Belief Space Planning for Autonomous Navigation while Modeling Landmark Identification

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TECHNION Israel Institute of Technology

Graduate seminar, September 2016

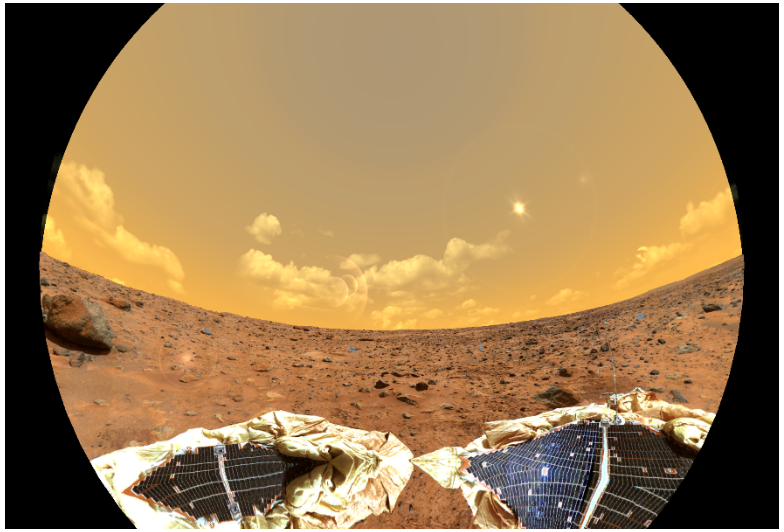
Introduction - Applications

Autonomous navigation in unknown environment

Under sea exploration

[listverse.com]

Space exploration



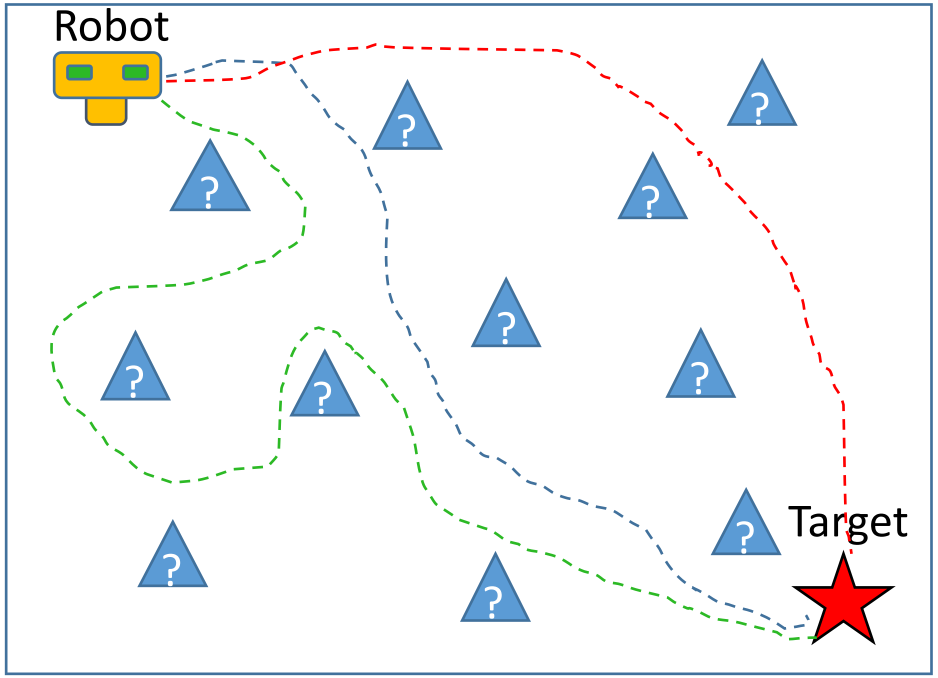
[Nasa.gov]

Navigation in GPS-deprived environments

[Nasa.gov]

Introduction - Problem

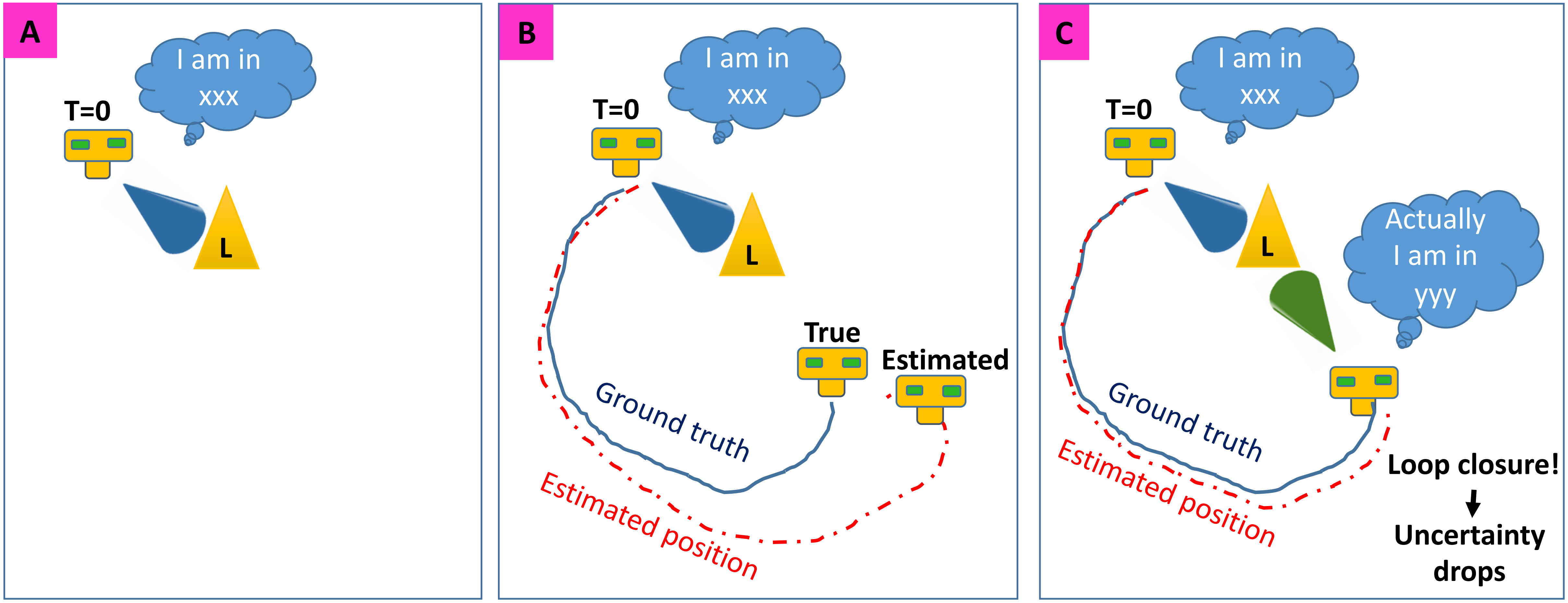
- Autonomous navigation in unknown environment
- Planning a suitable control strategy to accomplish a given task
- Reaching a goal with highest estimation accuracy



Introduction - SLAM

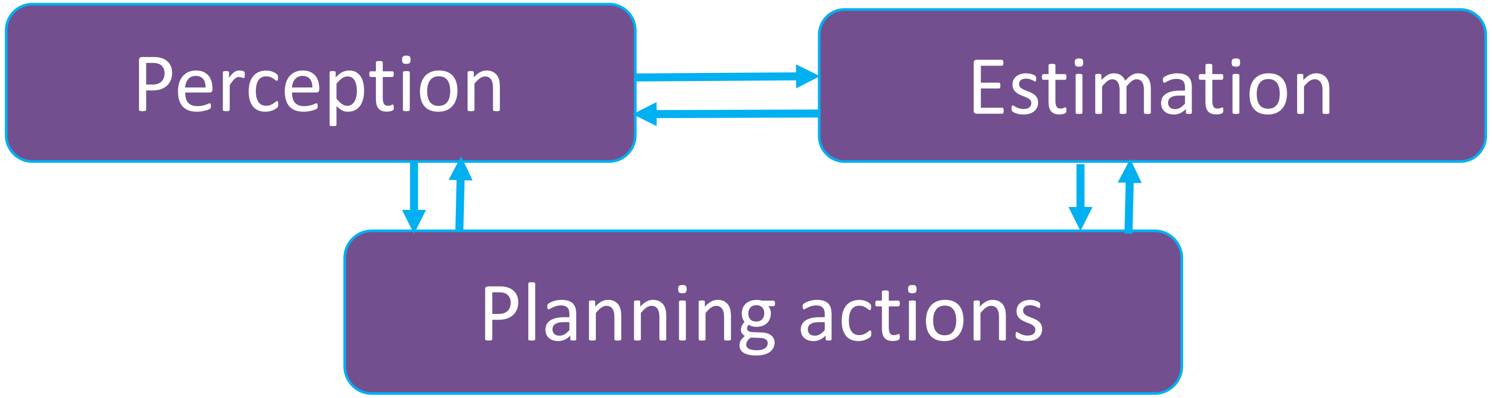
- **SLAM - simultaneous localization and mapping**
- Based on sensor observations, the robot :
  - Infers its own state
  - Creates a model of the environment

SLAM – Loop closure



Introduction - Belief space planning

Belief space planning (BSP) - Planning actions while taking into account different sources of uncertainty



- Optimizing an objective function, composed for an example by the objectives:
  - Minimum uncertainty
  - Path length
  - Reaching a specific goal

Related Work

- Many approaches assume environment/map is known
- Recent work relaxes this assumption and enables operation in unknown environments
- **BSP approaches typically consider perfect ability to re-identify an object**

In this work we:

- **Enable operation in unknown environments**
- **Not assuming perfect ability to re-identify an object**

How is a landmark being re-identified?

- It can be challenging!
- Depends on: camera viewpoint, sensor capabilities and image processing capabilities
- Different view angles may cause the landmark to look completely different

Same landmark – different view direction

- **Looks completely different!**
- **Challenging to identify even for human**

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Computer vision algorithms

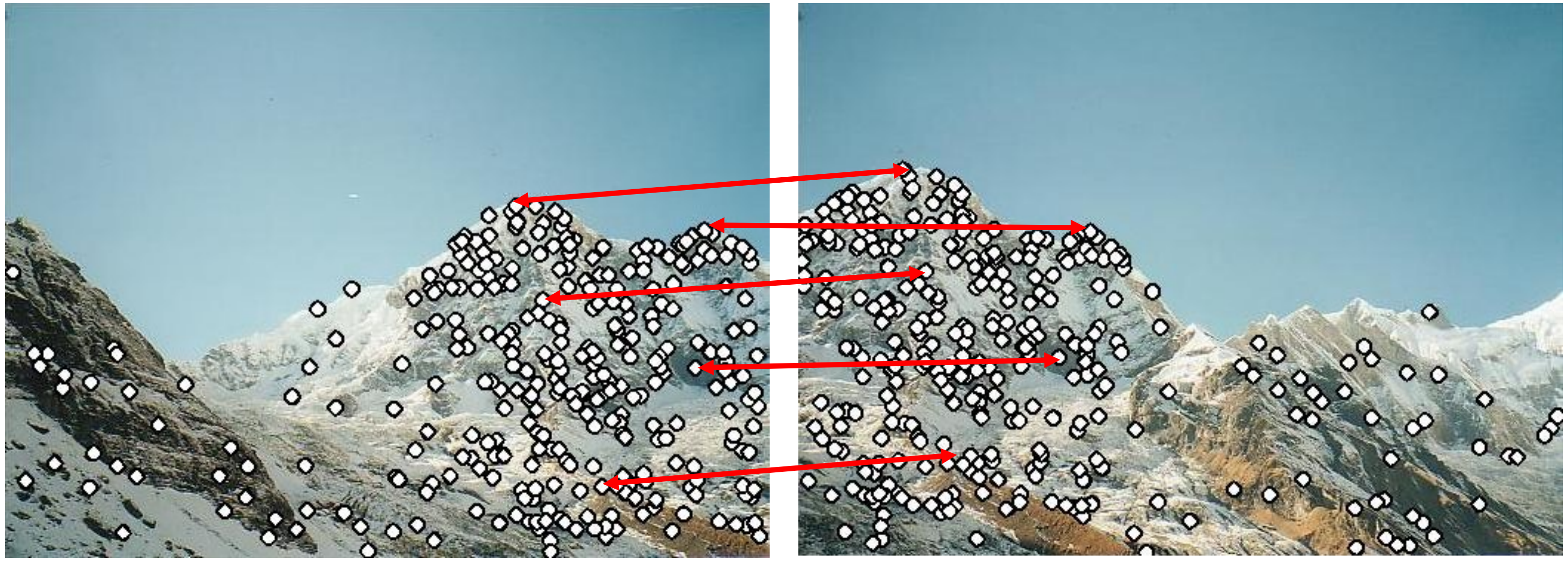
The decision on landmark identification depends on the computer vision algorithm

