Bearing-Only SLAM in everyday environments using Omnidirectional Vision

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http://www.zafh-servicerobotik.de/ULM/en/index.php

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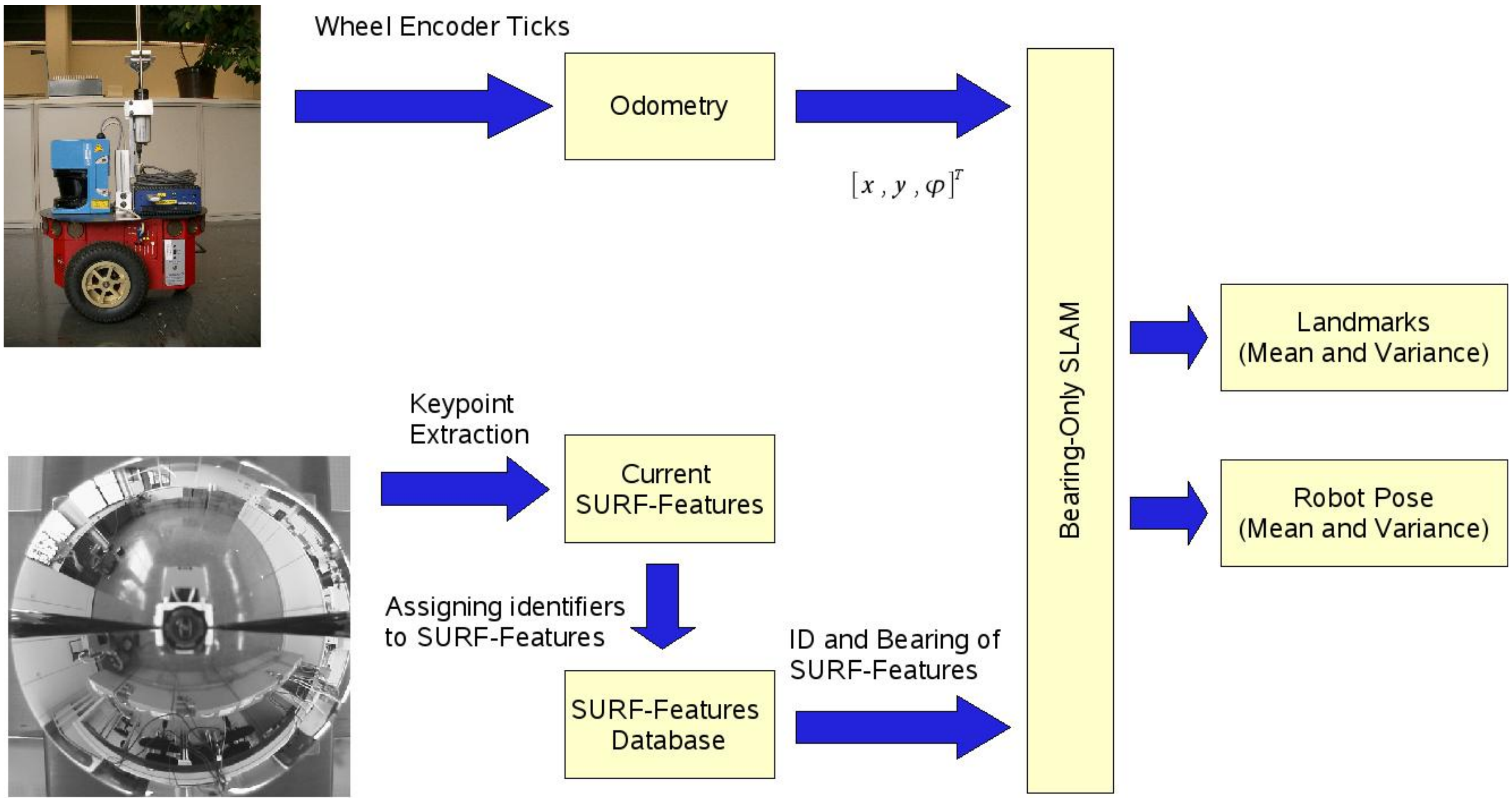
System Overview



Visual Landmarks

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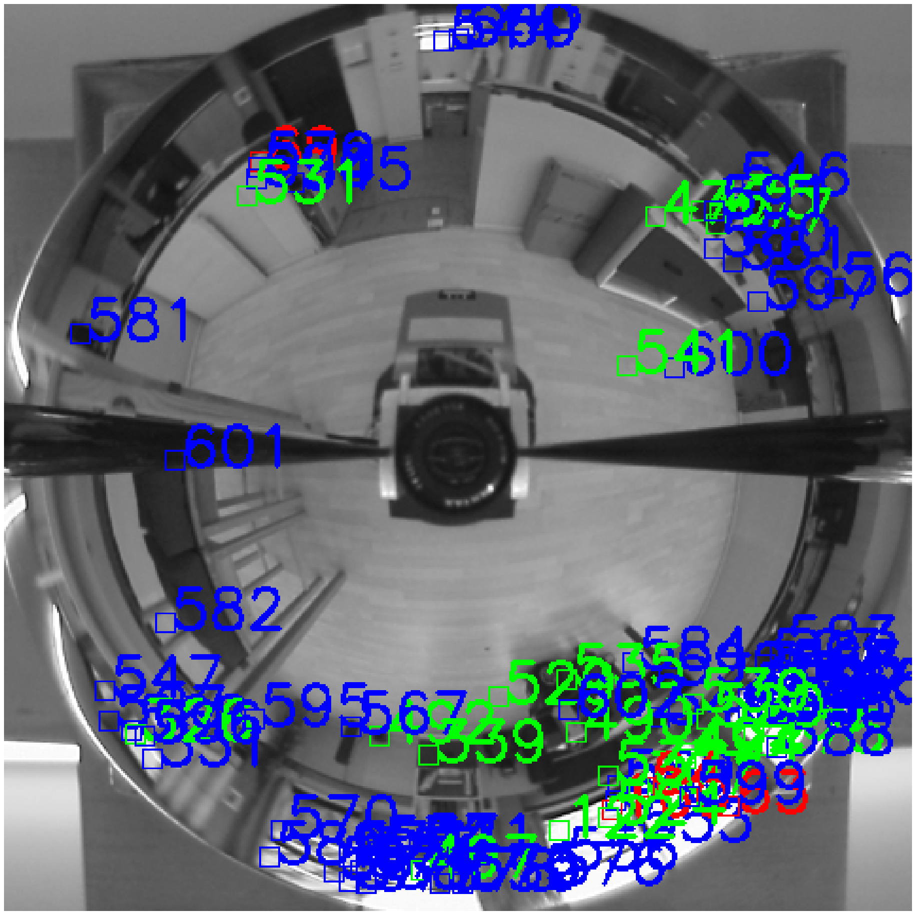
Visual Landmarks



SURF Features [3] as visual landmarks

scale-invariant

rotation-invariant

high repeatability

high distinctiveness

high robustness

Problem description:

Service robots should be designed for life-long and robust operation in dynamic environments.

→ goal 1: robust operation in dynamic everyday environments
→ goal 2: life-long operation

Goal 1:

Robustness in dynamic everyday environments

Problem:

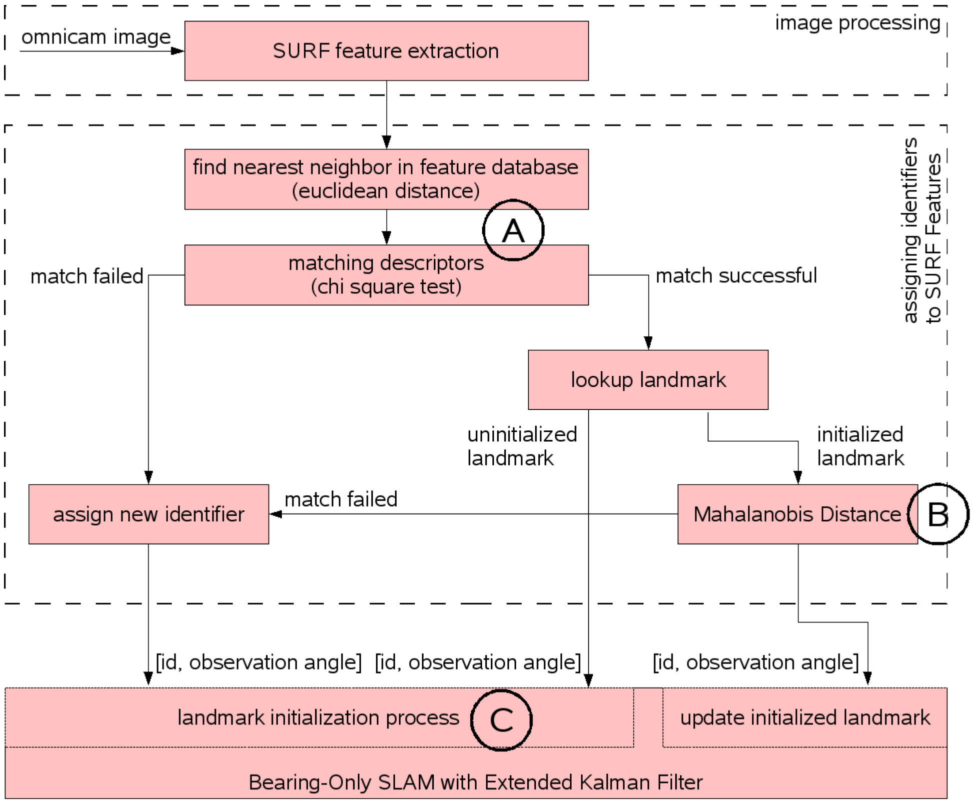
Natural landmarks often identified on recurring structures like doors and window frames. How can we distinguish them?

