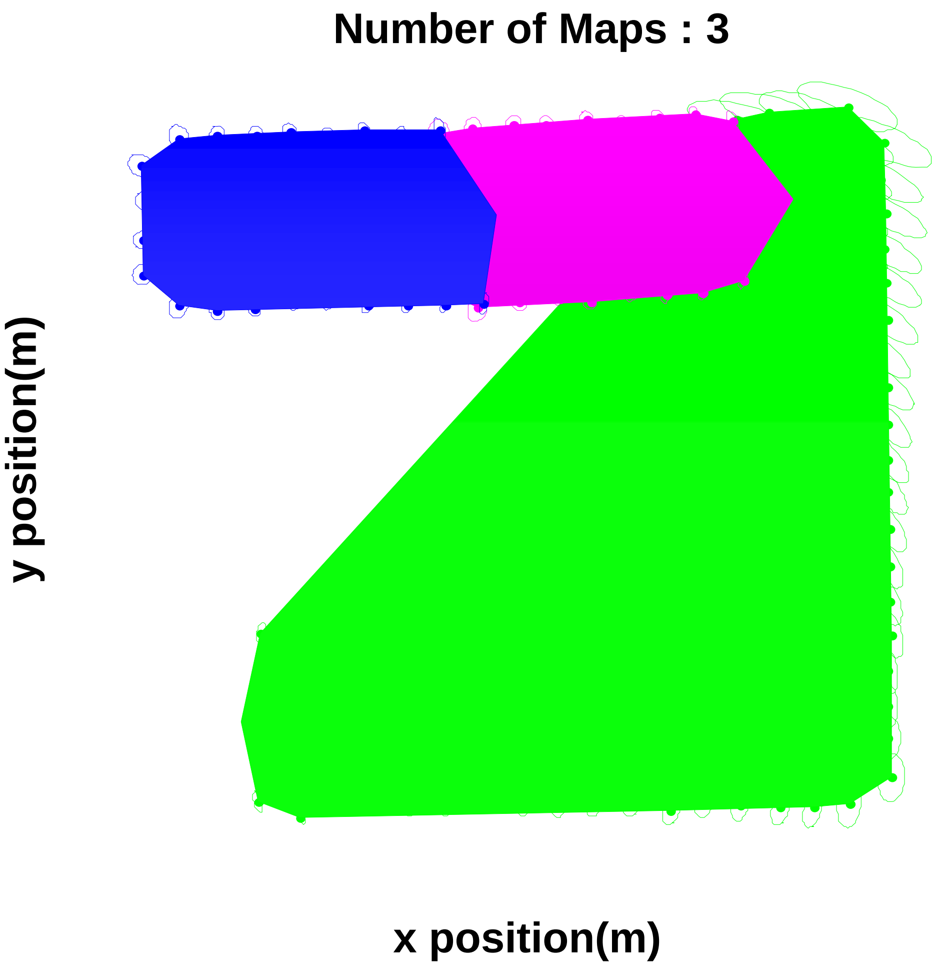

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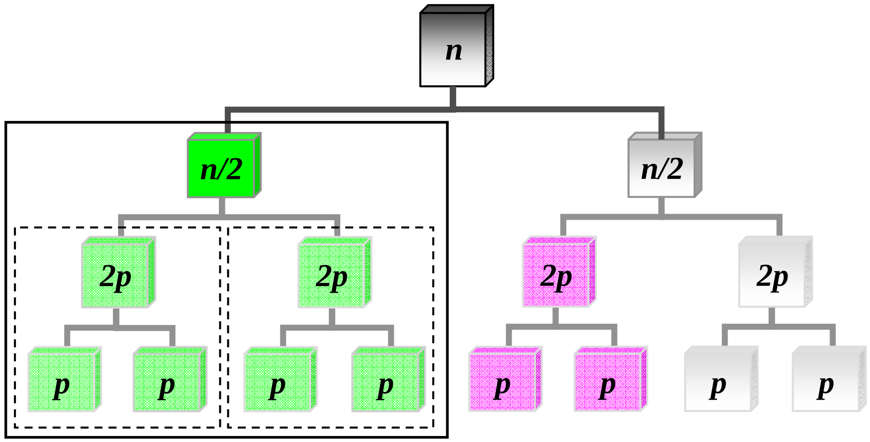