For an example, SIFT algorithm

Detects features in the image

Compares between features

Determines correspondence between features in two views



Images adapted from Steve Seitz and Rick Szeliski

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Computer vision algorithms

- Limited in their identification ability
- Defines the conditions in which two views of the same scene will be identified as same object
- In SIFT algorithm , an object will be identified when viewpoint direction is changing in up to 30° - 40°

Contribution

BSP approaches typically consider perfect ability to re-identify an object

↓

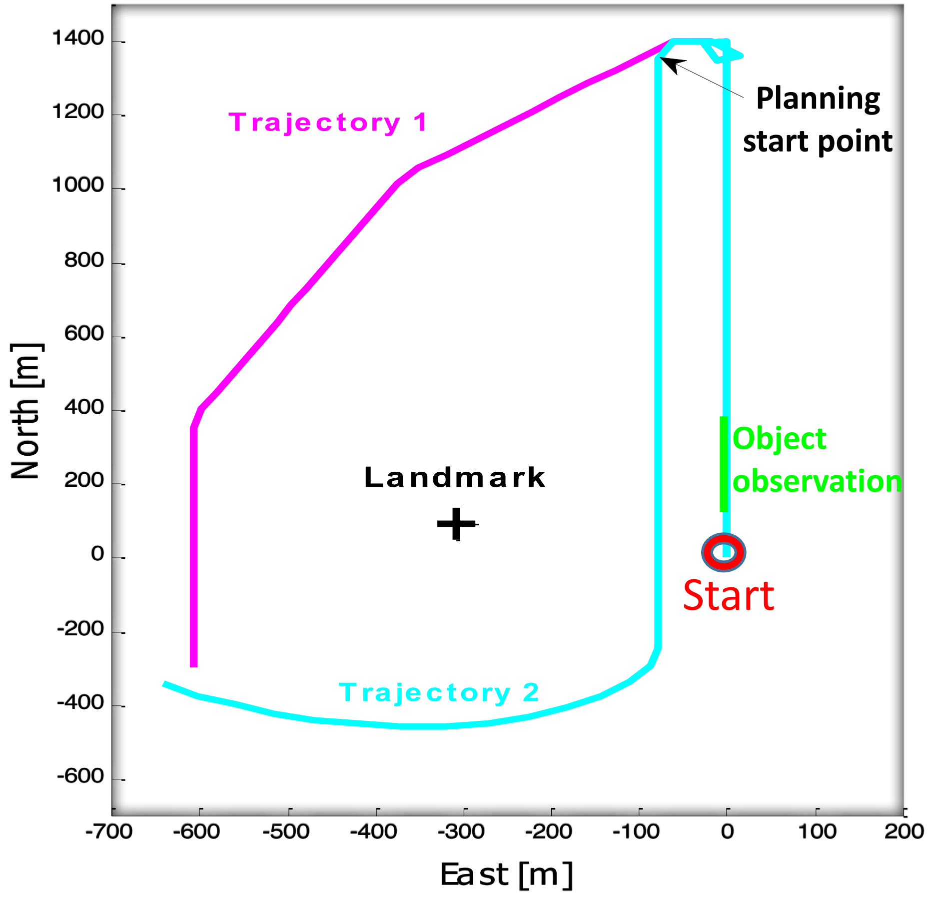
inconsistent uncertainty prediction with reality (inference)

↓

Incorrect planning and path choosing

Correct identification of landmarks is critical

Which trajectory is better?



Contribution

Develop a viewpoint aware BSP approach

Modeling object re-identification

Considering both SLAM and Planning aspects

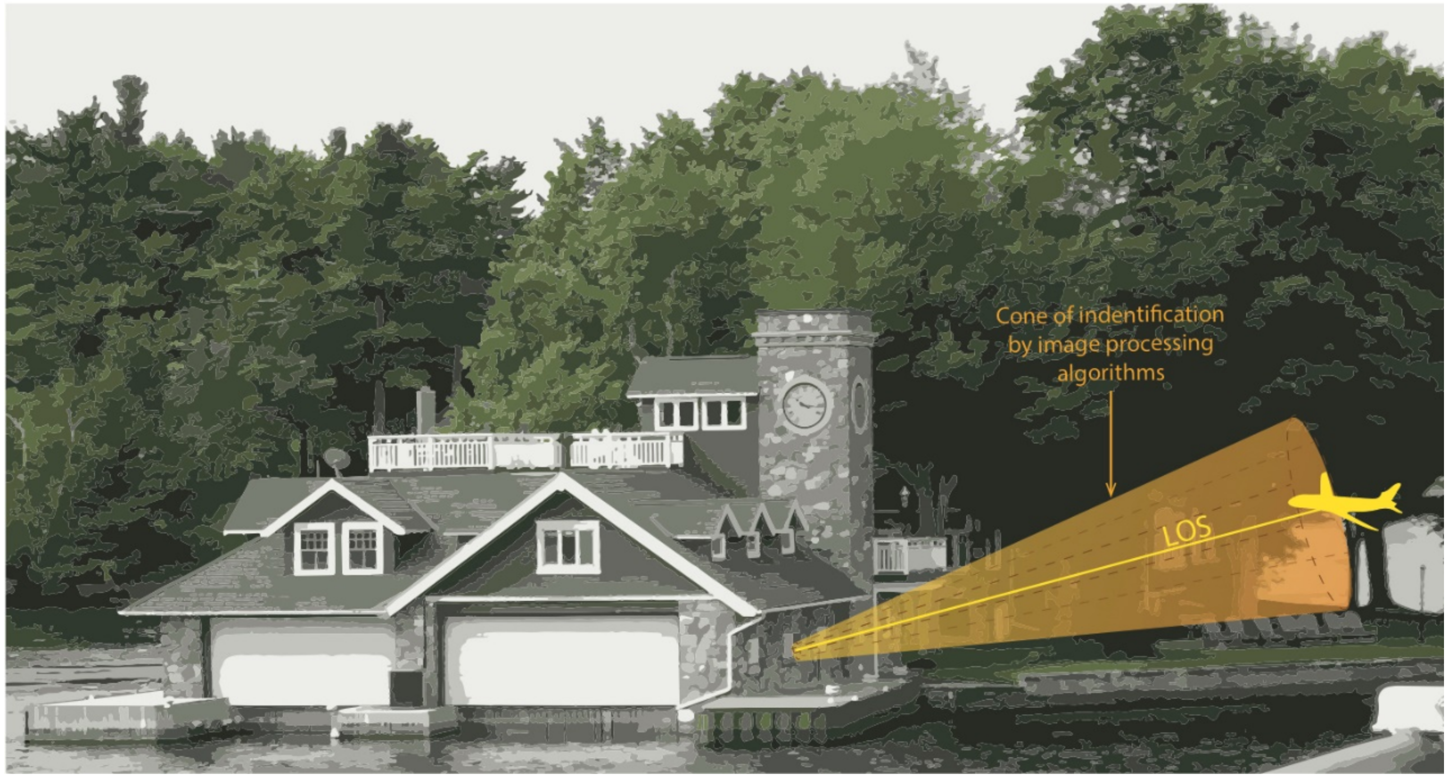
- **Focus on object re-identification from different viewpoint when the object is known**

Concept – Modeling Object Re-Identification

LOS (Line of sight) = Straight line between the robot's camera and observed scene

We define Cone of identification

- **In it, the landmark can be identified using image processing algorithms**



Concept – Modeling Object Re-Identification

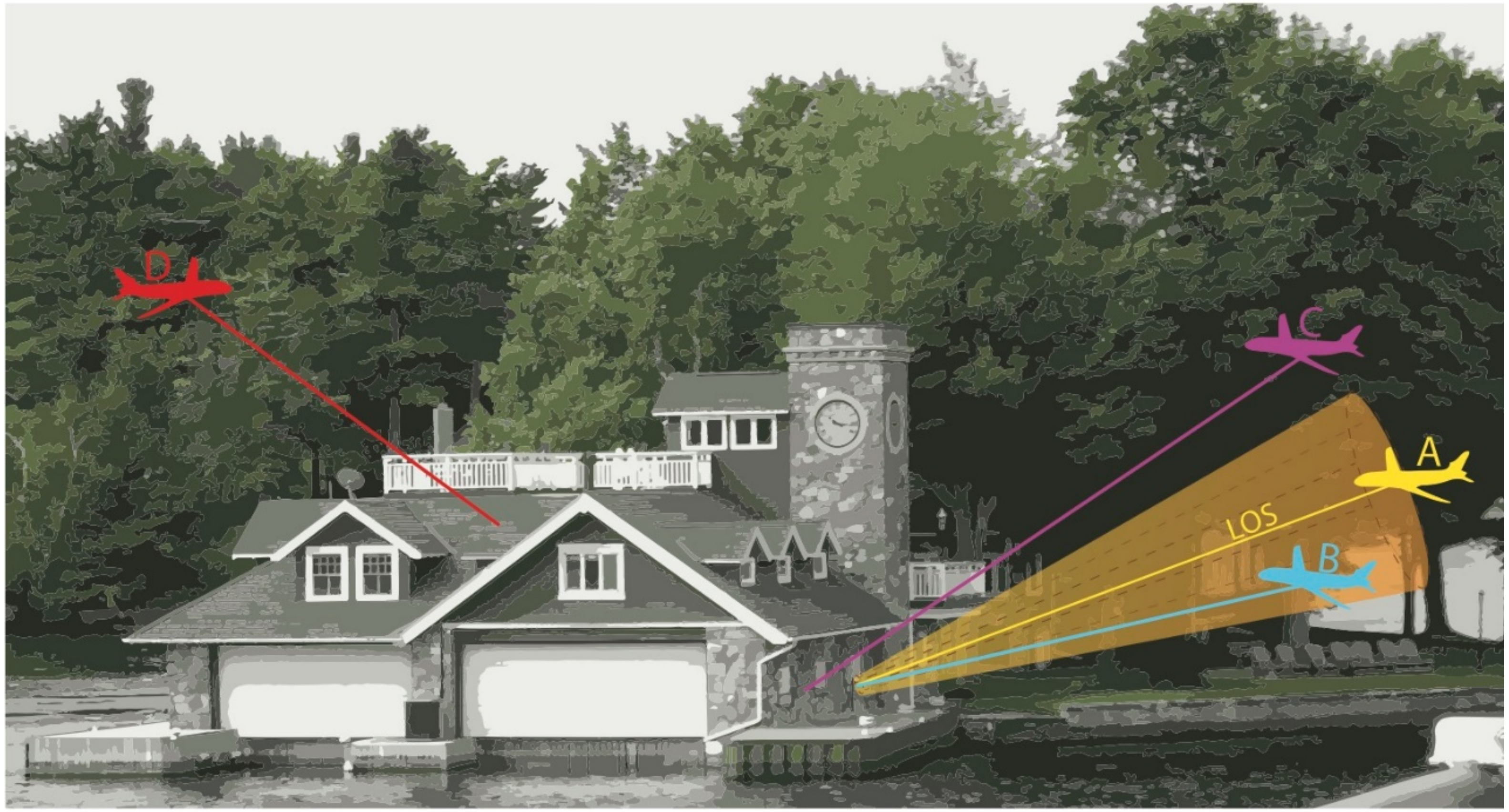
Preserving all LOS from the past → LOS are calculated using information from estimation

Calculating LOS for a future view point

Check if current LOS is inside a cone of identification from the past

Yes → Landmark is recognized

No → Landmark isn't recognized



Formulation -SLAM

x_i - Robot state at time i

u_i - Control action applied at time i

$z_{i,j}$ -measurement of the jth landmark at time I

$l_j -$ Coordinates of landmark j

Notations

- The motion model is :

$$x_{i+1} = f(x_i, u_i) + w_i \qquad w_i : N(0, \Sigma_W) \qquad p(x_{i+1} | x_i, u_i)$$