→ landmark assignment problem

Solution:

combine efficient feature retrieval with spatial plausibility

Assigning identifiers to SURF-Features



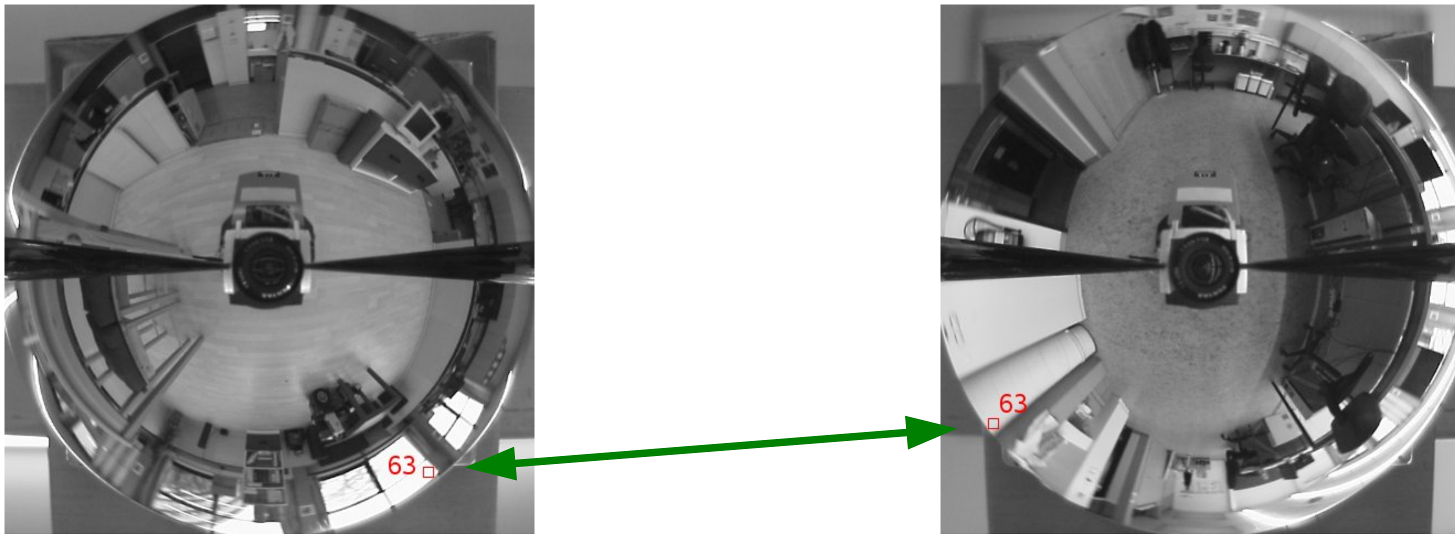
The first step (**A**) in the assignment process is to find the nearest neighbour (Euclidean distance) in the kd-tree. We then compare this descriptor from the database with the descriptor of the observed SURF feature by a chi^2 Test.

For spatial plausibility, initialized landmarks are checked by Mahalanobis distance (**B**).

At the landmark initialization process (**C**) we also check the landmark by a Mahalanobis distance test

All features which are not initialized within 10 timesteps, are deleted from the database. This limits the growing of the feature database.

Example



descriptor comparison

spatial plausibility test

Comparison Method	Value	Threshold	Classification
Lowe	0.15 < 0.6*0.29	$d_1 < 0.6 * d_2$	matching
Correlation Coefficient	0.9882	> 0.90	matching
Chi-Square Test	0.079	< 0.15	matching
Mahalanobis Distance	656.781	< 0.1015	not matching

Goal 2:

life-long operation

Problem:

Typically, feature based SLAM approaches just accumulate features over time and do not discard them anymore.

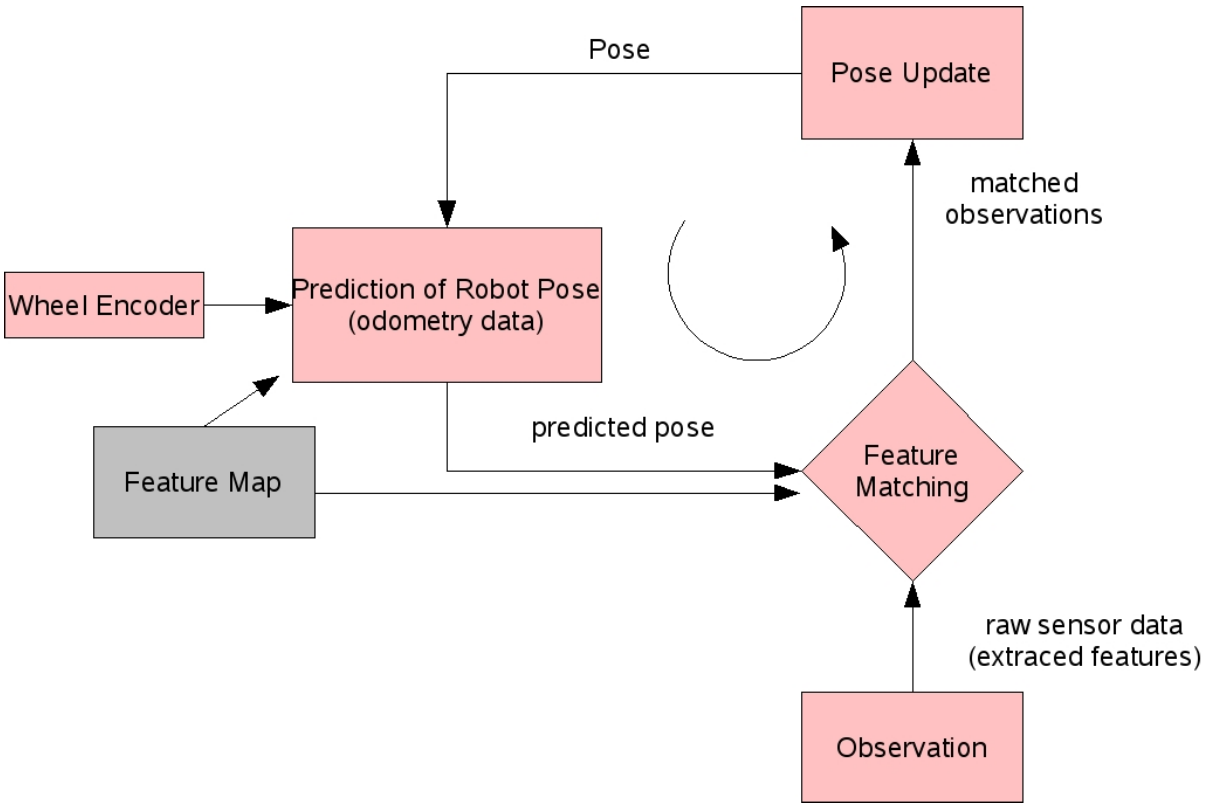
Therefore, the required resources in terms of memory and processing power are growing over time.