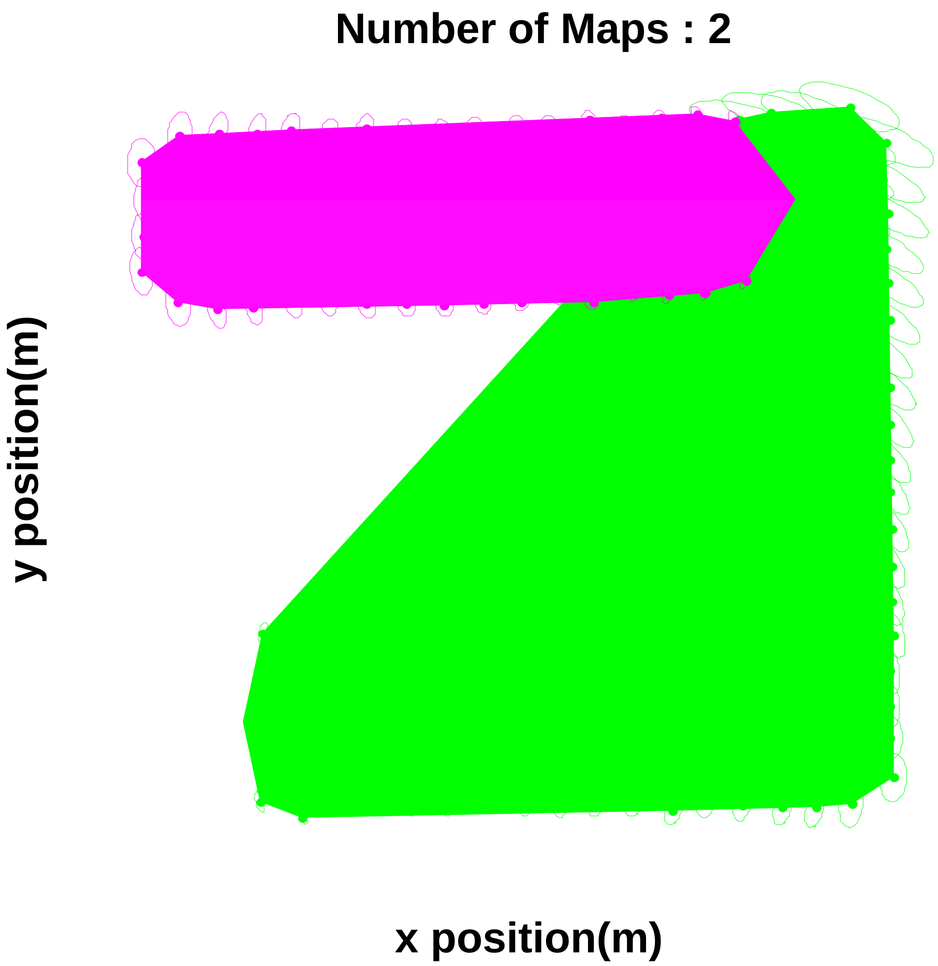

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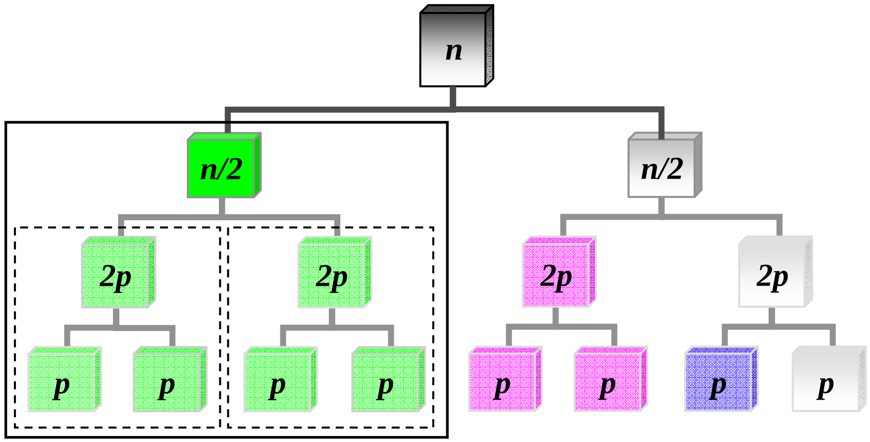