- The observation model is :

$$z_{i,j} = h(x_i, l_j) + v_{i,j} \qquad v_{i,j} : N(0, \Sigma_v) \qquad p(z_{i,j} | x_i, l_j)$$

Formulation -SLAM

X_k – All robot and world states until time k
Z_k – All available observations at time k
u_k – Control action at time k
Notations

- The problem to be solved in the SLAM part:

$$p(X_k \mid Z_{0:k}, u_{0:k-1})$$

Joint state vector X_k B $\{\underbrace{x_0, \ldots, x_k}_{\text{Past \& current robot states}}, \underbrace{L_k}_{\text{Mapped environment}}\}$

Past & current robot states **Mapped environment**

We use maximum a posteriori (MAP) estimation in order to estimate X_k^*

$$p(X_k \mid Z_{0:k}, u_{0:k-1}) \sim N(X_k^*, \Sigma_k) \qquad X_k^* = \arg\max_{X_k} \left(p(X_k \mid Z_{0:k}, u_{0:k-1}) \right)$$

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Formulation - SLAM

X_k – All robot and world states until time k
Z_k – All available observations at time k
u_k – Control action at time k
n_i – Number of observations at time i
l_j – Coordinates of landmark j

Notations

- Mathematical development will lead to:

$$b(X_k) \doteq p(X_k \mid \underbrace{Z_{0:k}, u_{0:k-1}}_{\triangleq H_k}) = priors \cdot \prod_{i=1}^{k} \left[\underline{p(x_i \mid x_{i-1}, u_{i-1})} \prod_{j=1}^{n_i} \underline{p(z_{i,j} \mid x_i, l_j)} \right]$$

Motion model

Measurement model

Data Association and landmark identification

Formulation
Belief Space Planning

Notations

X_k – All robot and world states until time k
Z_k – All available observations at time k
u_k – Control action at time k
l_j – Coordinates of landmark j

$$b(X_{k+l}) \text{ B } p(\underbrace{X_{k+l}}_{\text{Joint state at the } l\text{-th look ahead step}} \mid \underbrace{Z_{0:k}, u_{0:k-1}}_{\text{Past controls \& measurements}}, \underbrace{Z_{k+1:k+l}, u_{k:k+l-1}}_{\text{Controls \& measurements at the first } l \text{ look-ahead steps}})$$

Joint state at the *l*-th look ahead step

Past controls & measurements

Controls & measurements at the first *l* look-ahead steps

- This belief is represented by a Gaussian:

$$b(X_{k+l}) : \; N\left(X^{*}_{k+l}, \Sigma_{k+l}\right)$$

Formulation
Belief Space Planning

X_k – All robot and world states until time k
Z_k – All available observations at time k
u_k – Control action at time k
L – Number of planning steps

Notations

We want to find the planning actions

Optimizing an objective function:

$$J(u_{k:k+L-1}) @ \underset{Z_{k+1:k+L}}{\mathrm{E}} \left\{ \sum_{l=0}^{L-1} c_l \left(b\left(X_{k+l}\right), u_{k+l} \right) \right\}$$

Expectation on all future unknown measurements $Z_{k+1:k+L}$

Sum of all L future planning steps

General cost function depends on the belief $b(X_{k+l})$ and on the control action u_{k+l}

Composed, for example, by:
- minimum uncertainty
- path length
- reaching a specific goal

Formulation
Belief Space Planning

X_k – All robot ($x_{1:k}$) until time k and world states ($l_{1:j}$)
Z_k – All available observations at time k
u_k – Control action at time k
l_j – Coordinates of landmark j
n_i – Number of observations at time i
$H_k \triangleq \{Z_{0:k}, u_{0:k-1}\}$ Past measurements and controls
Notations

Existing BSP approaches are solving the problem while considering ideal data association and ideal ability of object re-identification

In this case, develop of the belief space leads to:

$$p\left(X_{k+l} \mid H_{k+l}\right) \propto p\left(X_k \mid H_k\right) \cdot \prod_{i=1}^{l} p\left(x_{k+i} \mid x_{k+i-1}, u_{k+i-1}\right) \cdot \prod_{j=1}^{n_i} p\left(z_{k+i,j} \mid x_{k+i}, l_j\right)$$

Inference until planning time k (SLAM)

Motion model for future states from planning time k

Measurement model for future measurements from planning time k
Assuming ideal data association

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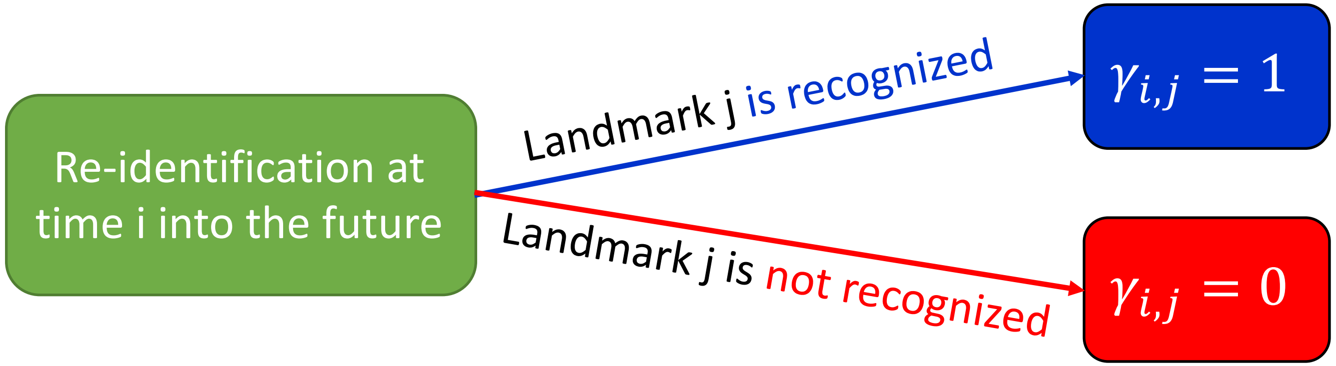
Formulation
Belief Space Planning

In reality – re-identification is not perfect → Define a binary random variable $\gamma_{i,j}$



$\Gamma_i \, \mathrm{B} \left\{\gamma_{i,j}\right\}_{j=1}^{n_i}$ n_i is the number of possible observations at time i

Formulation
Belief Space Planning

X_k – All robot ($x_{1:k}$) until time k and world states ($l_{1:j}$)
Z_k – All available observations at time k
u_k – Control action at time k
l_j – Coordinates of landmark j
$H_k \triangleq \{Z_{0:k}.u_{0:k-1}\}$ Past measurements and controls
$\gamma_{i,j}$ – Event of acquiring measurement j at time I
$\Gamma_i \triangleq \{\gamma_{i,j}\}_{j=1}^{n_i}$

Notations

$$p(X_{k+l},\Gamma_{k+1:k+l} \mid H_{k+l}) \propto p(X_k \mid H_k)\cdot\prod_{i=1}^{l} p(x_{k+i} \mid x_{k+i-1},u_{k+i-1})\cdot\prod_{j=1}^{n_i} p(z_{k+i,j} \mid x_{k+i},l_j,\gamma_{k+i,j})\,p(\gamma_{k+i,j} \mid H_{k+i-1},x_{k+i},l_j)$$

Inference until planning time k (SLAM)

Motion model for future states from planning time k

Measurement model for future measurements from planning time k taking into account the event of acquiring a measurement

$p(z_{k+i,j} \mid x_{k+i},l_j,\gamma_{k+i,j})$

$\gamma_{k+i,j}=1$ → $p(z_{k+i,j} \mid x_{k+i},l_j)$

$\gamma_{k+i,j}=0$ → ~~$p(z_{k+i,j} \mid x_{k+i},l_j,\gamma_{k+i,j})$~~

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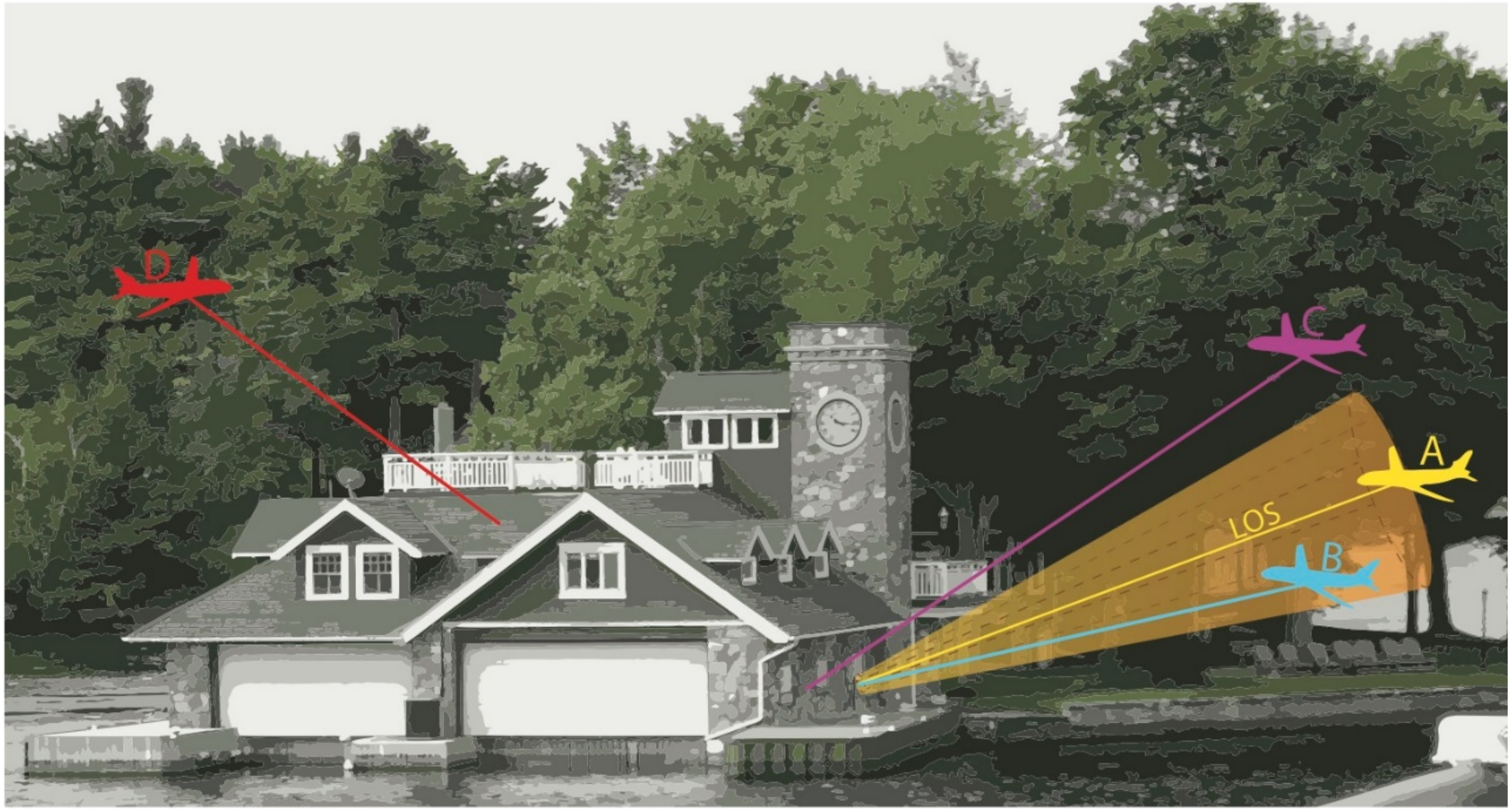
Formulation – Belief Space Planning