Solution:

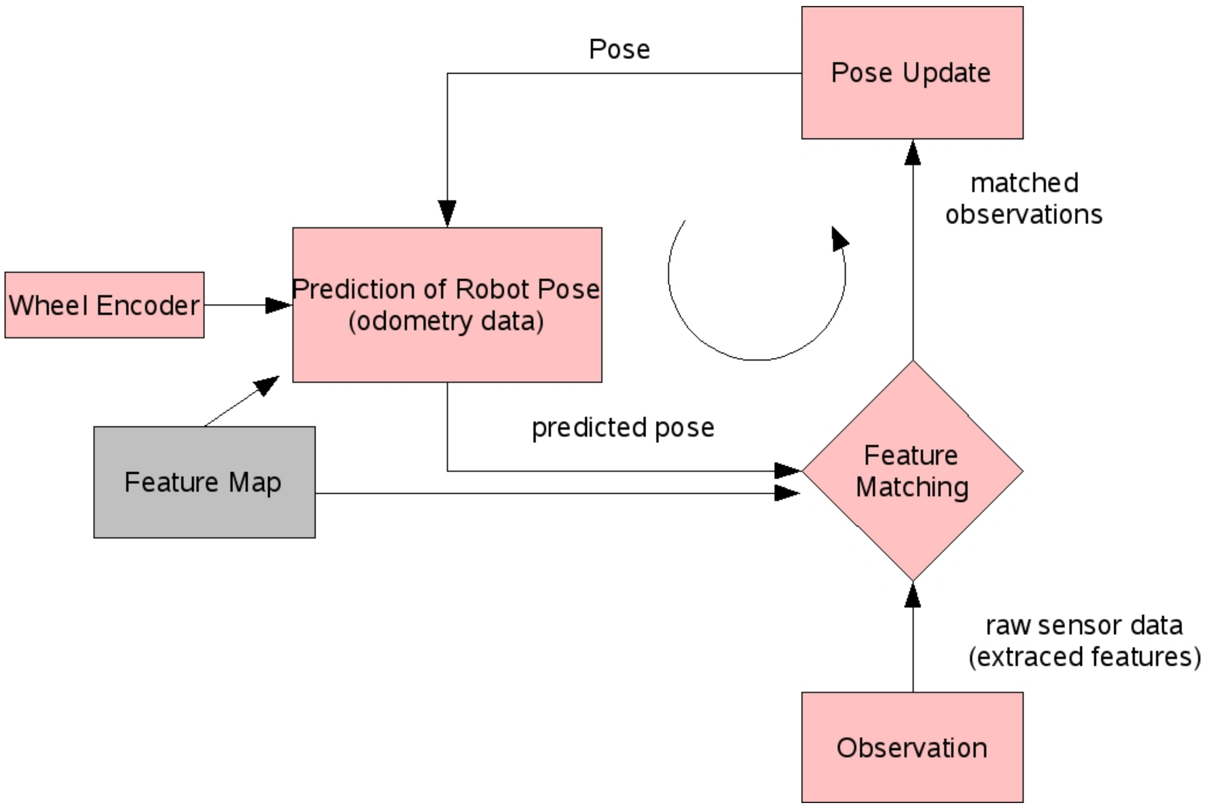
Restrict the absolute number of landmarks by an upper bound.

Evaluate landmarks based on their utility for localization purposes which is different from just replacing the most uncertain landmark.

Ever growing number of Landmarks

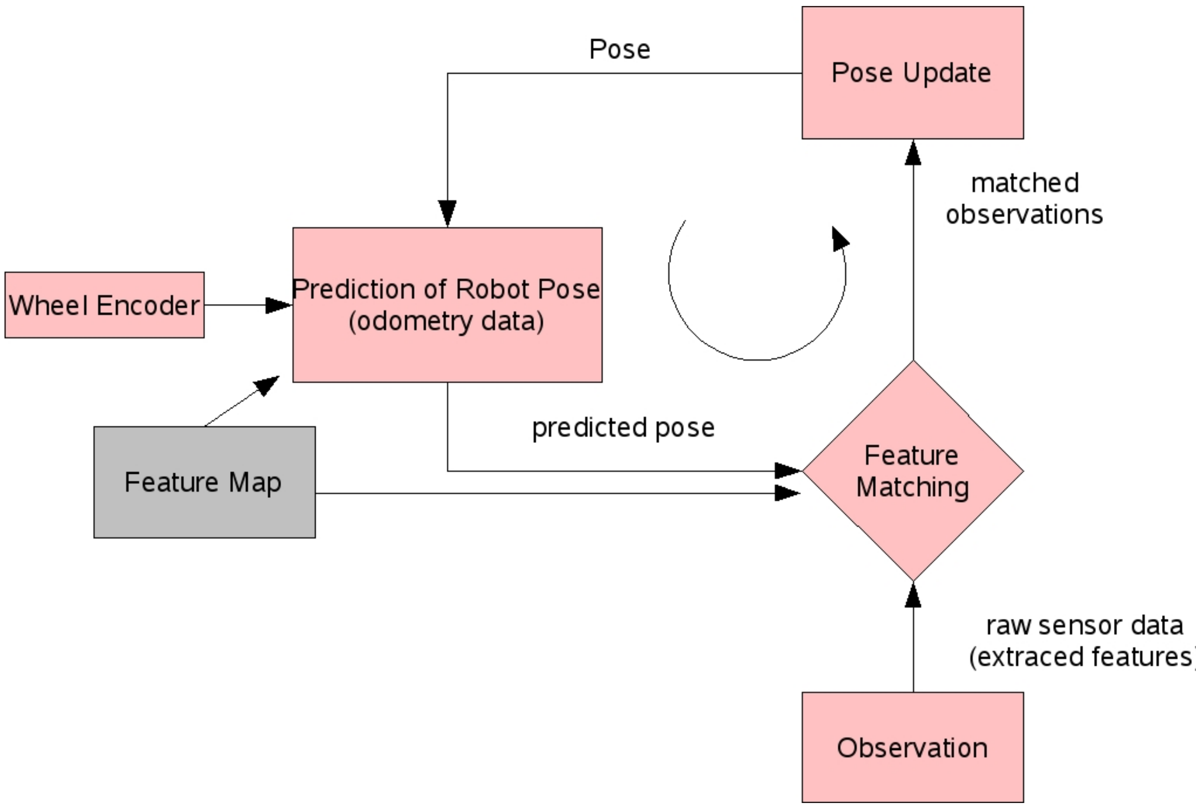


Ever growing number of Landmarks



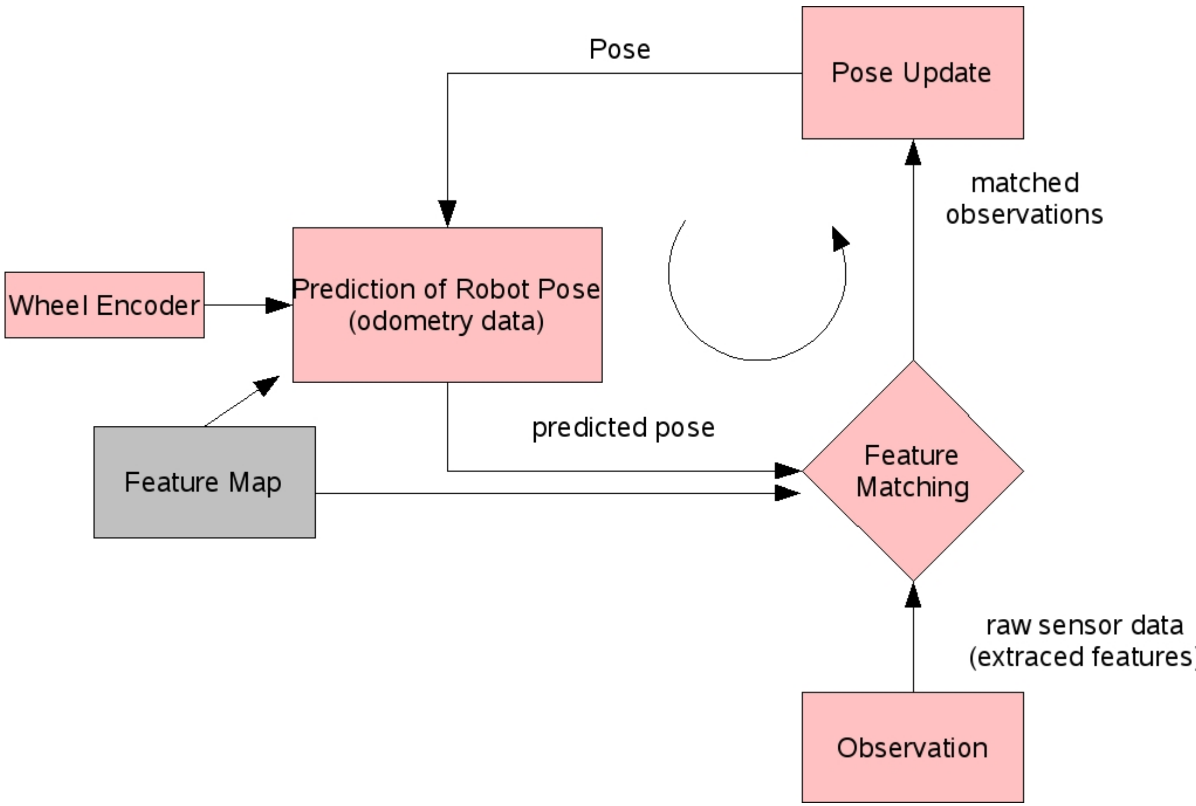
state vector: $x=\left[x_v^T, x_{v_m}^T, \ldots, x_1^T, x_{f_1}^T\right]$