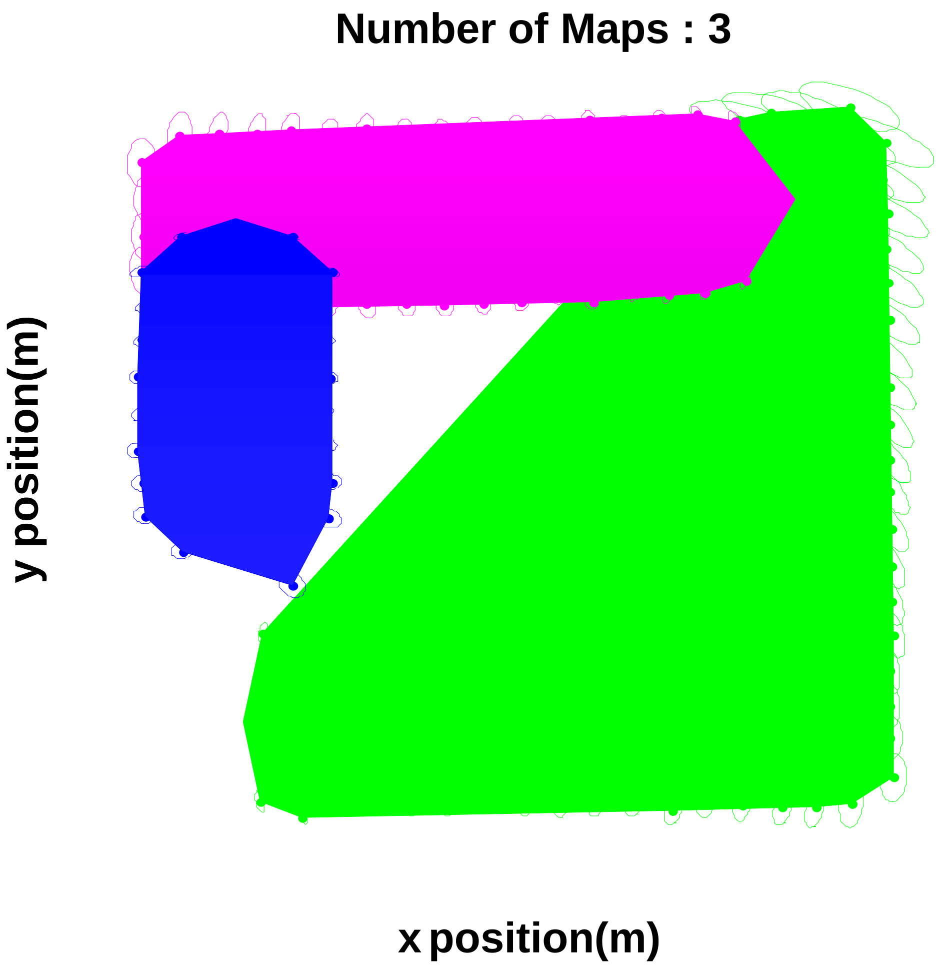

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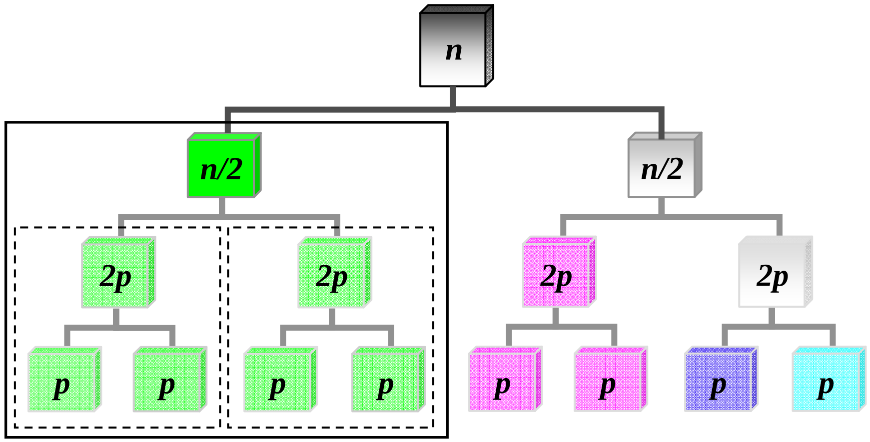