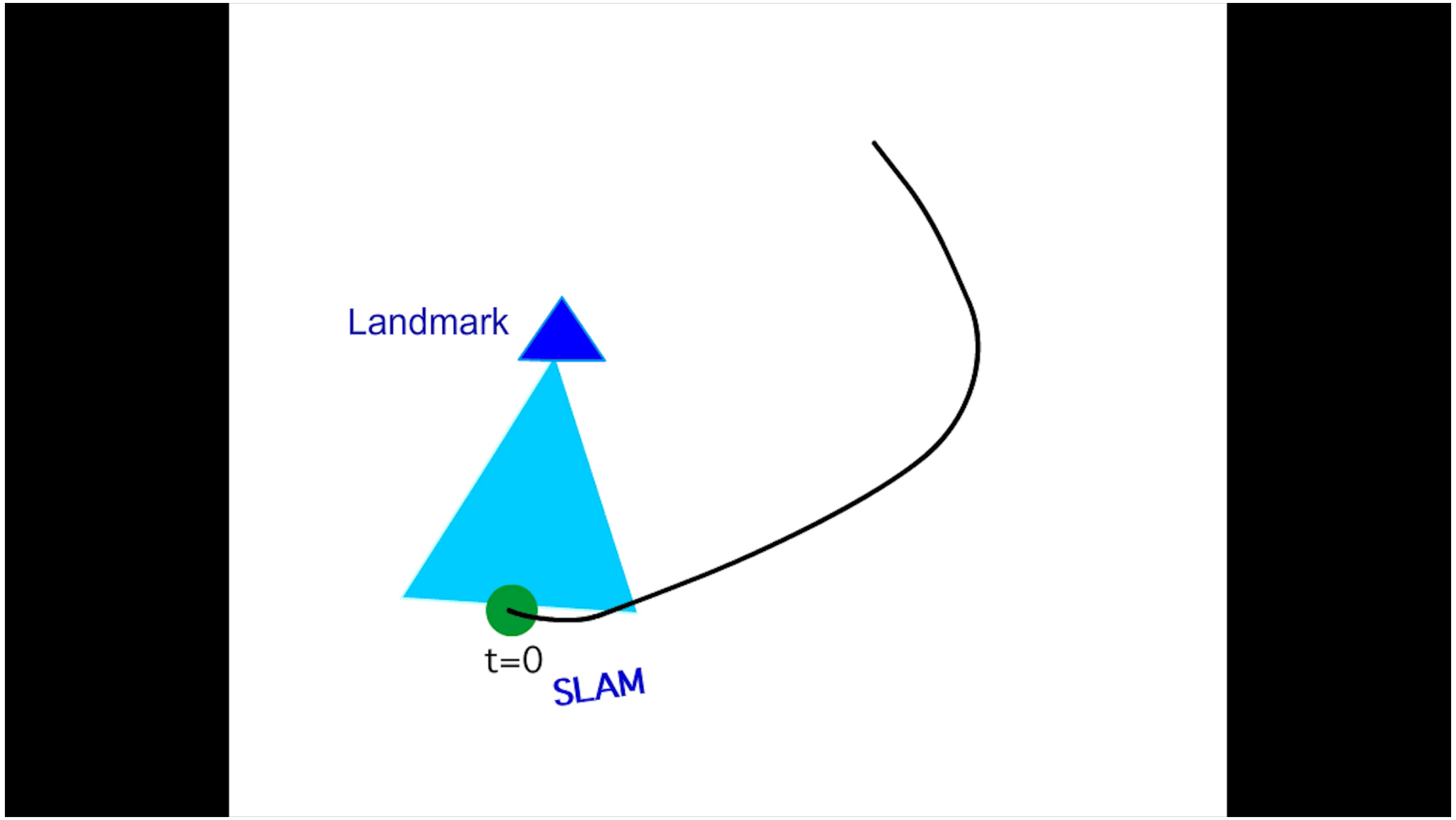
Recall - Modeling Object Re-Identification



Formulation – Belief Space Planning

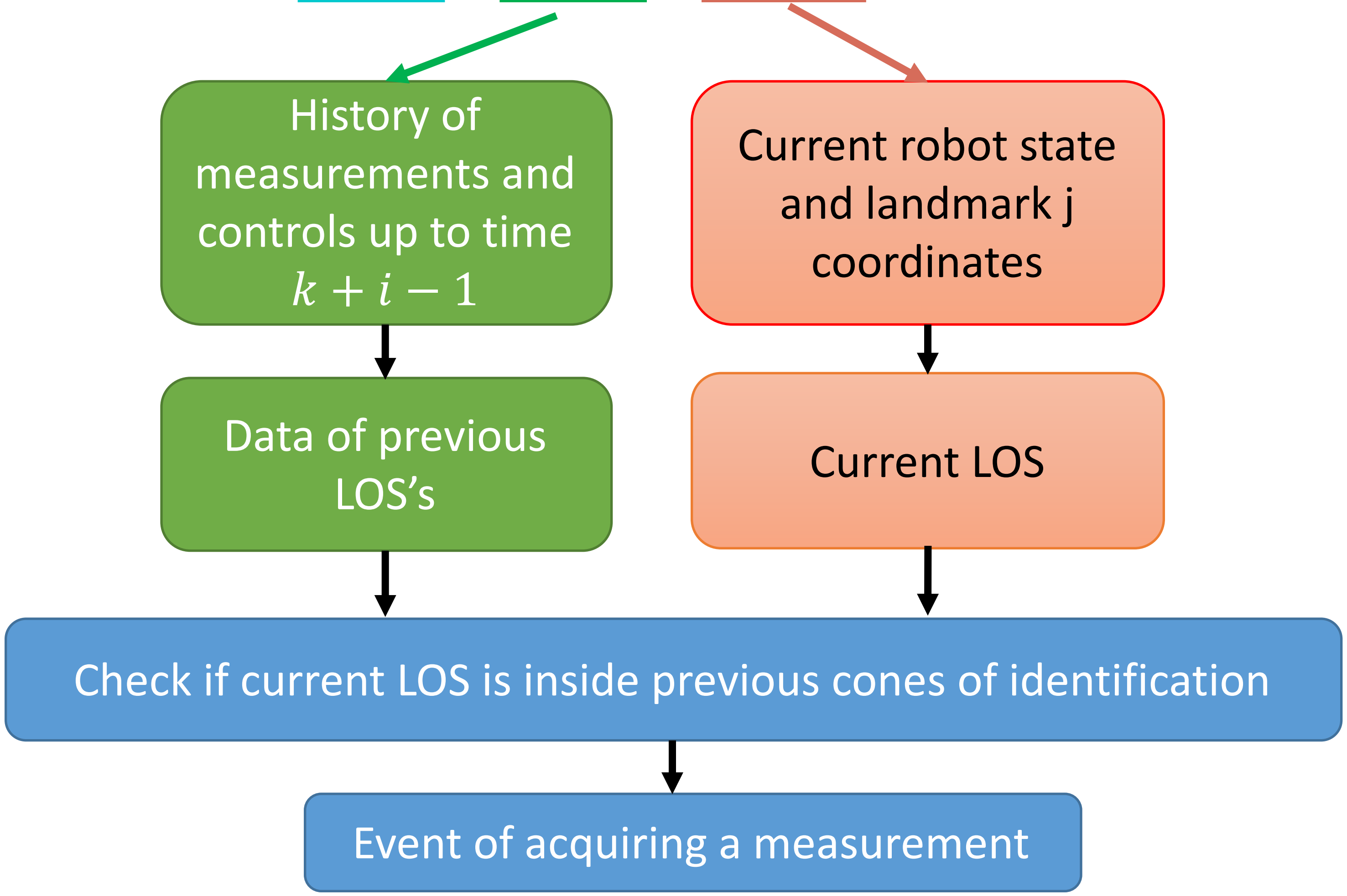
$$p\left(\gamma_{k+i,j} \mid H_{k+i-1}, x_{k+i}, l_j\right)$$

$H_k \triangleq \{Z_{0:k}. u_{0:k-1}\}$ Past measurements and controls $\quad H_{k+i-1} = \{H_k, u_{k:k+i-2}, z_{k+1:k+i-1}\}$



Formulation – Belief Space Planning

$$p\left(\gamma_{k+i,j} \mid H_{k+i-1}, x_{k+i}, l_j\right)$$



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Formulation
Belief Space Planning

X_k – All robot ($x_{1:k}$) until time k and world states ($l_{1:j}$)
$H_k \triangleq \{Z_{0:k}, u_{0:k-1}\}$ Past measurements and controls
$\gamma_{i,j}$ – Event of acquiring measurement j at time I
$\Gamma_i \triangleq \{\gamma_{i,j}\}_{j=1}^{n_i}$

Notations

$$p\left(X_{k+l}, \Gamma_{k+1:k+l} \mid H_{k+l}\right) \propto p\left(X_k \mid H_k\right) \cdot \prod_{i=1}^{l} p\left(x_{k+i} \mid x_{k+i-1}, u_{k+i-1}\right) \cdot \prod_{j=1}^{n_i} p\left(z_{k+i,j} \mid x_{k+i}, l_j, \gamma_{k+i,j}\right) p\left(\gamma_{k+i,j} \mid H_{k+i-1}, x_{k+i}, l_j\right)$$

The event of acquiring a measurement in the future is unknown → $\boldsymbol{\Gamma_i}$ is a random variable

Joint probability function:

$$p(X_{k+l}, \Gamma_{k+1:k+l} | H_{k+l})$$

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Formulation
Belief Space Planning

X_k – All robot ($x_{1:k}$) until time k and world states ($l_{1:j}$)
$H_k \triangleq \{Z_{0:k}.\, u_{0:k-1}\}$ Past measurements and controls
$\gamma_{i,j}$ – Event of acquiring measurement j at time l
$\Gamma_i \triangleq \{\gamma_{i,j}\}_{j=1}^{n_i}$

Notations

Recall, in order to calculate the objective function J, we are using the belief $b(X_{k+l})$:

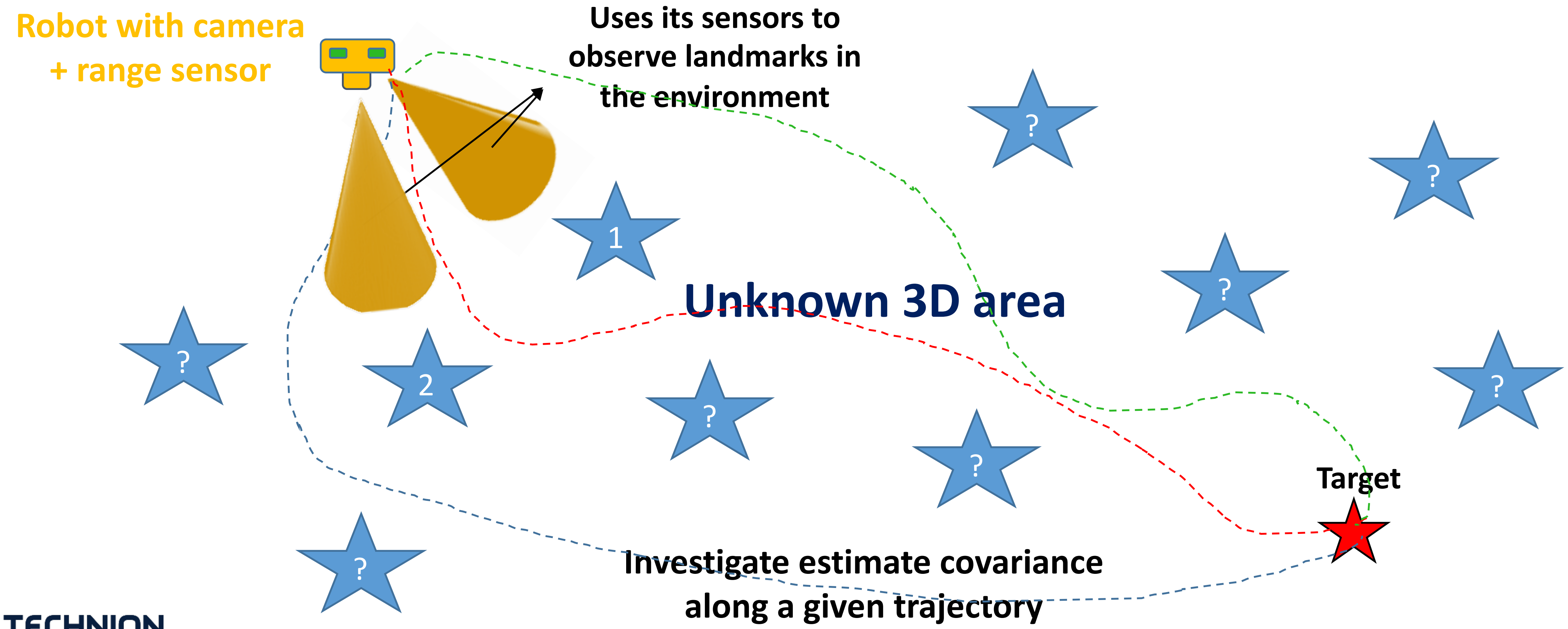
$$J(u_{k:k+L-1}) @ \underset{Z_{k+1:k+L}}{\mathrm{E}} \left\{ \sum_{l=0}^{L-1} c_l \left(b\left(X_{k+l}\right), u_{k+l} \right) \right\}$$