Ever growing number of Landmarks



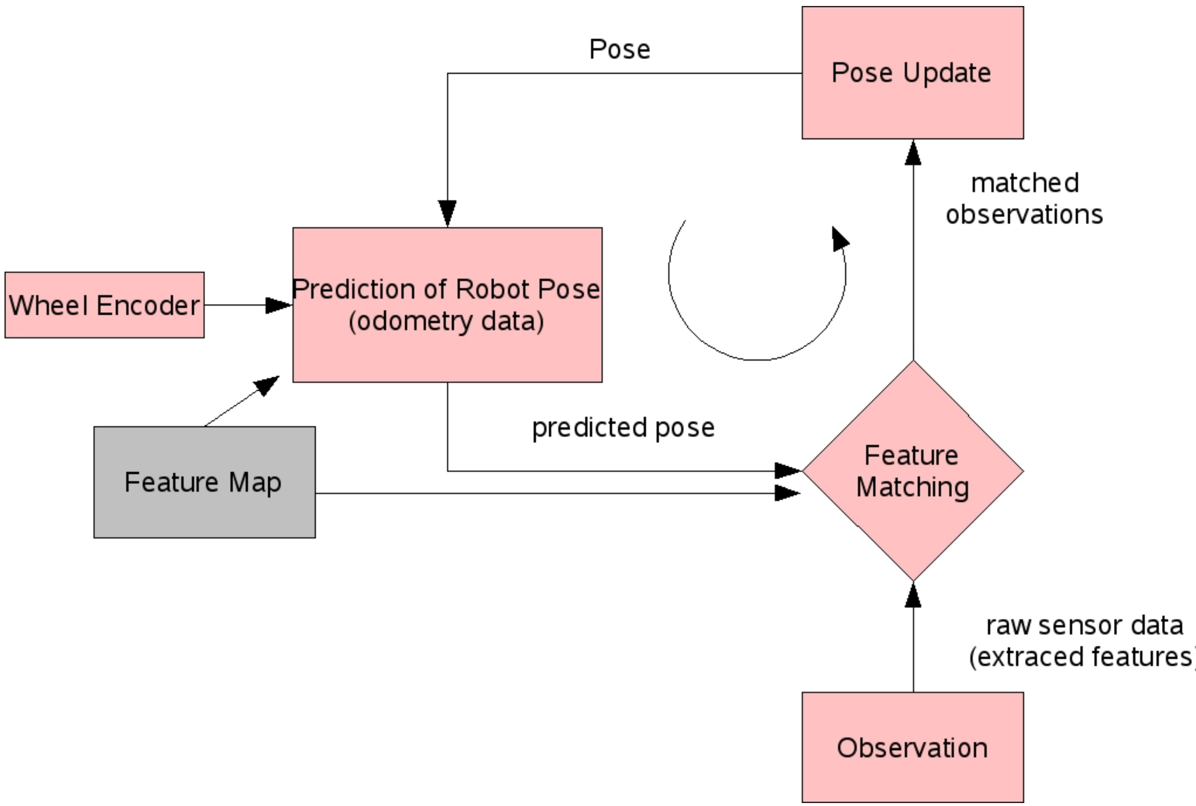
state vector: $$x=\left[x_v^T, x_{v_m}^T, \ldots, x_1^T, x_{f_1}^T, x_{f_2}^T\right]$$

Ever growing number of Landmarks



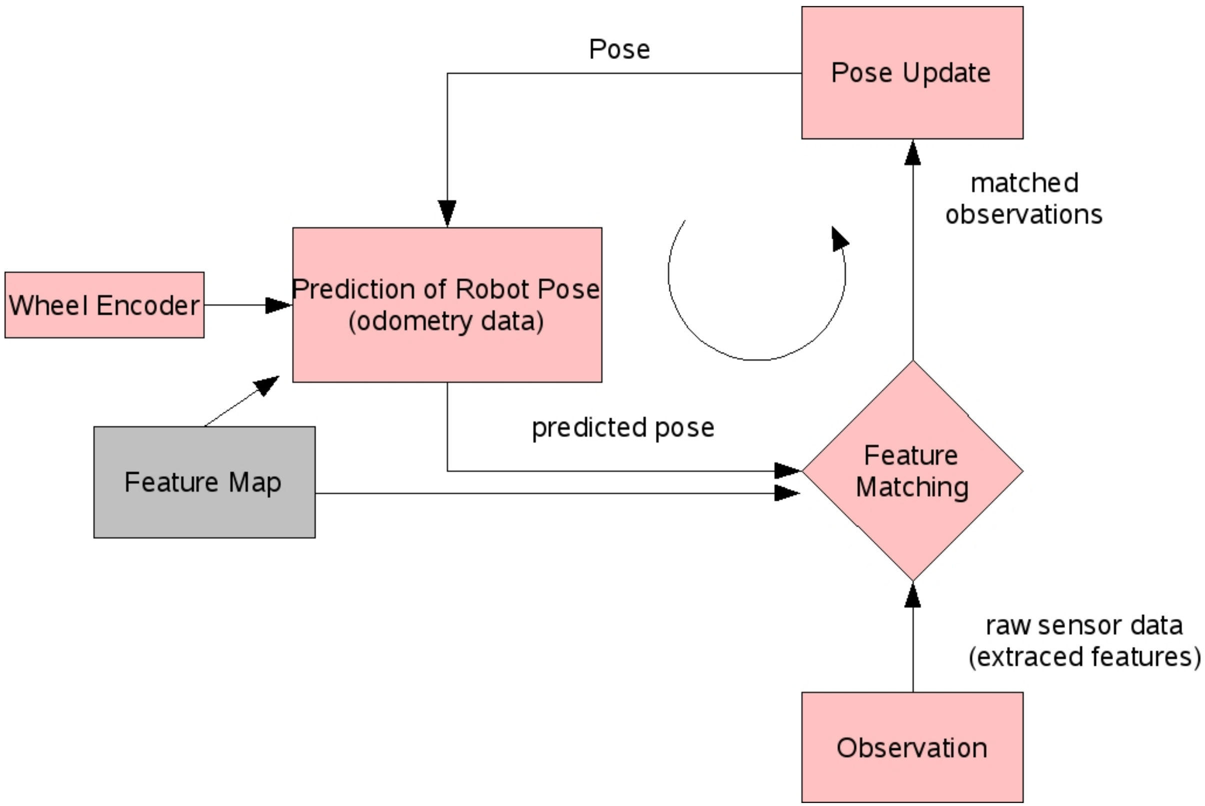
state vector: $$x = \left[x_v^T, x_{v_m}^T, \ldots, x_1^T, x_{f_1}^T, x_{f_2}^T, x_{f_3}^T \right]$$