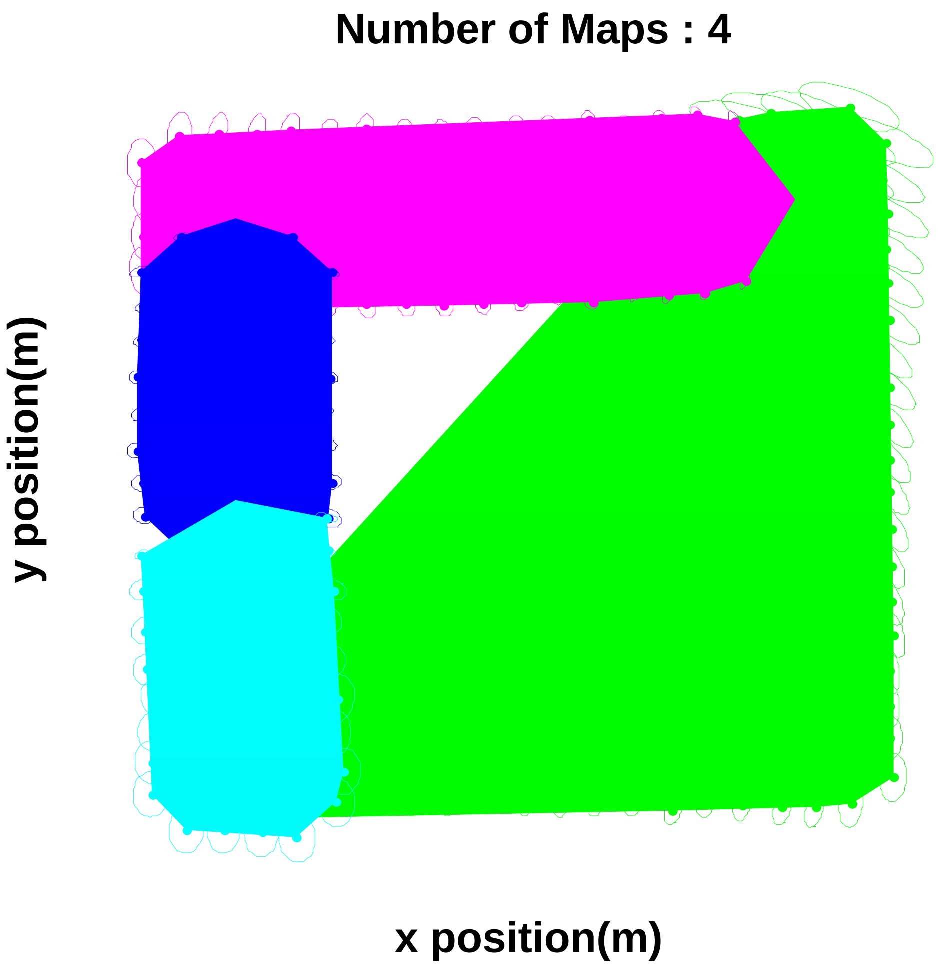

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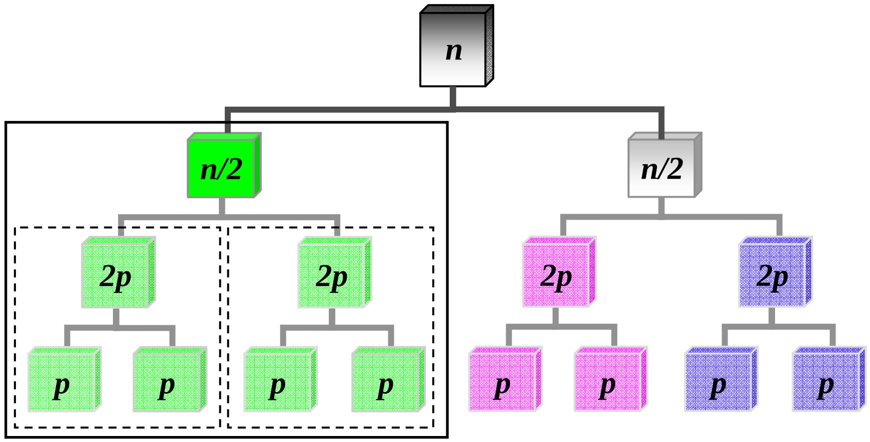
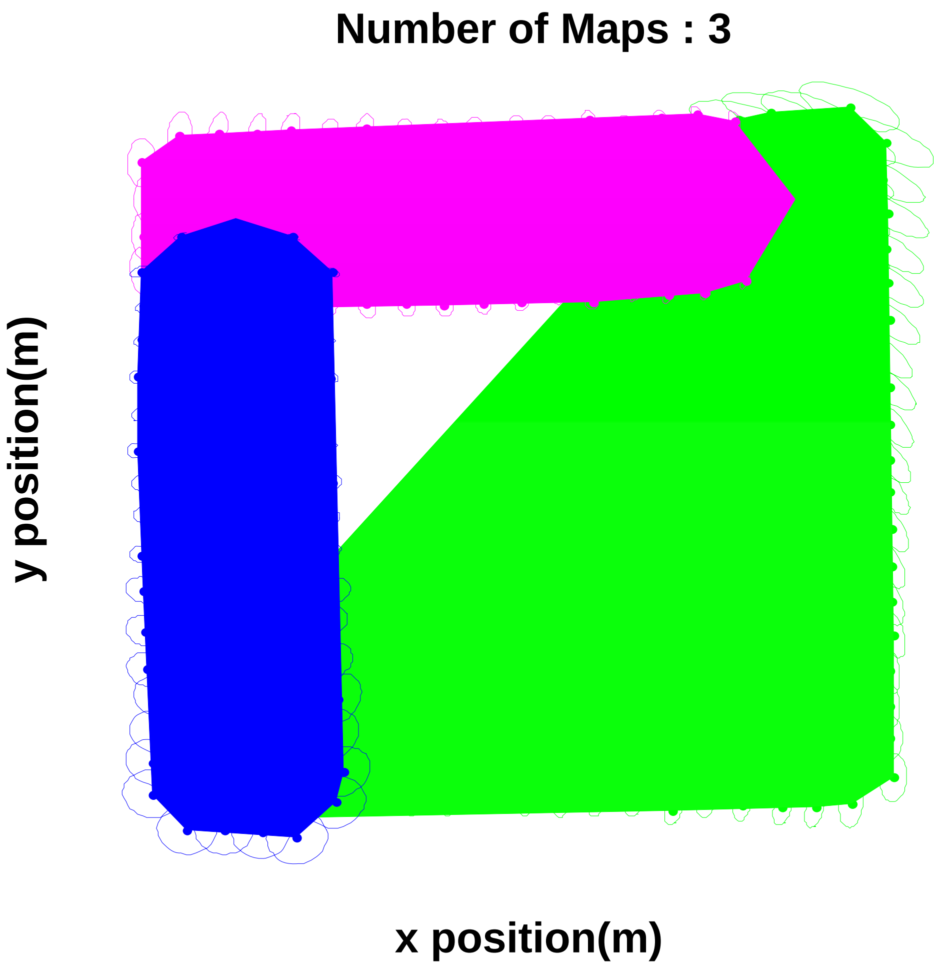
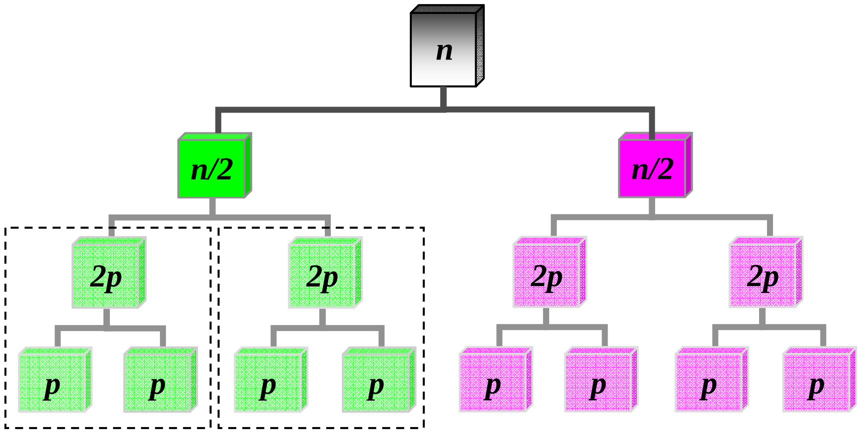
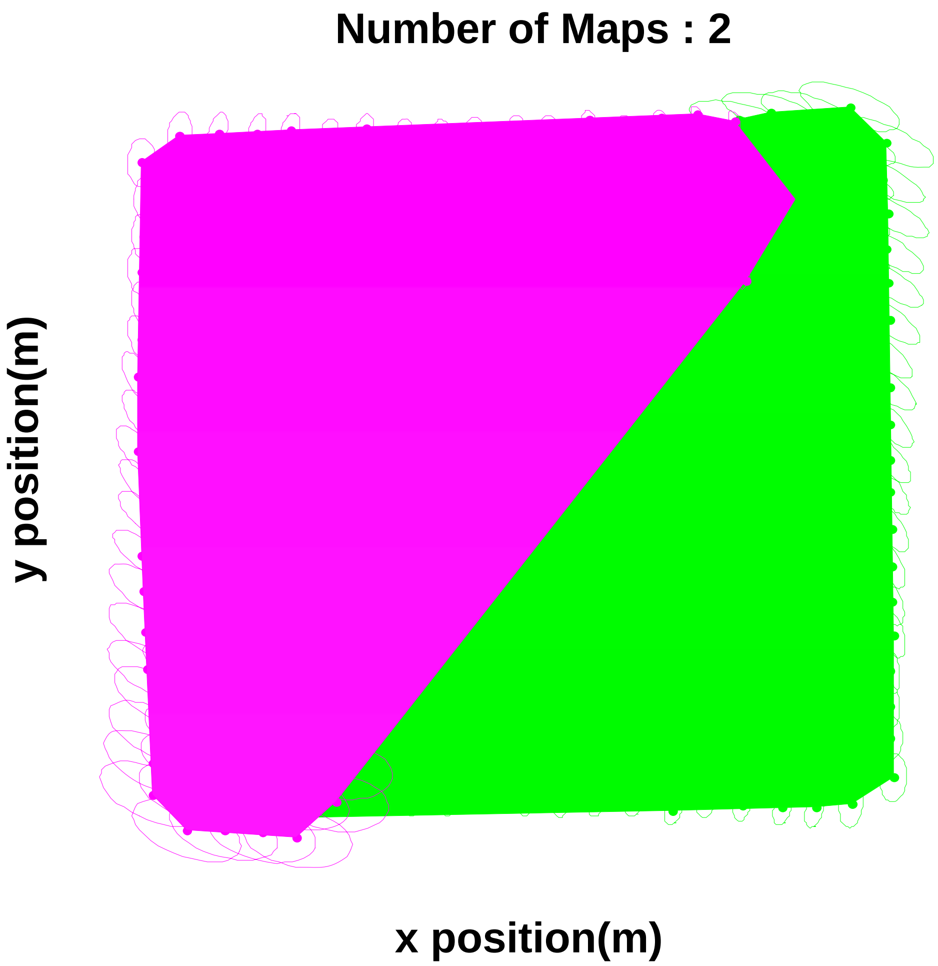
Divide & Conquer SLAM