Therefore we do Marginalization:

$$b(X_{k+l}) = p(X_{k+l}|H_{k+l}) = \sum_{\Gamma_{k+1:k+l}} p(X_{k+l}, \Gamma_{k+1:k+l}|H_{k+l})$$

Results – Simulation overview

Using a simulation to check the influence of modeling object re-identification

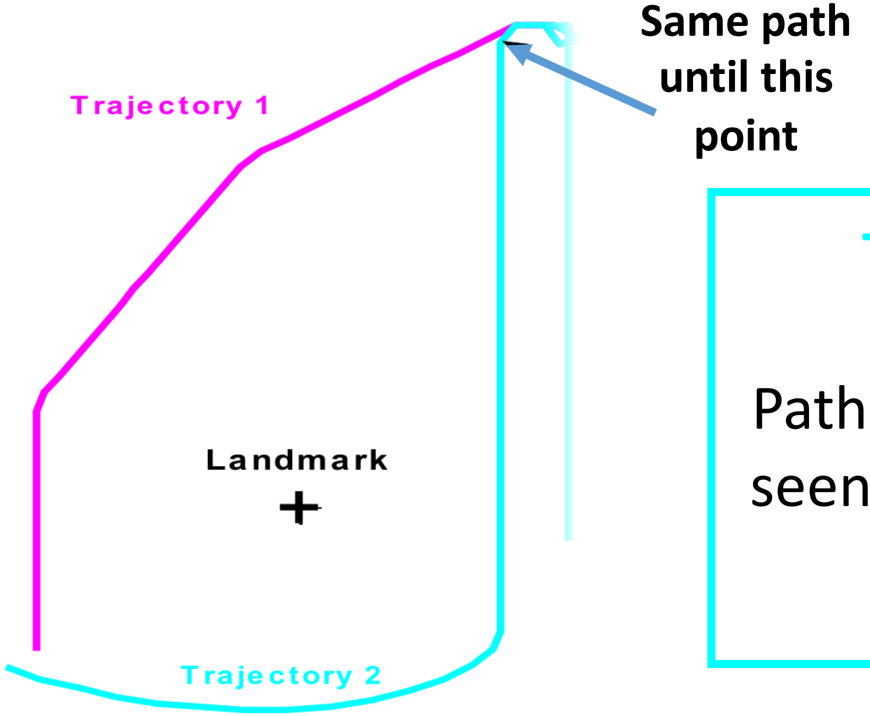


Results – problem definition

The objectives are:
- **Minimum uncertainty**
- **Path length**
- **Reaching a specific target**

- Checking two predefined trajectories that differ in:
  - Landmark's view directions
  - Trajectory length

Trajectory 1:
Shorter,
Path includes new landmark's view point



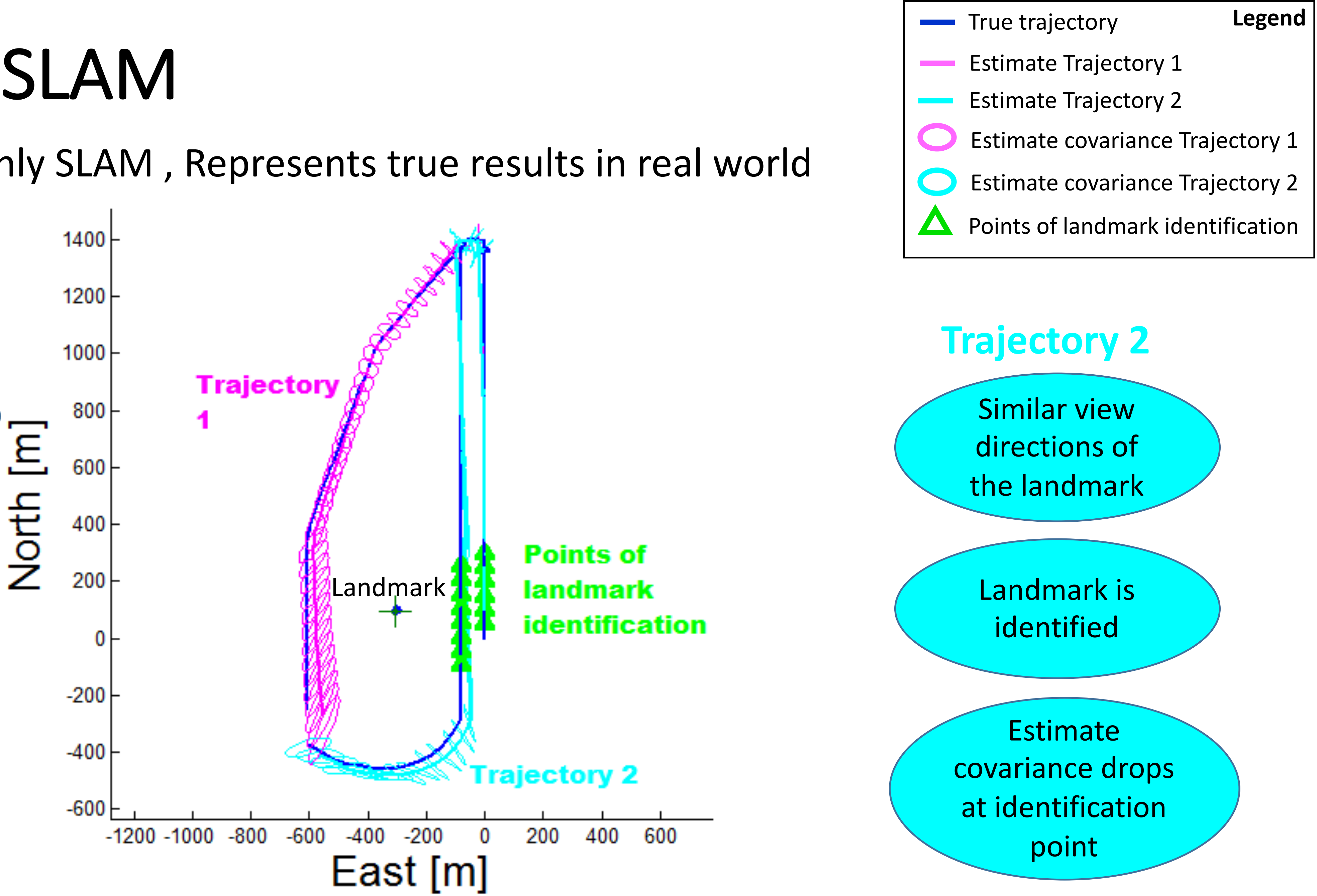
Trajectory 2:
Longer,
Path includes already seen landmark's view point

Results -SLAM

Using only SLAM , Represents true results in real world

Trajectory 1

- Completely different view directions of the landmark
- Landmark isn't identified
- Estimate covariance keep growing



Trajectory 2

- Similar view directions of the landmark
- Landmark is identified
- Estimate covariance drops at identification point

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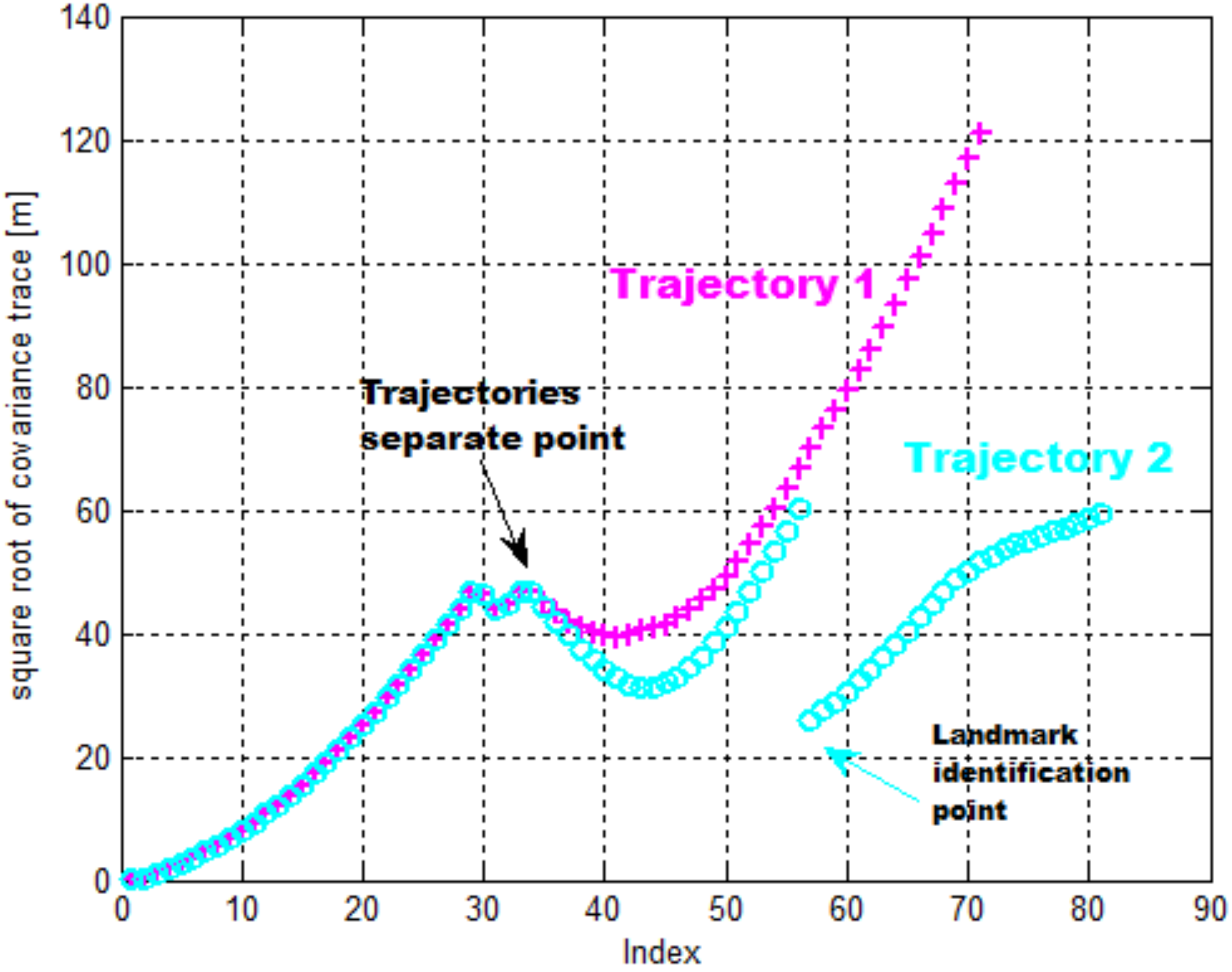
Results -SLAM