Ever growing number of Landmarks



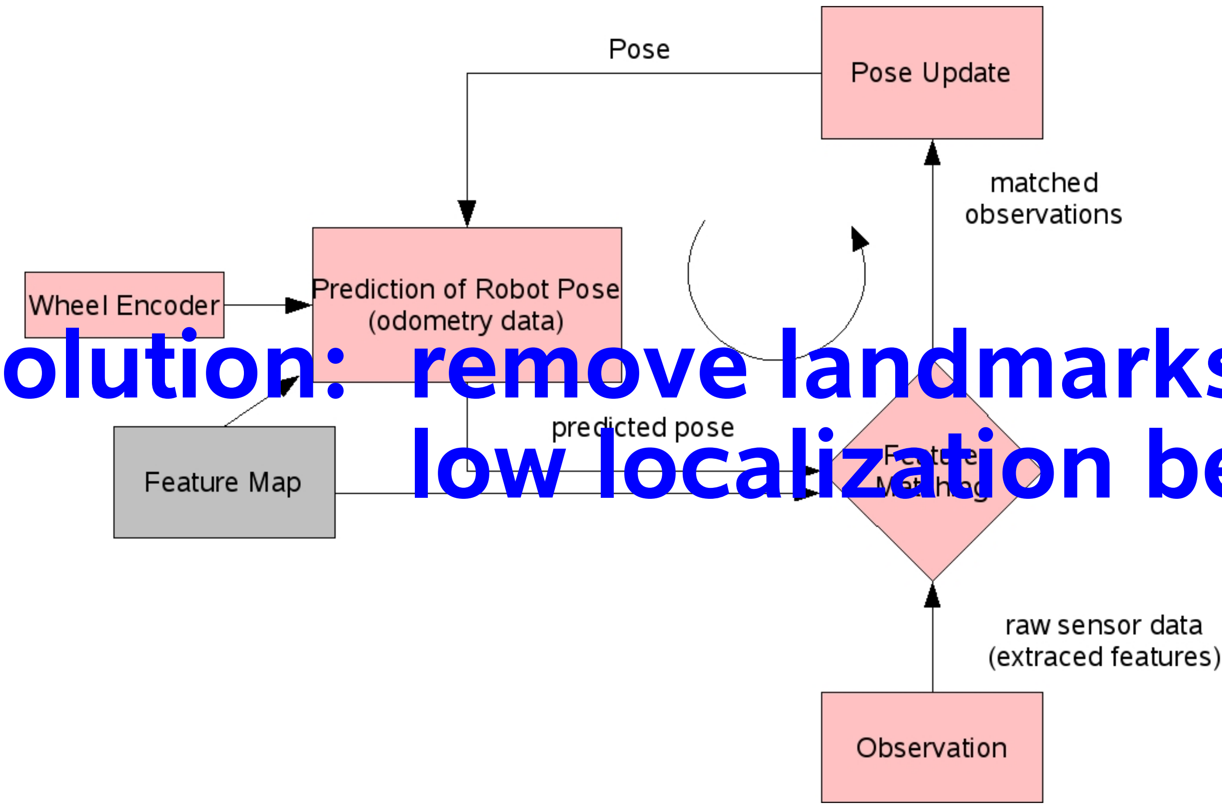
state vector: $$x=\left[x_v^T, x_{v_m}^T, \ldots, x_1^T, x_{f_1}^T, x_{f_2}^T, x_{f_3}^T, x_{f_4}^T\right]$$

Ever growing number of Landmarks



state vector: $x = \left[x_v^T, x_{v_m}^T, \ldots, x_1^T, x_{f_1}^T, x_{f_2}^T, x_{f_3}^T, x_{f_4}^T, x_{f_5}^T \right]$

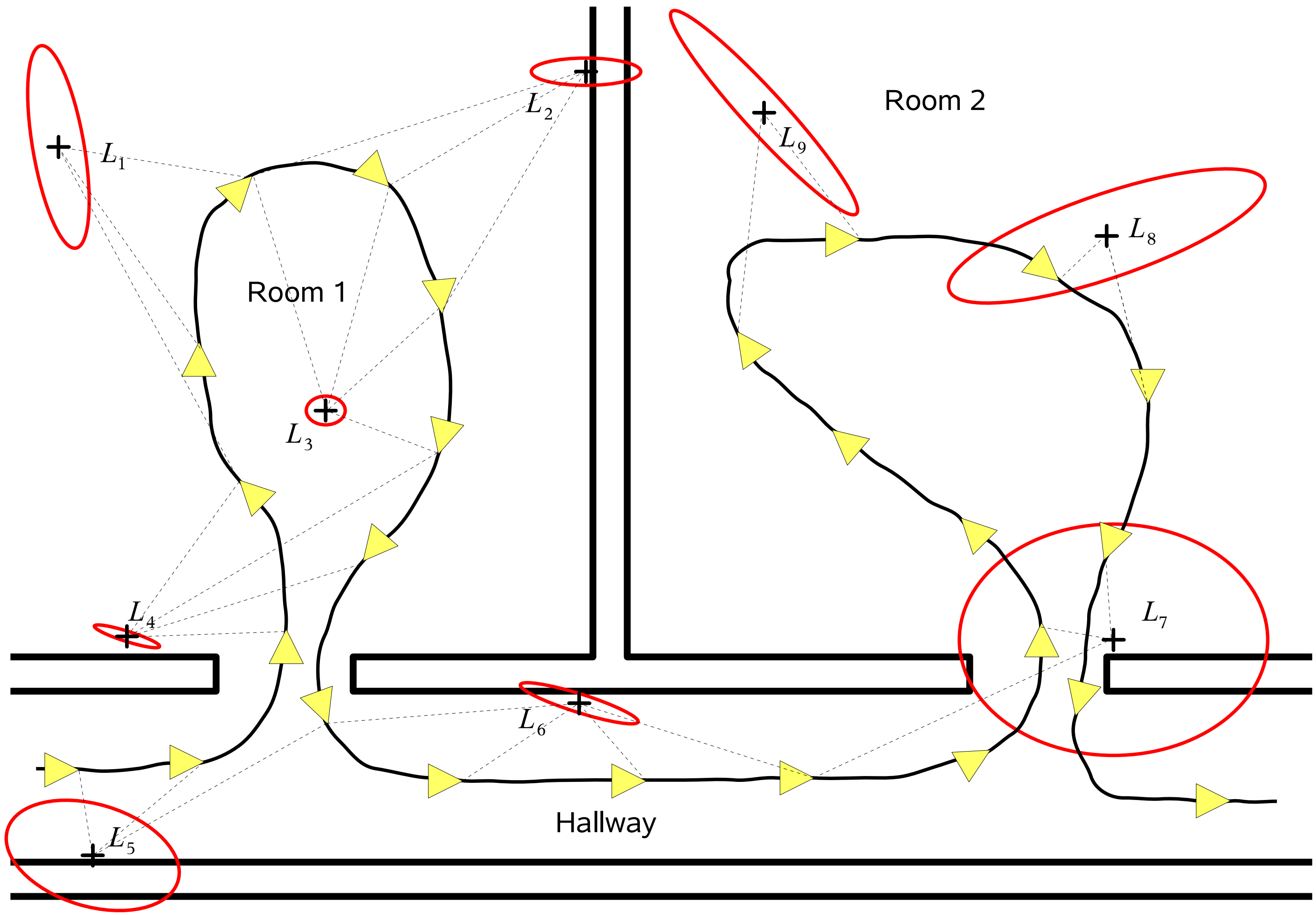
Ever growing number of Landmarks



Solution: remove landmarks with low localization benefit

state vector: $x=\left[x_v^T, x_{v_m}^T, \ldots, x_1^T, x_{f_1}^T, x_{f_2}^T, x_{f_3}^T, x_{f_4}^T, x_{f_5}^T\right]$

Which Landmark has a low benefit?