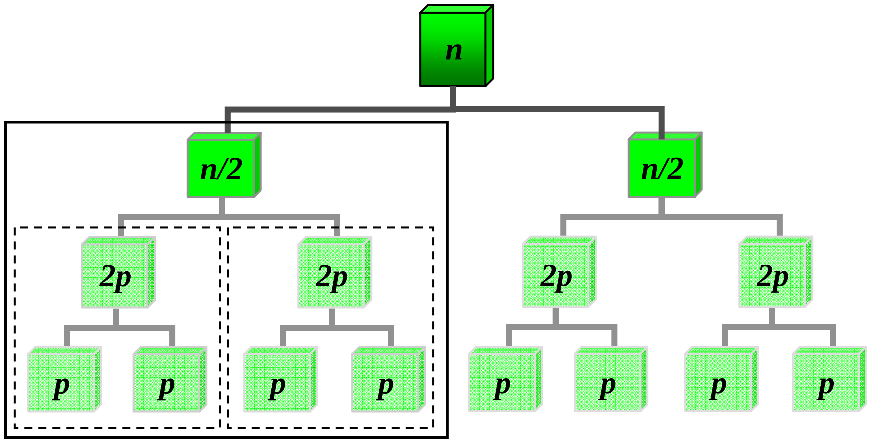


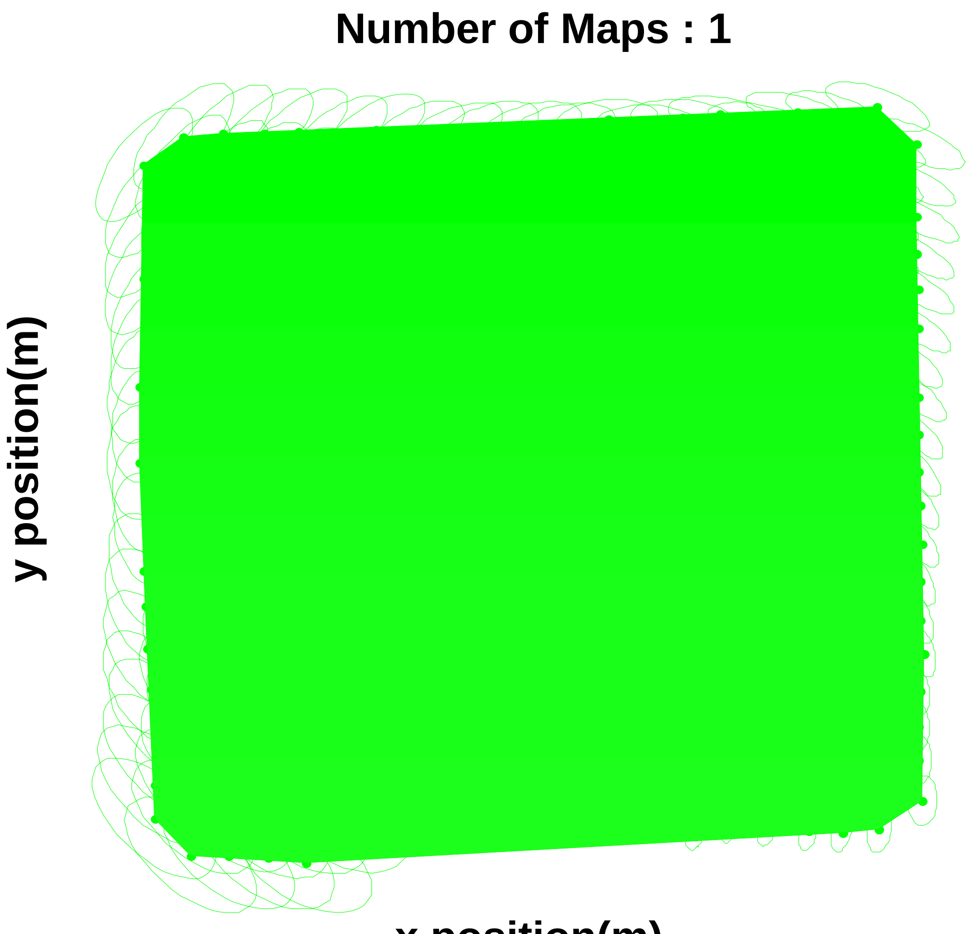
Divide & Conquer SLAM





Divide & Conquer SLAM





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