Trajectory 1

Landmark isn't identified

Estimate covariance keep growing



Trajectory 2

Landmark is identified

Estimate covariance drops at identification point

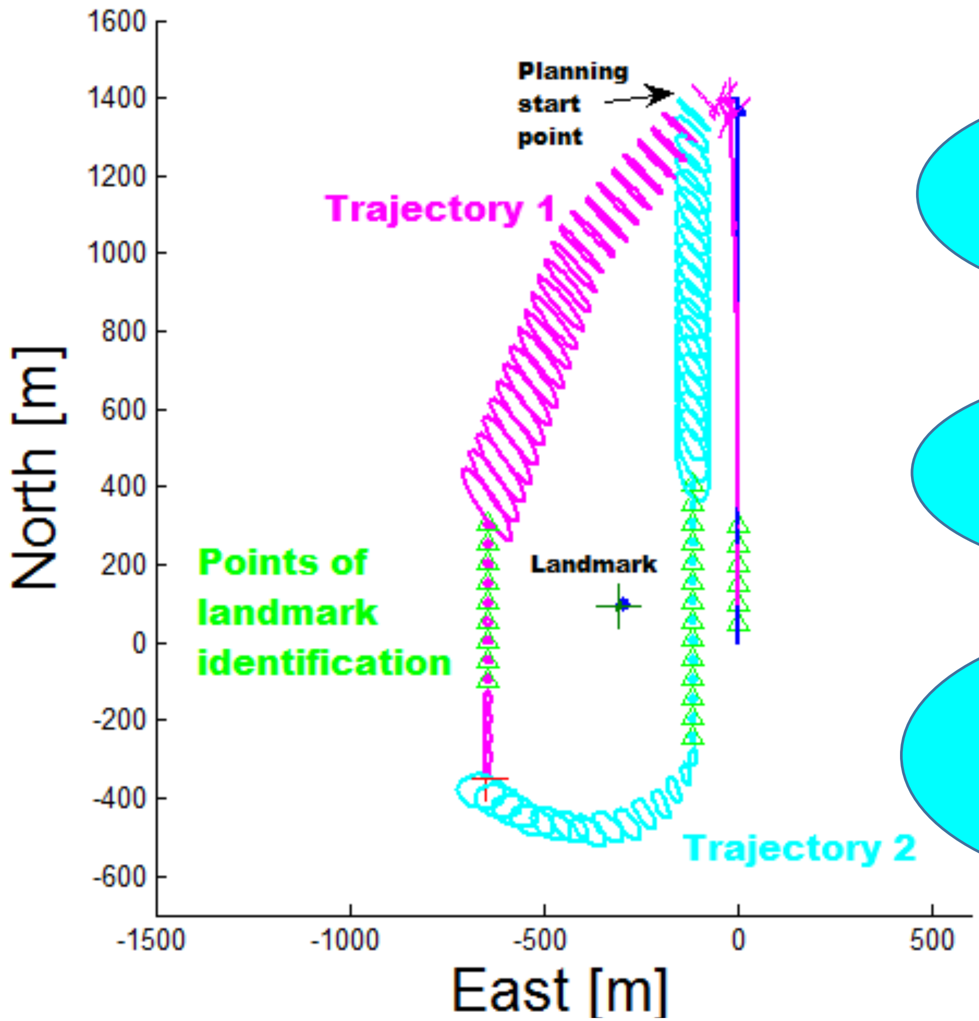
Trajectory 2 has lower estimate covariance though it is longer → preferred

Results - Planning
Without applying object identification

Legend
- True trajectory
- Estimate Trajectory 1
- Estimate Trajectory 2
- Estimate covariance Trajectory 1
- Estimate covariance Trajectory 2
- Points of landmark identification

Trajectory 1

- New view directions of the landmark
- Landmark is **incorrectly identified** (Differently than SLAM)
- Estimate covariance **incorrectly drops**



Trajectory 2

- Similar view directions of the landmark
- Landmark is identified
- Estimate covariance drops at identification point

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Results - Planning
Without applying object identification

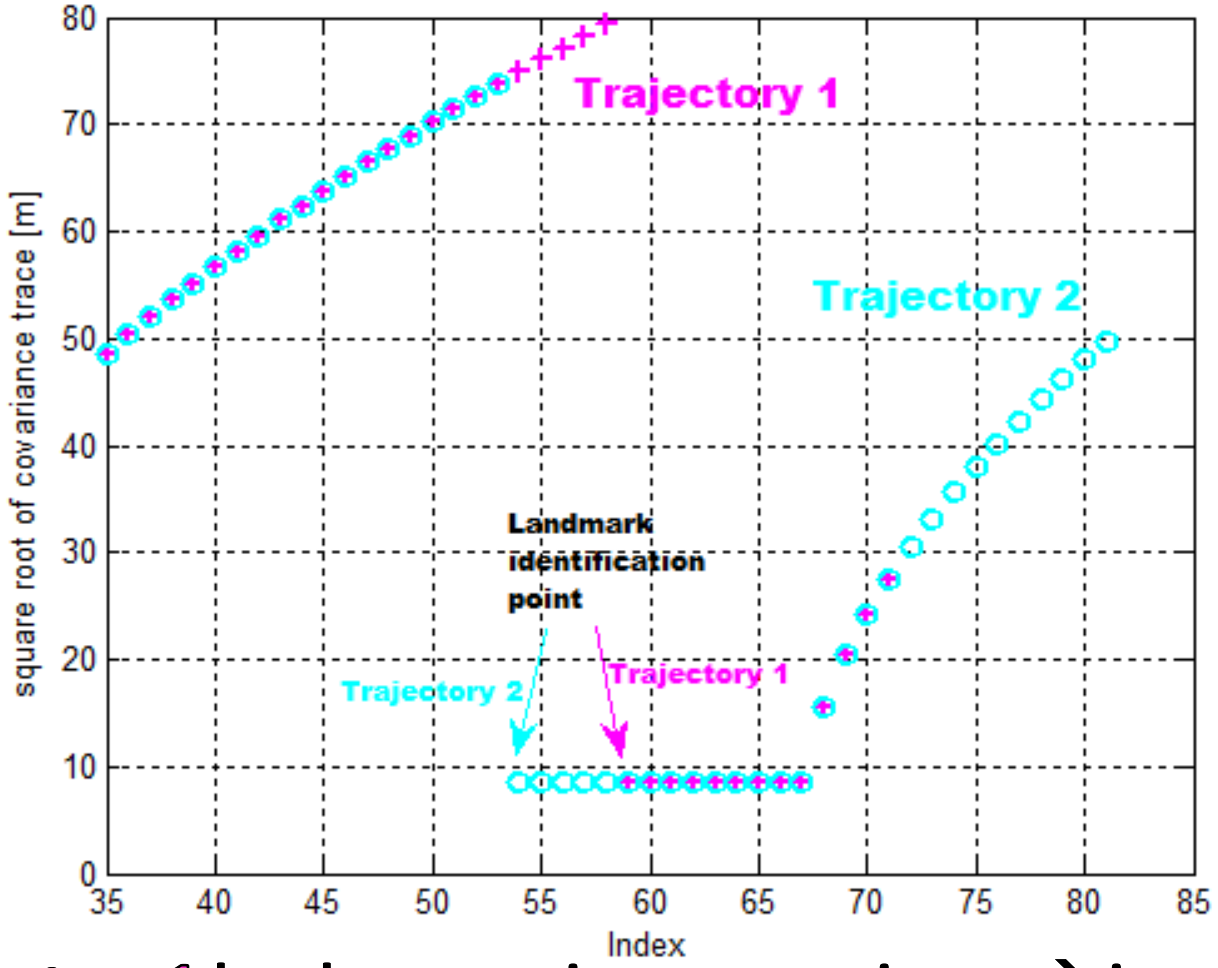
Trajectory 1

Landmark is **incorrectly identified**

covariance **incorrectly drops** at identification point

⇩

Inconsistent with SLAM



Trajectory 2

Landmark is identified

Estimate covariance drops at identification point

Trajectory 1 has lower estimate covariance → incorrectly preferred

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Results - Planning
With applying object identification

Legend
- True trajectory
- Estimate Trajectory 1
- Estimate Trajectory 2
- Estimate covariance Trajectory 1
- Estimate covariance Trajectory 2
- Points of landmark identification

Trajectory 1

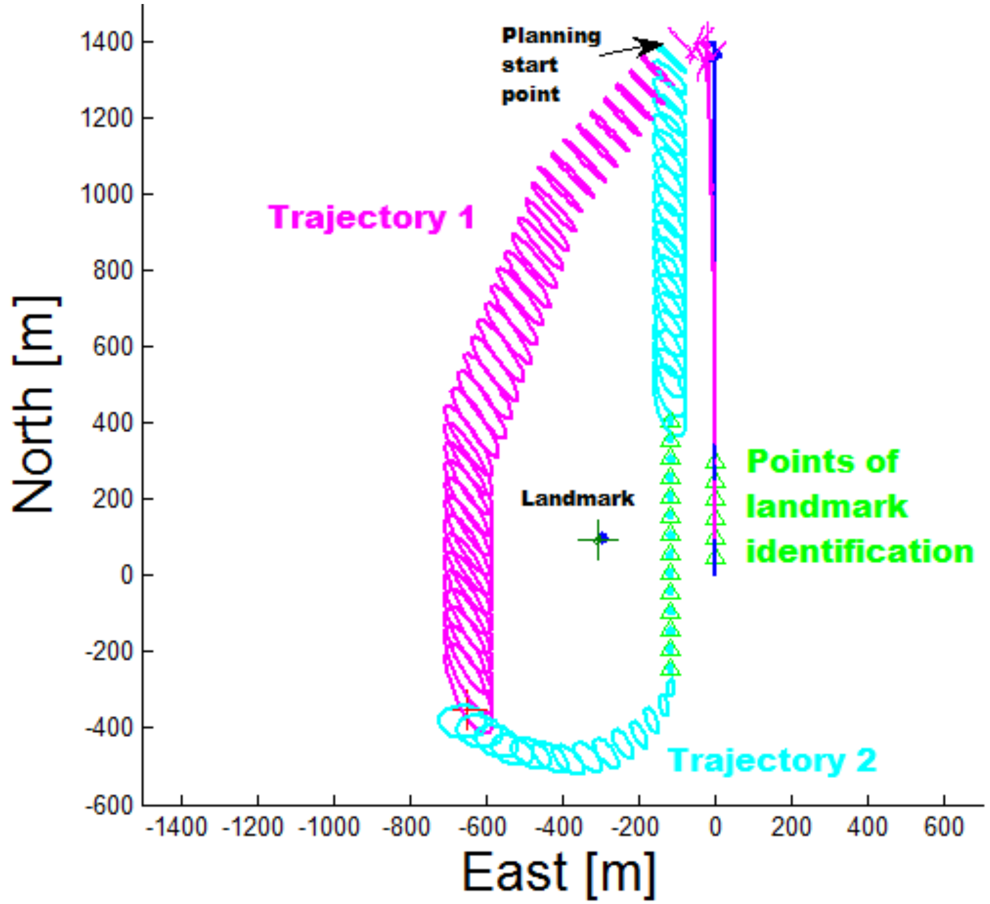
New view directions of the landmark

Landmark isn't identified

Estimate covariance keep growing

⇩

Consistent with SLAM



Trajectory 2

Similar view directions of the landmark

Landmark is identified

Estimate covariance drops at identification point

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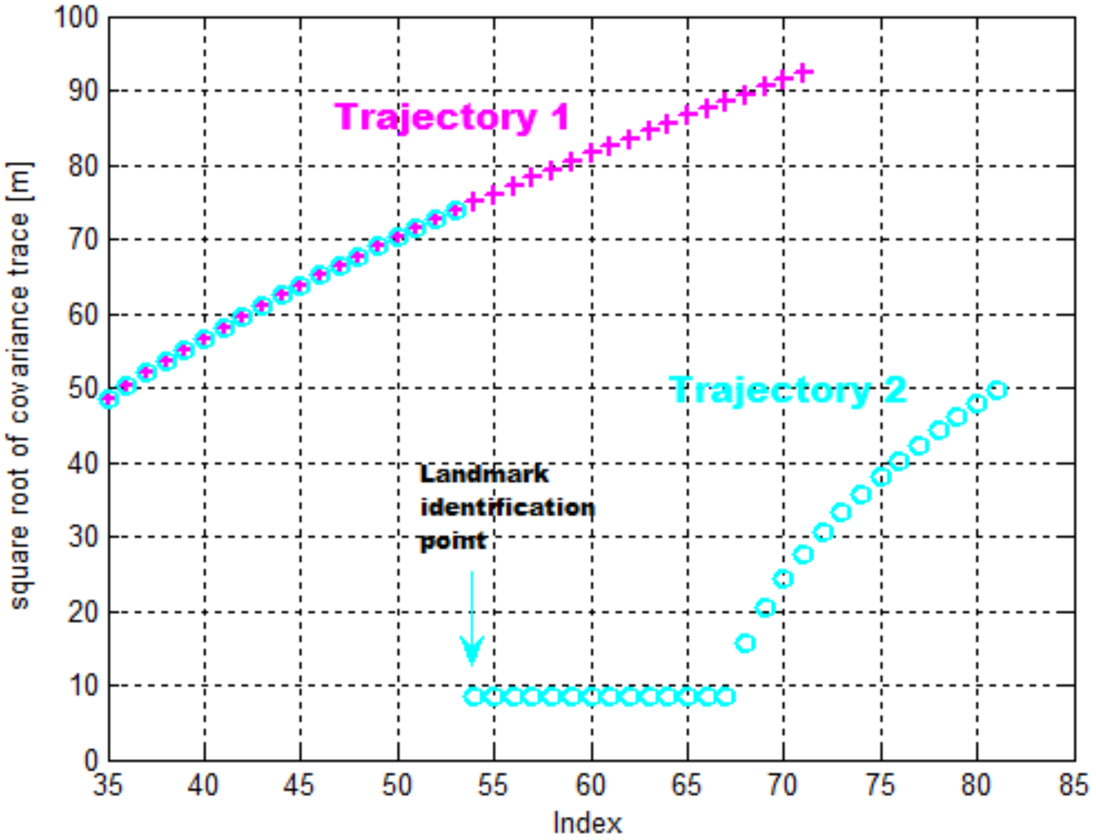
Results - Planning
With applying object identification