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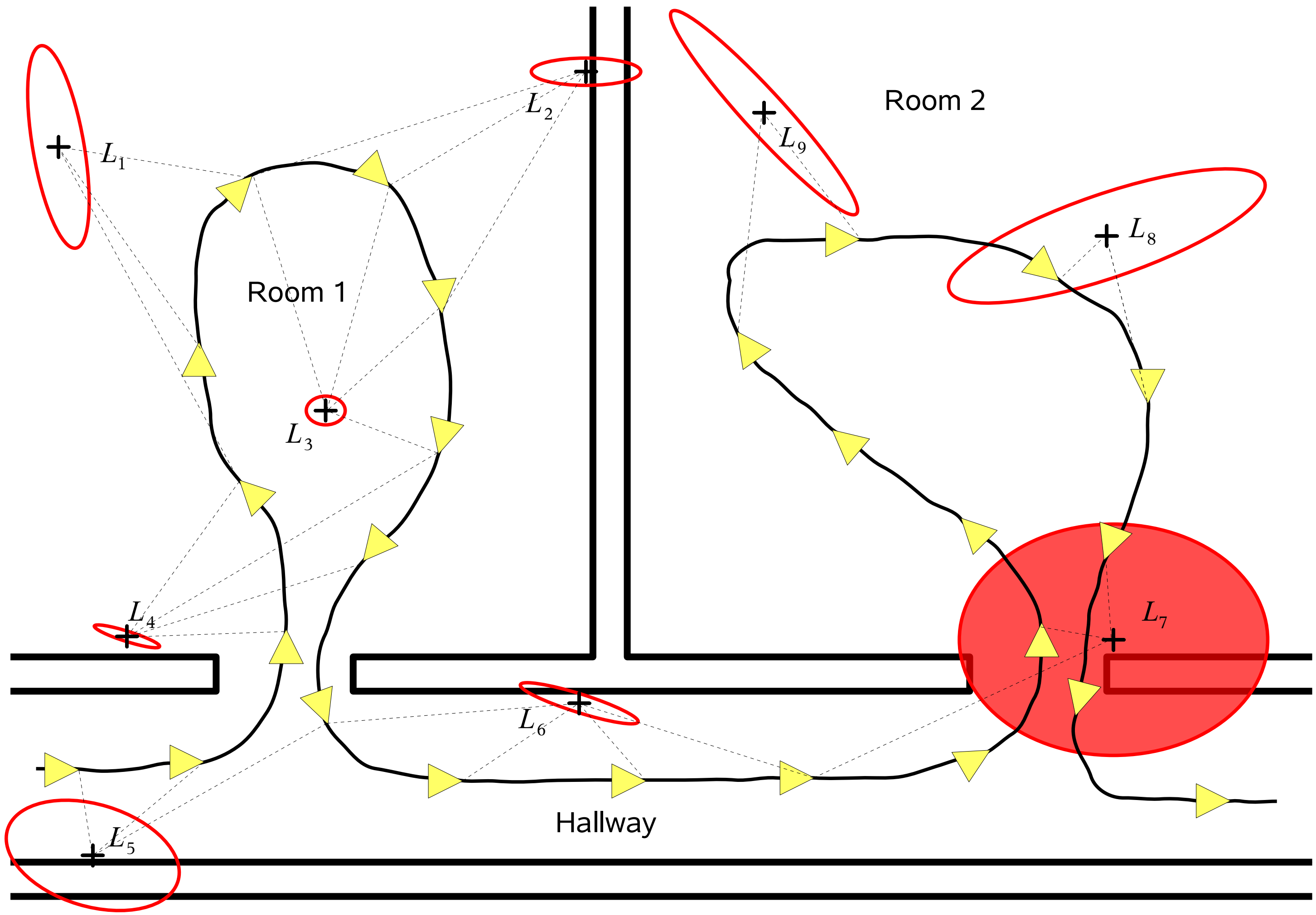
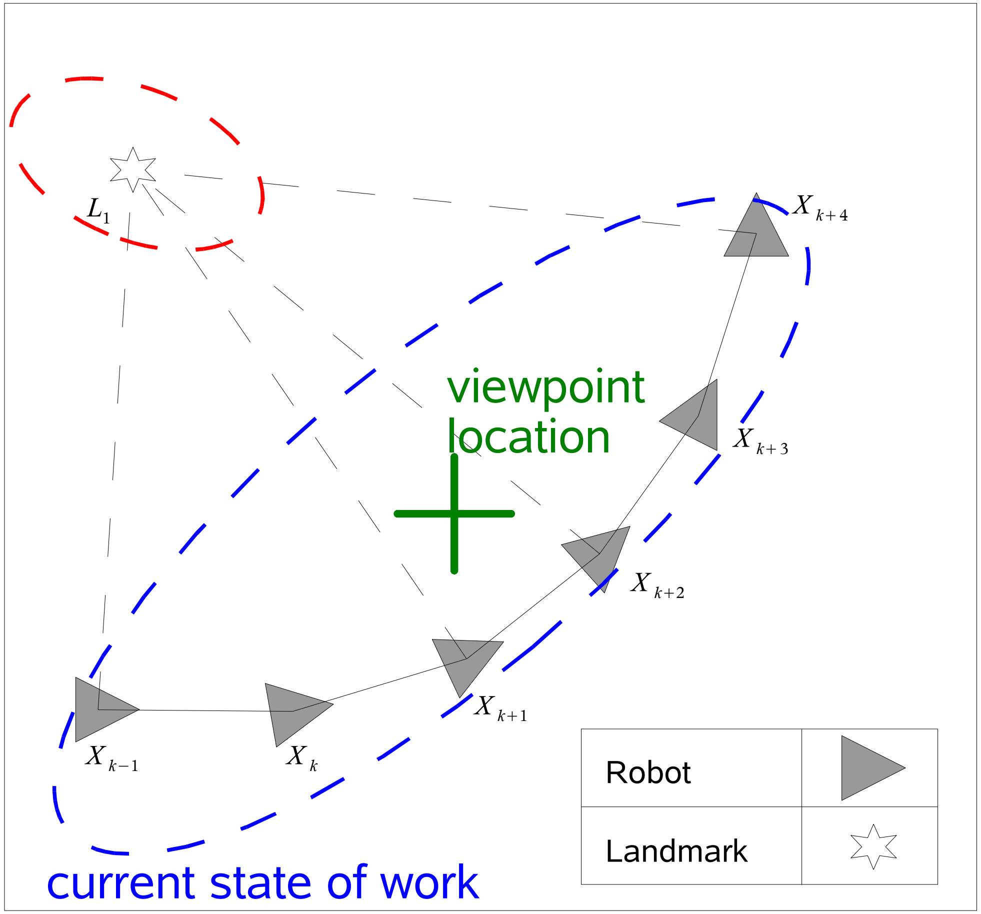


Landmark rating and selection

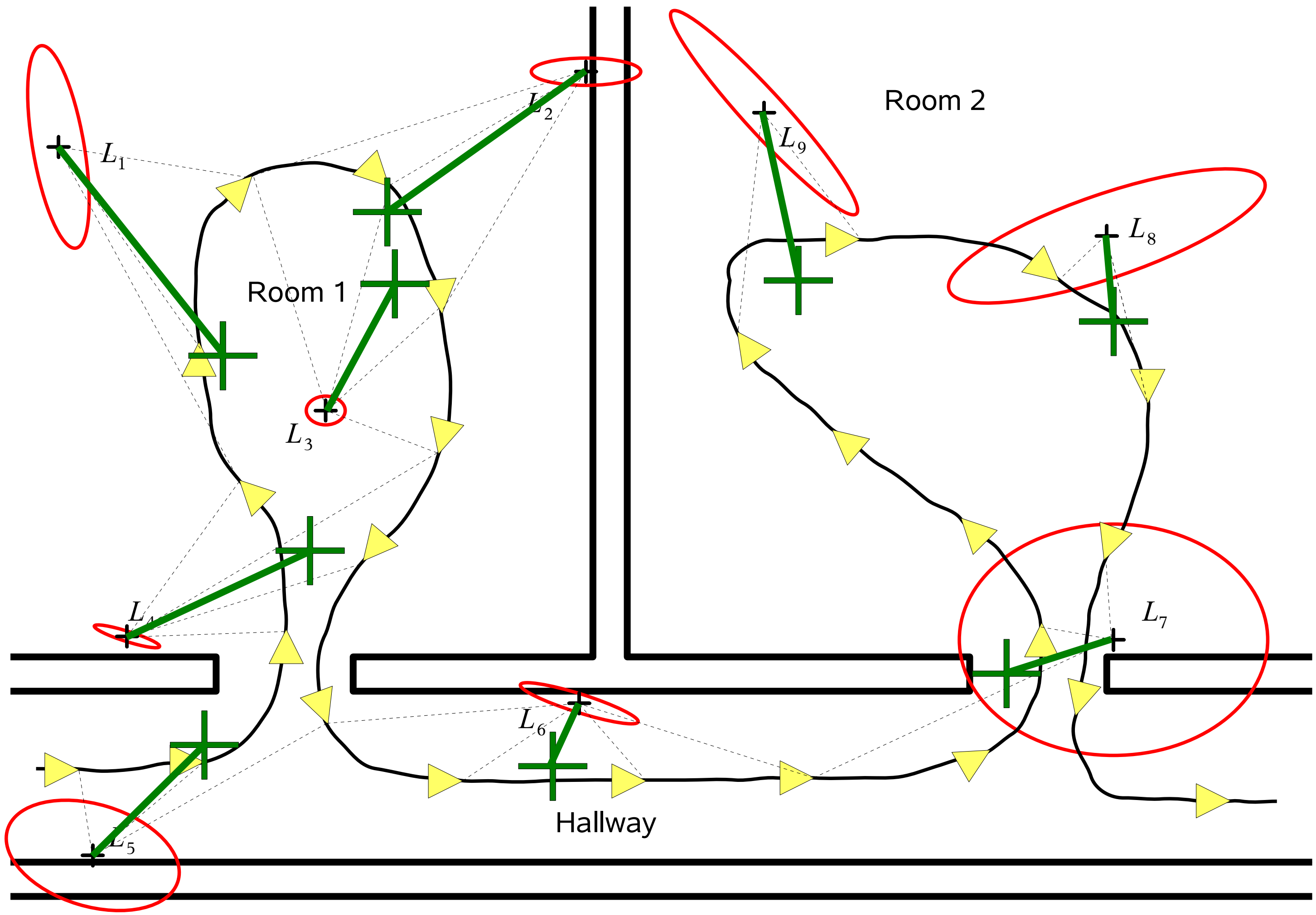


The position of a landmark does not itself give a hint on its usefulness for localizing a robot.