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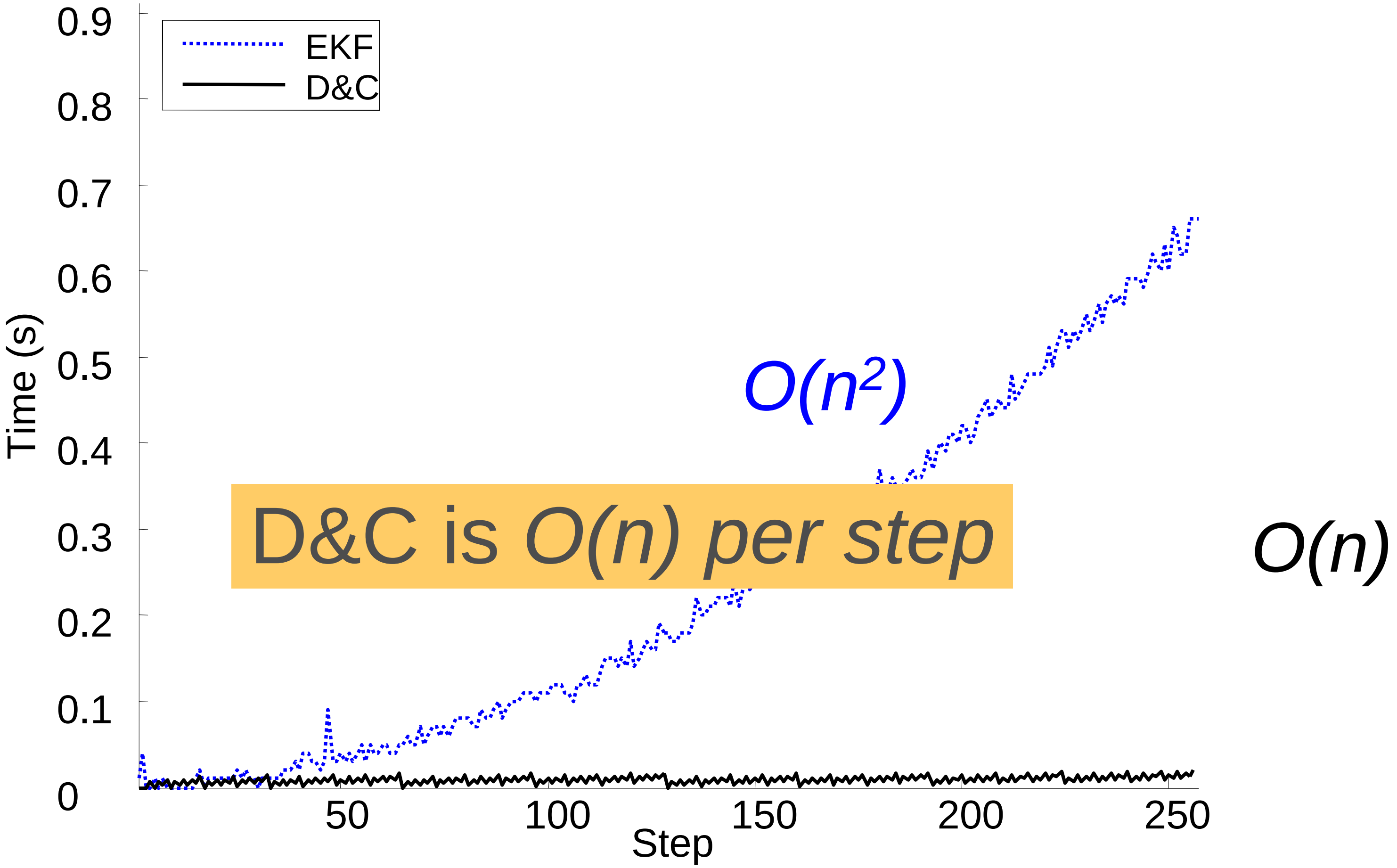
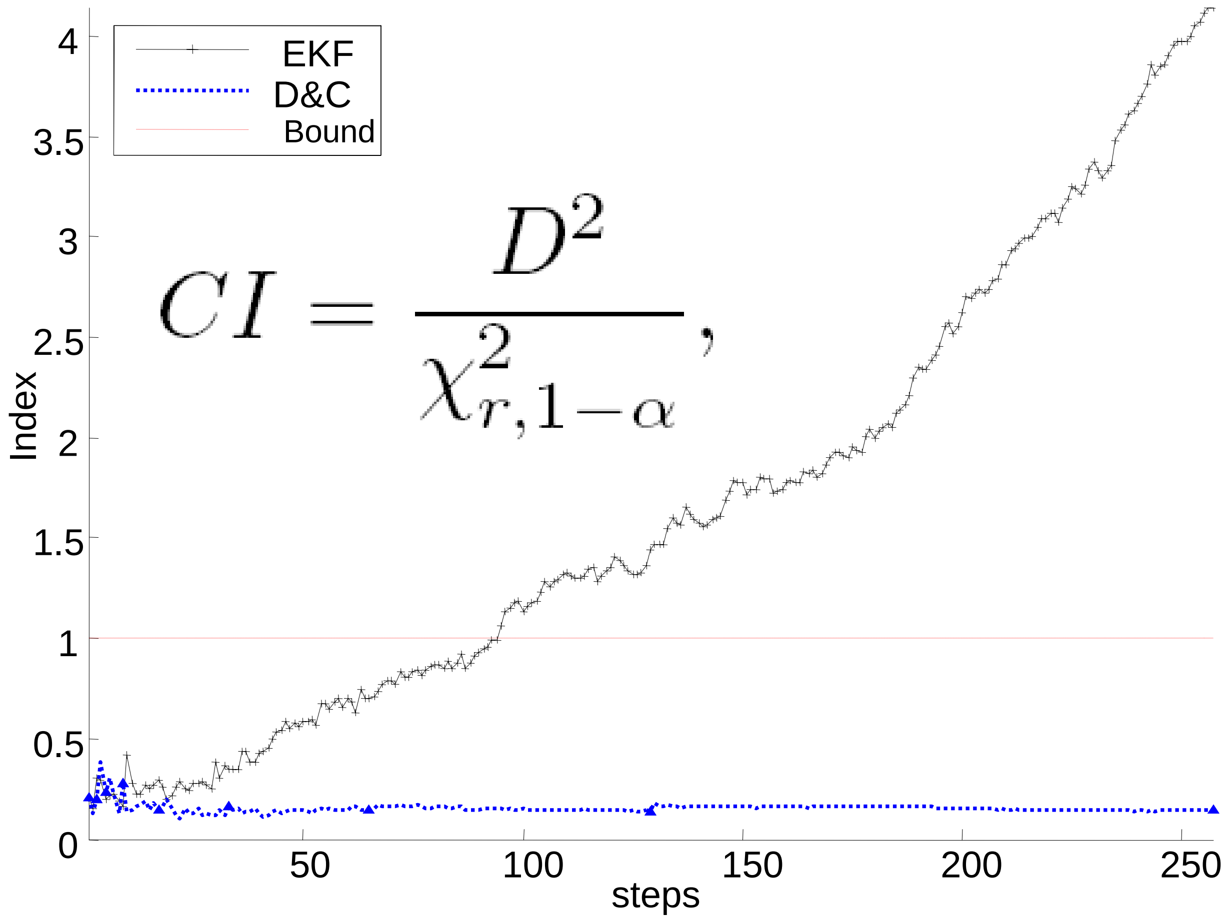
Loop Trajectory