Trajectory 1

Landmark isn't identified

Estimate covariance keep growing

Consistent with SLAM



Trajectory 2

Landmark is identified

Estimate covariance drops at identification point

Trajectory 2 has lower estimate covariance though it is longer → preferred

Consistent with SLAM

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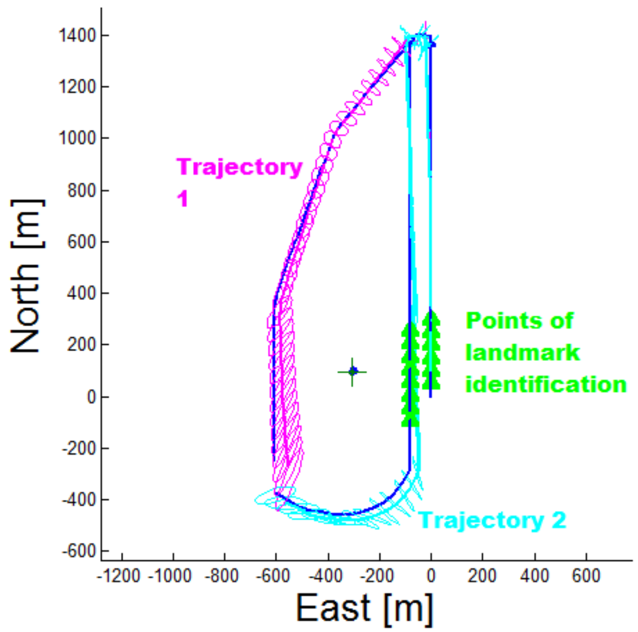
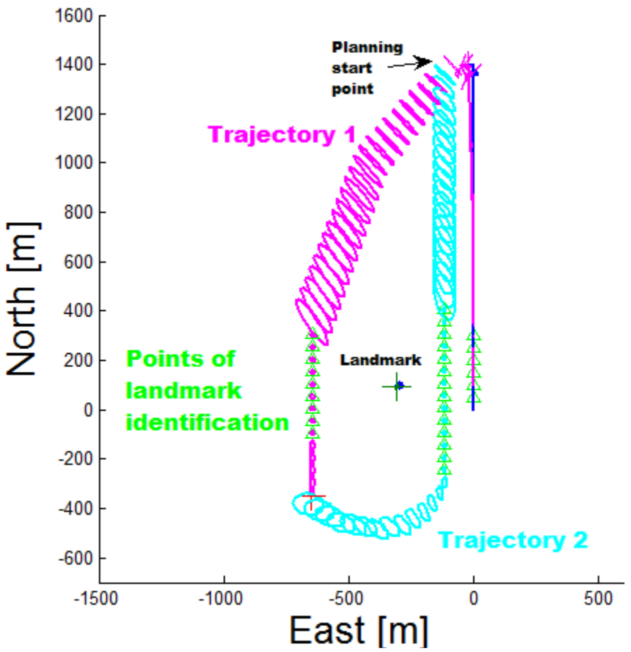
Results - summary

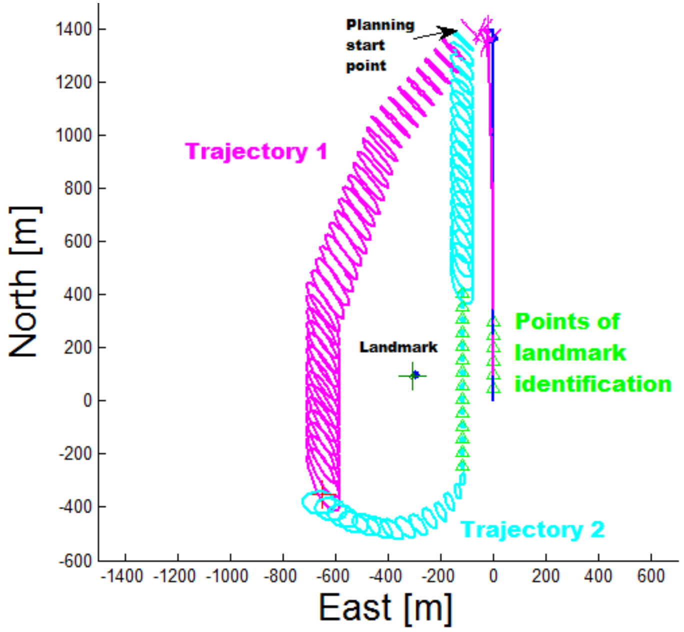
SLAM



Planning - Without applying object identification



Planning – With applying object identification



In reality – the landmark is re-identified only in trajectory 2

When not applying object identification – the landmark is re-identified incorrectly also in trajectory 1

When applying object identification – the landmark is re-identified only in trajectory 2, similarly to reality

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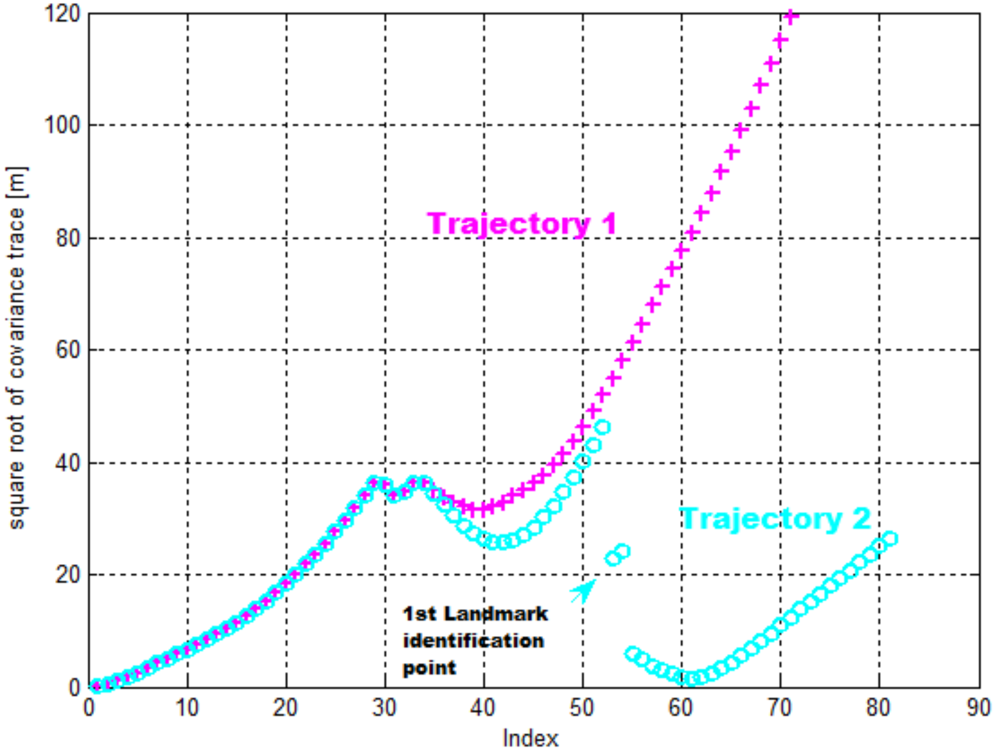
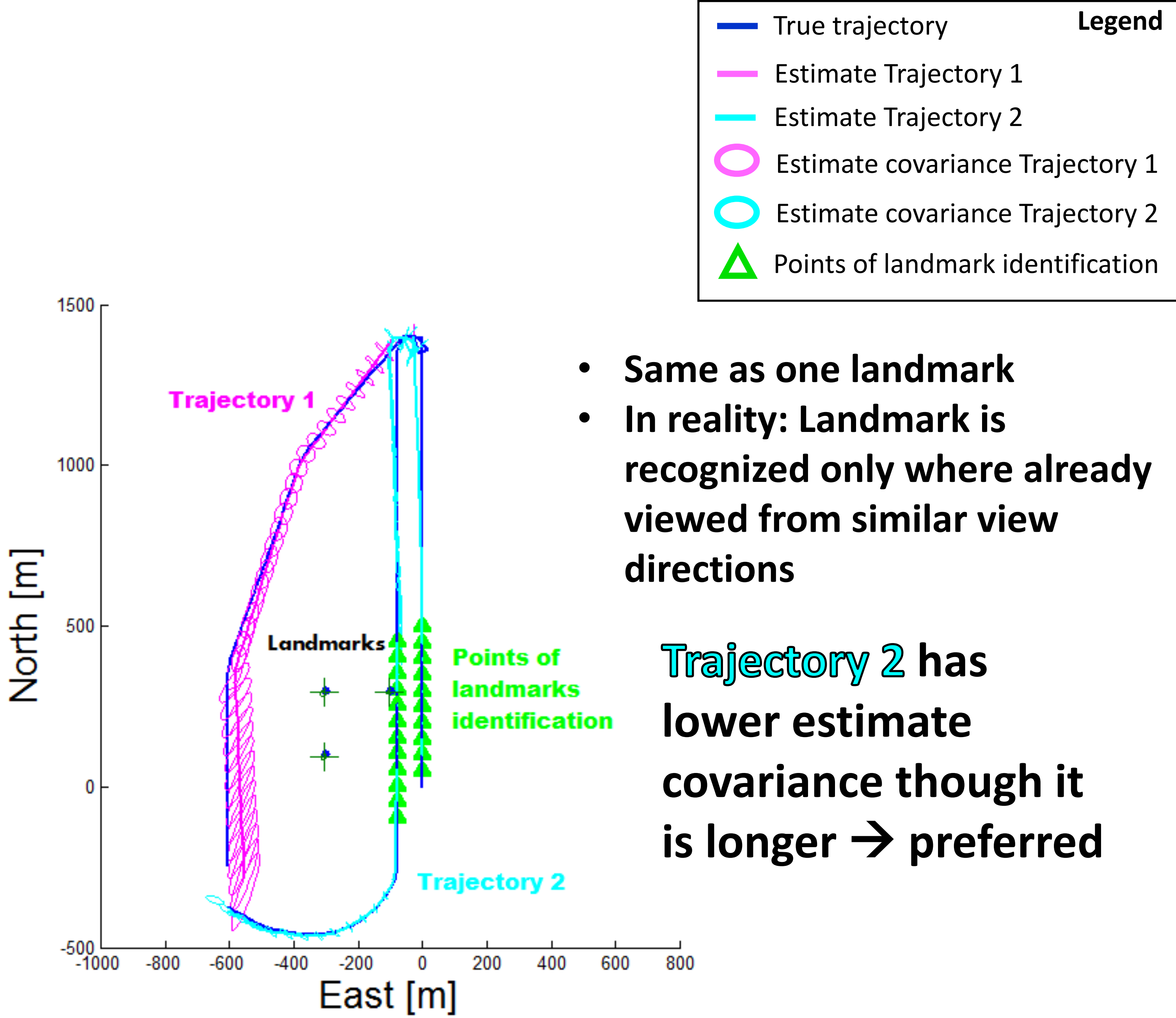
Results – SLAM
Multiple landmarks





- **Same as one landmark**
- **In reality: Landmark is recognized only where already viewed from similar view directions**