In fact, we require to know the poses from which a landmark can be observed to know in which parts of an environment this landmark can be used for localization purposes.

represent the observability region of each landmark by calculating arithmetic mean of the observation poses

Which Landmark has a low benefit?



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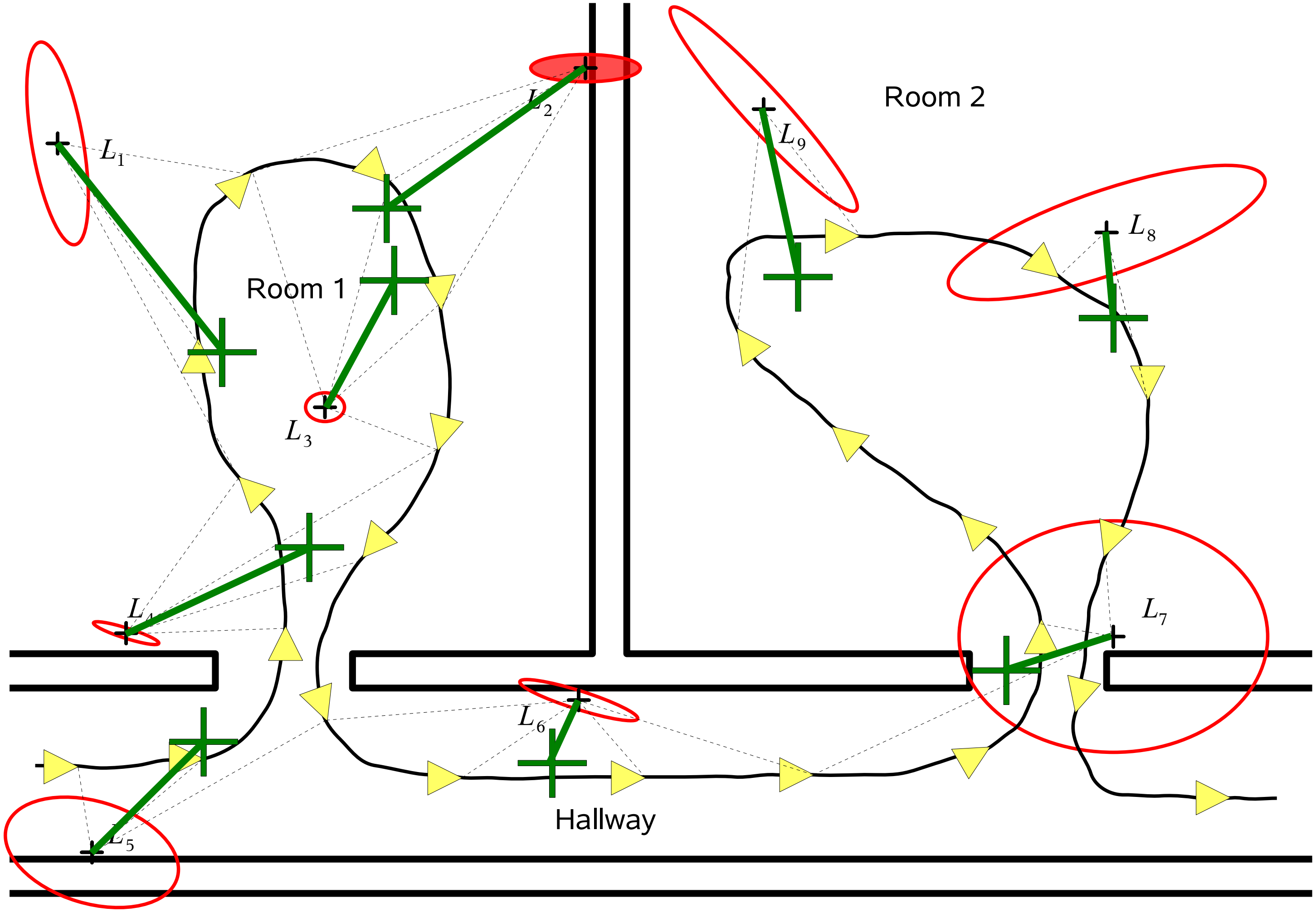
Which Landmark has a low benefit?