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

Amortized cost per step



Improved Consistency over EKF SLAM



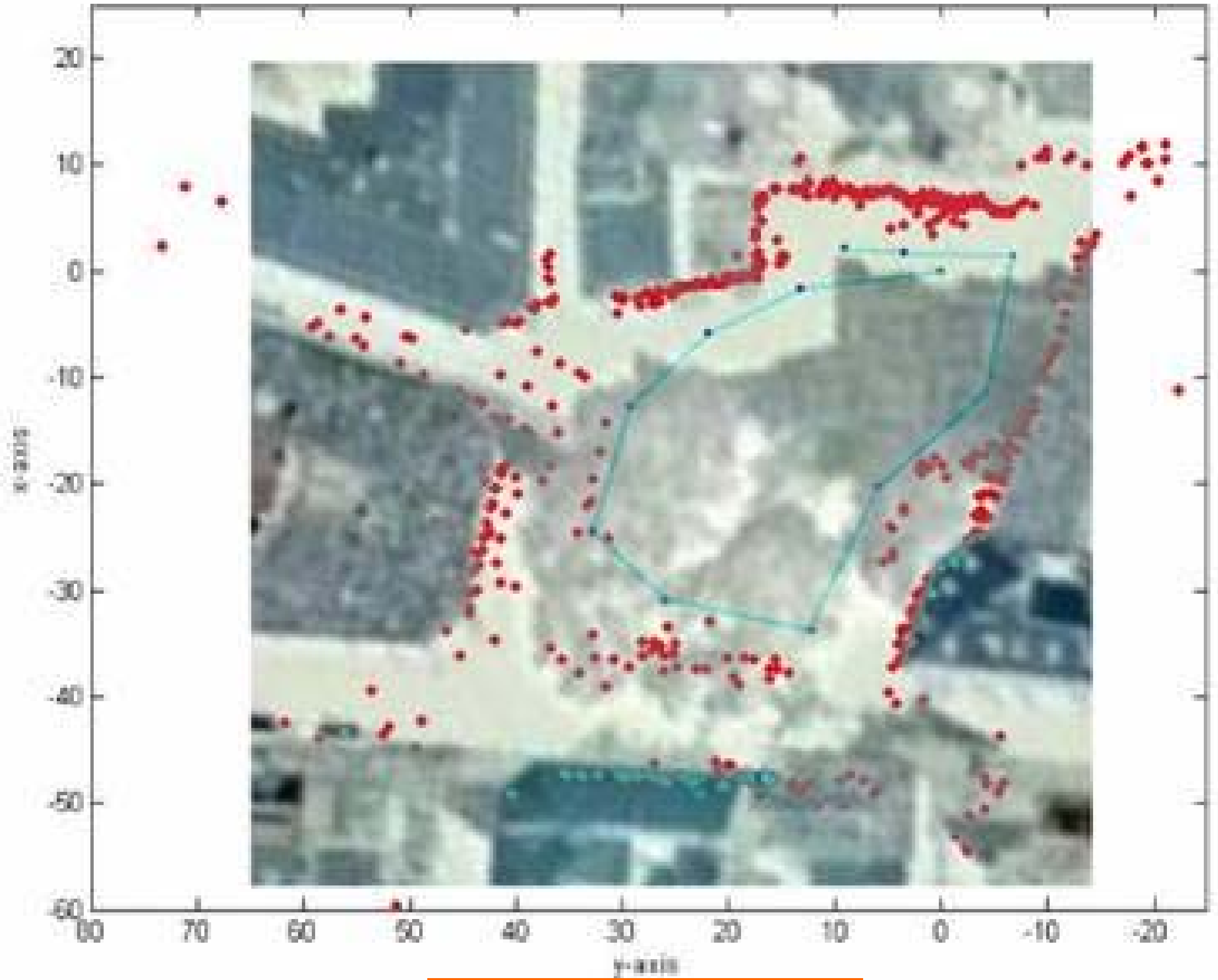
$$CI = \frac{D^2}{\chi^2_{r,1-\alpha}},$$