Trajectory 2 has lower estimate covariance though it is longer → preferred

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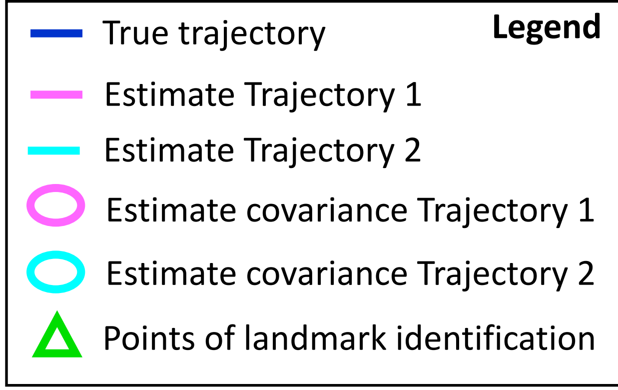
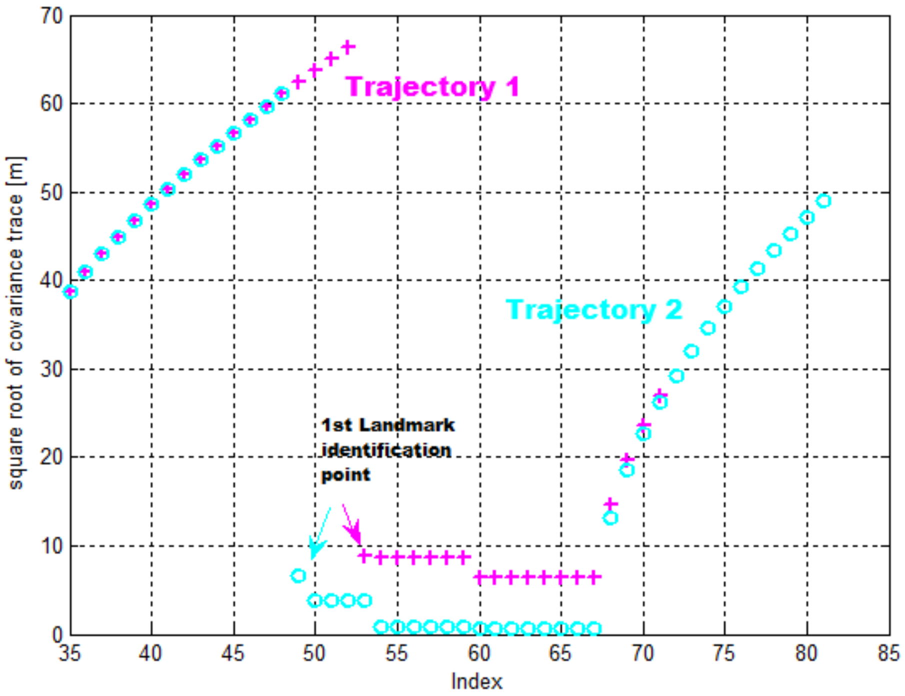
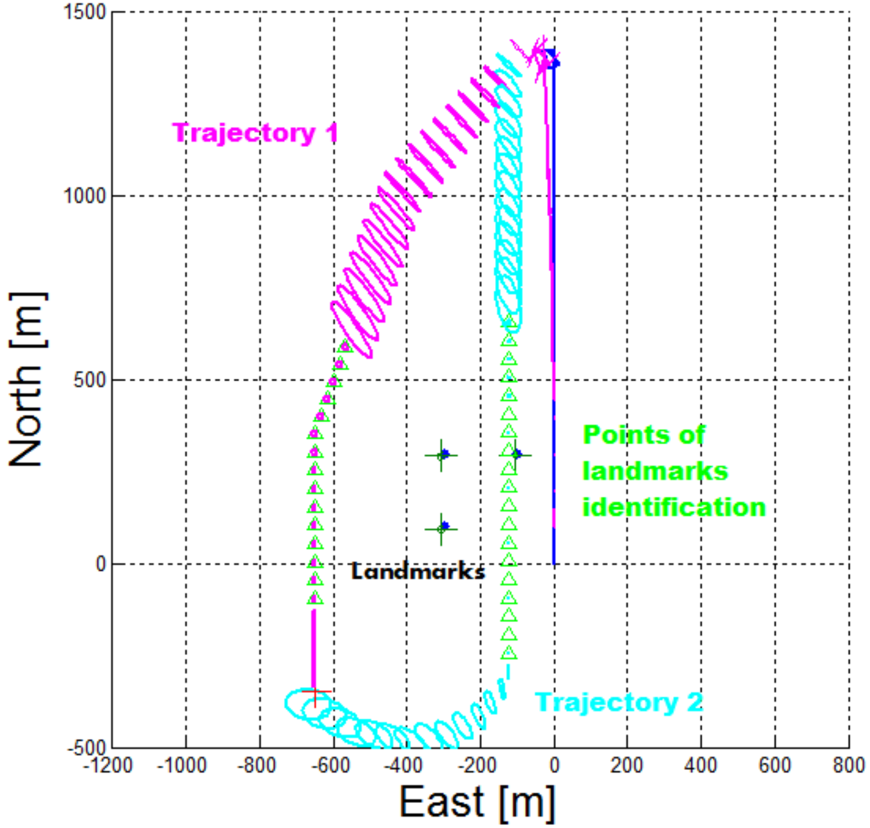
S.Har-Nes, Graduate Seminar, September 2016

Results – Planning
Multiple landmarks
Without applying object identification





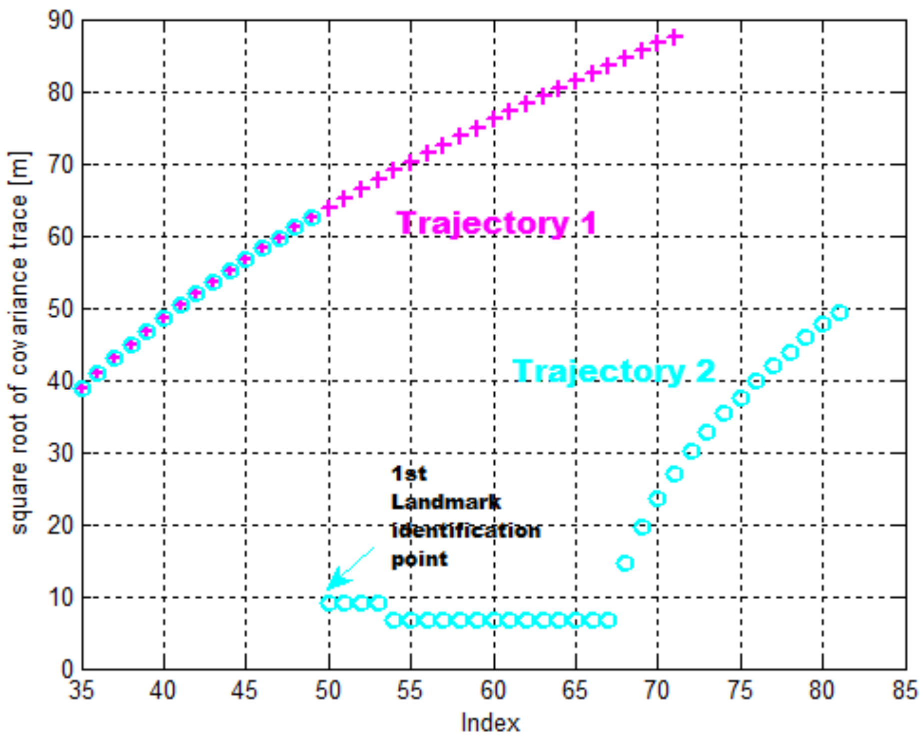


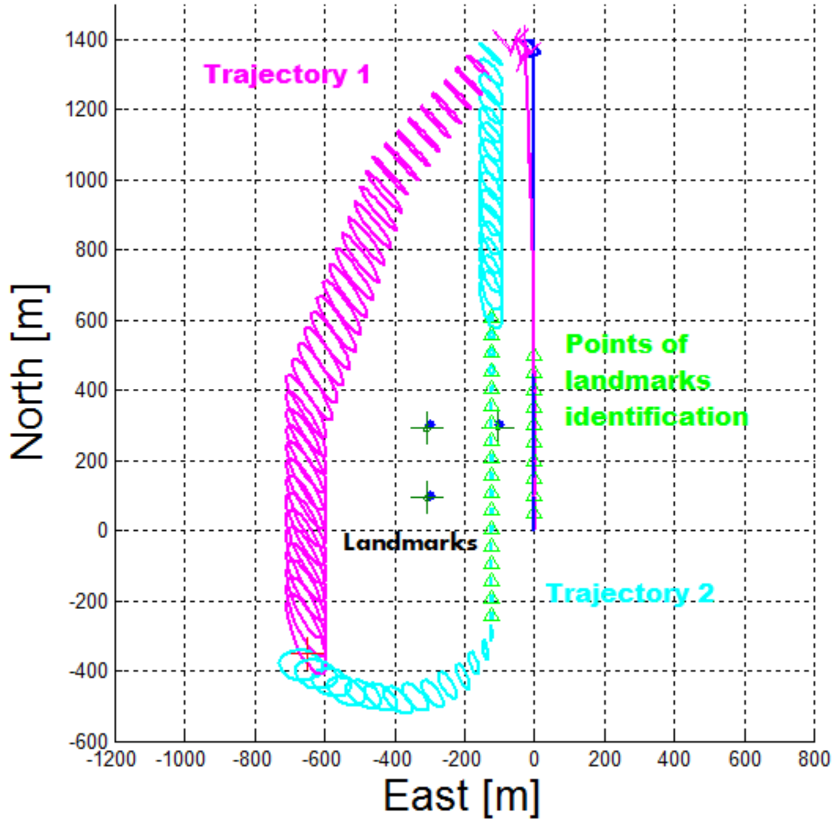
- **Same as one landmark**
- **When not applying object identification: landmark is recognized incorrectly from new view directions**

Trajectory 1 has lower estimate covariance → <u>incorrectly</u> preferred

Results – Planning
Multiple landmarks
With applying object identification

Legend
- True trajectory
- Estimate Trajectory 1
- Estimate Trajectory 2
- Estimate covariance Trajectory 1
- Estimate covariance Trajectory 2
- Points of landmark identification





- **Same as one landmark**
- **Similar to reality: Landmark is recognized only where already viewed from similar view directions**

Trajectory 2 has lower estimate covariance though it is longer → preferred

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Conclusions

We developed a viewpoint aware BSP approach
and modeled object re-identification

Correct identification of landmarks is critical
Uncertainty prediction consistent with reality (inference)
Correct planning and path choosing

Thank you

Why $p\left(z_{k+i,j} \mid x_{k+i}, l_j, \gamma_{k+i,j}\right)$ is uninformative?

$p\left(z_{k+i,j} \mid x_{k+i}, l_j, \gamma_{k+i,j}\right)$

- $\gamma_{k+i,j} = 1$ → $p\left(z_{k+i,j} \mid x_{k+i}, l_j\right)$
- $\gamma_{k+i,j} = 0$ → ~~$p\left(z_{k+i,j} \mid x_{k+i}, l_j, \gamma_{k+i,j}\right)$~~

Observation model:

$$z_{i,j} = h(x_i, l_j) + v_{i,j}(\gamma_{i,j}) \qquad \mathrm{v}_{i,j} \sim N(0, \Sigma_v)$$

$$\Sigma_v = \begin{cases} \Sigma_v & \gamma_{i,j} = 1 \\ \rightarrow \infty & \gamma_{i,j} = 0 \end{cases}$$

How we use the belief $b(X_{k+l})$ when the future measurements are unknown?

$$b(X_{k+l}) : N\left(X^*_{k+l}, \Sigma_{k+l}\right)$$

- We solve $X^*_{k+l} = \underset{X_{k+l}}{\operatorname{argmax}}\left(b(X_{k+l})\right)$ using optimization method Non linear least squares
- In order to find the covariance Σ_{k+l} we do not need to know the measurements, only the fact that they were acquired or not
- We assume Maximum likelihood assumption:

$$z = h(\bar{x}) \rightarrow x^* = \bar{x}$$

- Where $\bar{x}$ is the predicted value of x, according to motion model

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Marginalization

X_k – All robot ($x_{1:k}$) until time k and world states ($l_{1:j}$)
$H_k \triangleq \{Z_{0:k}. u_{0:k-1}\}$ Past measurements and controls
$\gamma_{i,j}$ – Event of acquiring measurement j at time I
$\Gamma_i \triangleq \{\gamma_{i,j}\}_{j=1}^{n_i}$

Notations

$$p(X_{k+l}|H_{k+l}) = \sum_{\Gamma_{k+1:k+l}} p(X_{k+l}, \Gamma_{k+1:k+l}|H_{k+l})$$

For example, for only one observation (Γ_{k+1}):

$$p(X_{k+1}|H_{k+1}) = p\left(X_{k+1}, \gamma_{k+1,1} = 1|H_{k+1}\right) + p\left(X_{k+1}, \gamma_{k+1,1} = 0|H_{k+1}\right)$$