D&C SLAM is always more consistent

6DOF SLAM with stereo

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

6Dof Stereo SLAM, outdoors



150 m loop

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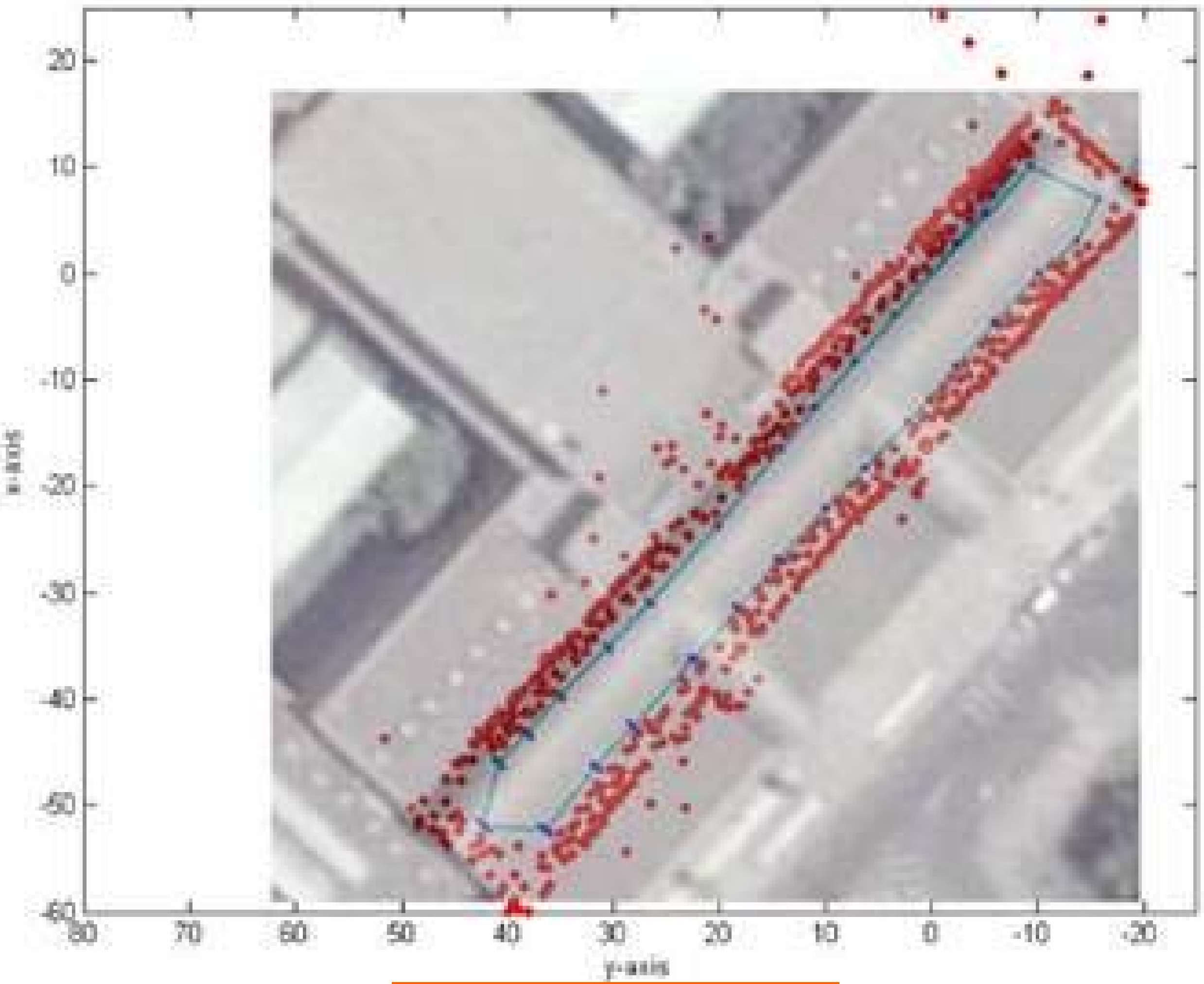
6DOF SLAM with stereo

6Dof Stereo SLAM, indoors



180 m loop

Conclusions

- Pure visual SLAM
  - 3D points and inverse depth points
  - Conditionally independent local maps
  - Near real-time execution
  - Loops of hundreds of meters
  - Stereo: no scale drift
- Working on
  - Larger loops
  - Robust place recognition for loop closing