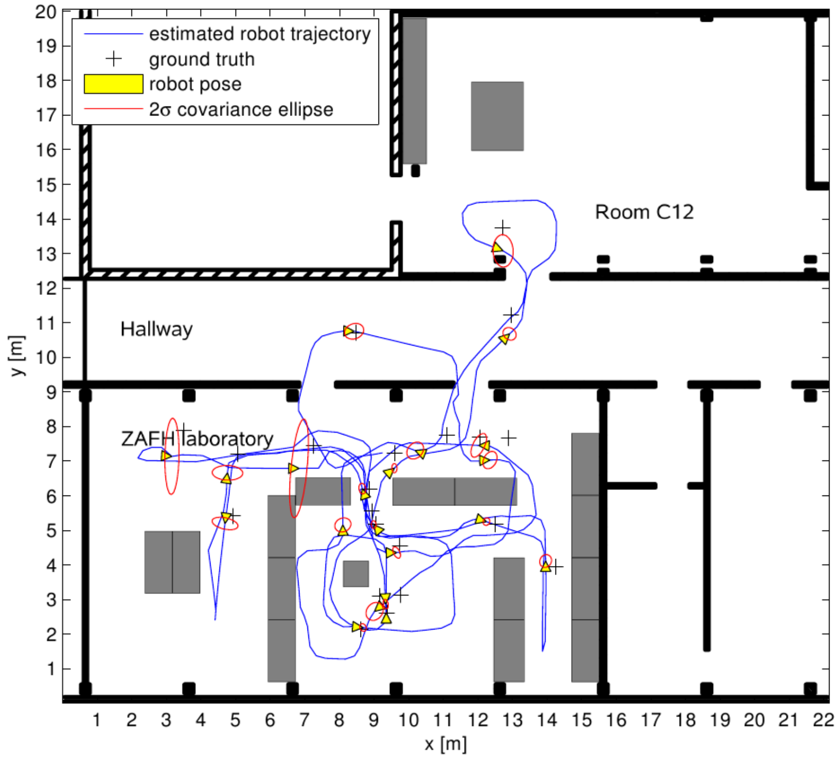
Results

Everyday Indoor Environment

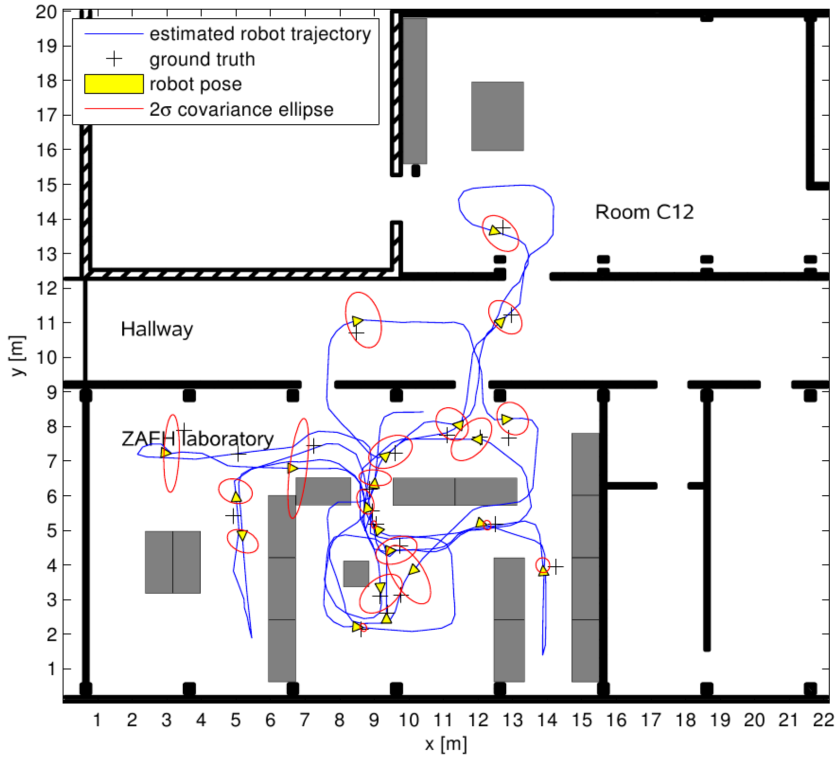



Mobile Robot
Pioneer 3DX

Results: Localization Quality

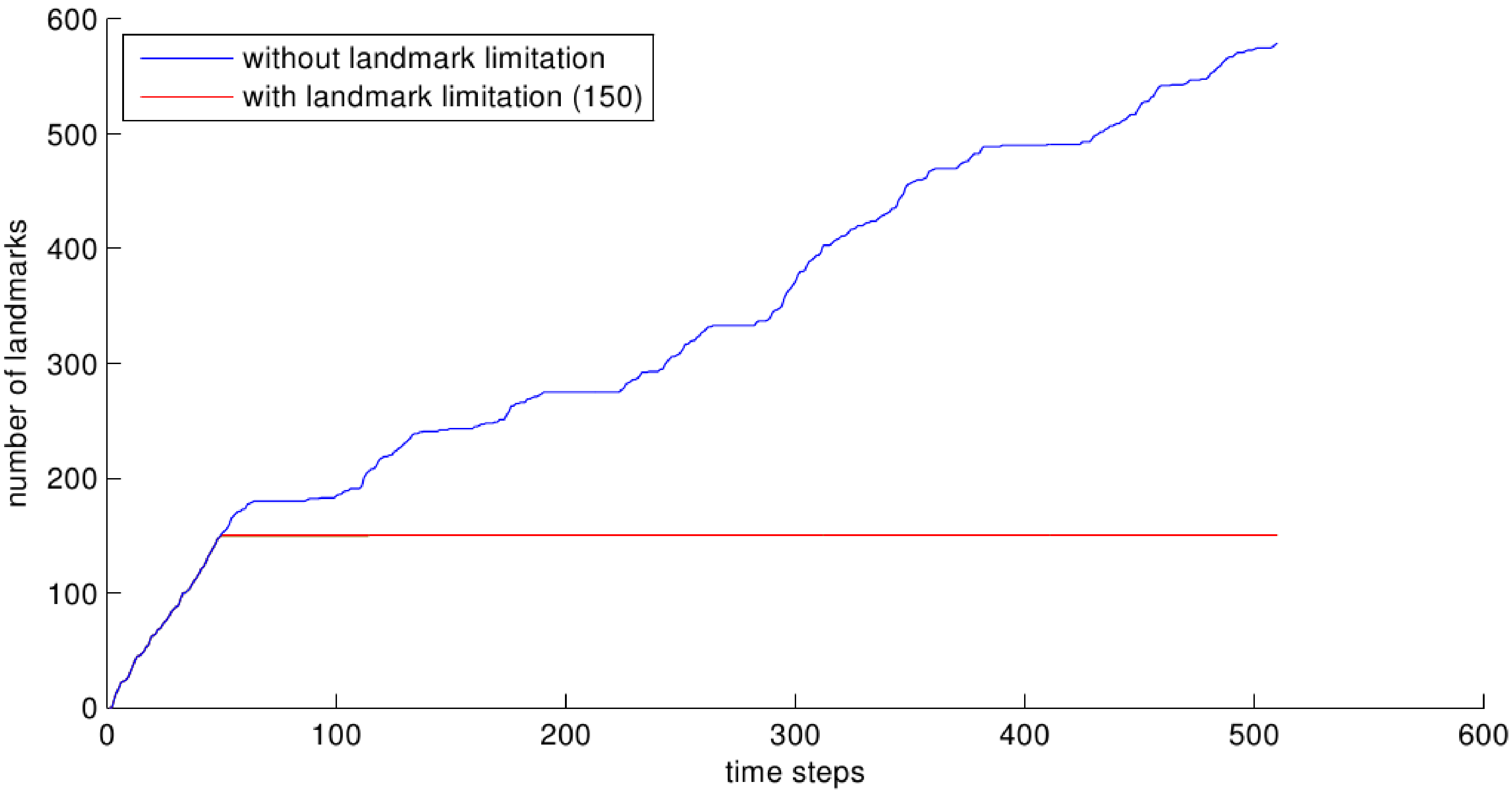


Estimated trajectory without any landmark limitations (up to 579 landmarks)



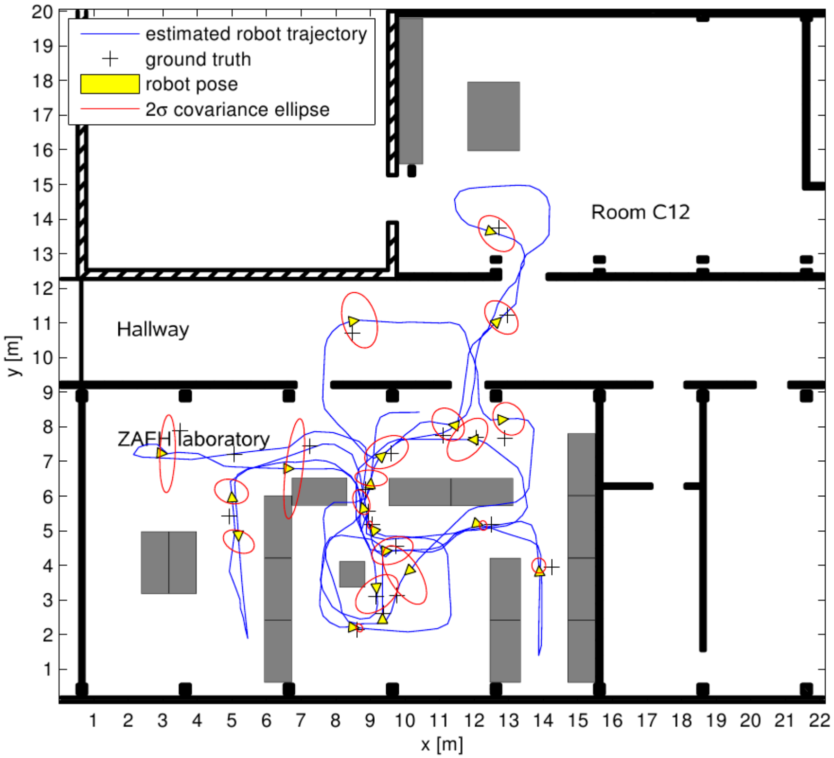
DBSCAN clustering based limitation with a maximum of 150 landmarks

Results: Localization Quality

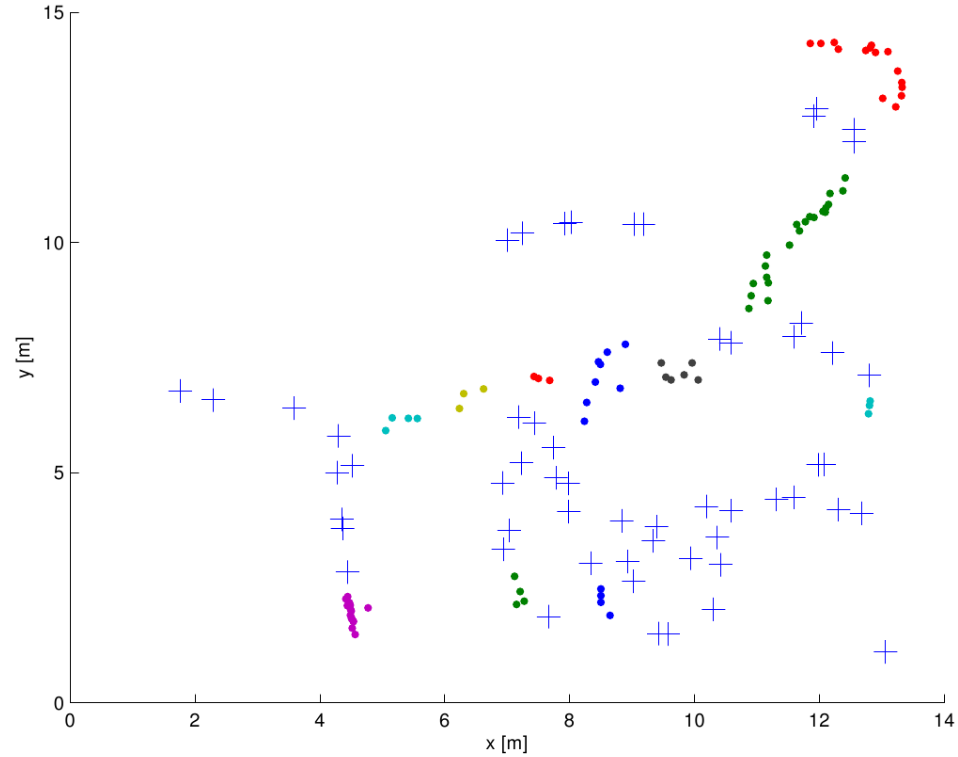


Number of landmarks during our experiment with 510 timesteps.
(Without limitation 579 and with landmark limitation 150)

Results: Landmark Coverage



Robot Trajectory during the experiment



Landmark coverage of the environment

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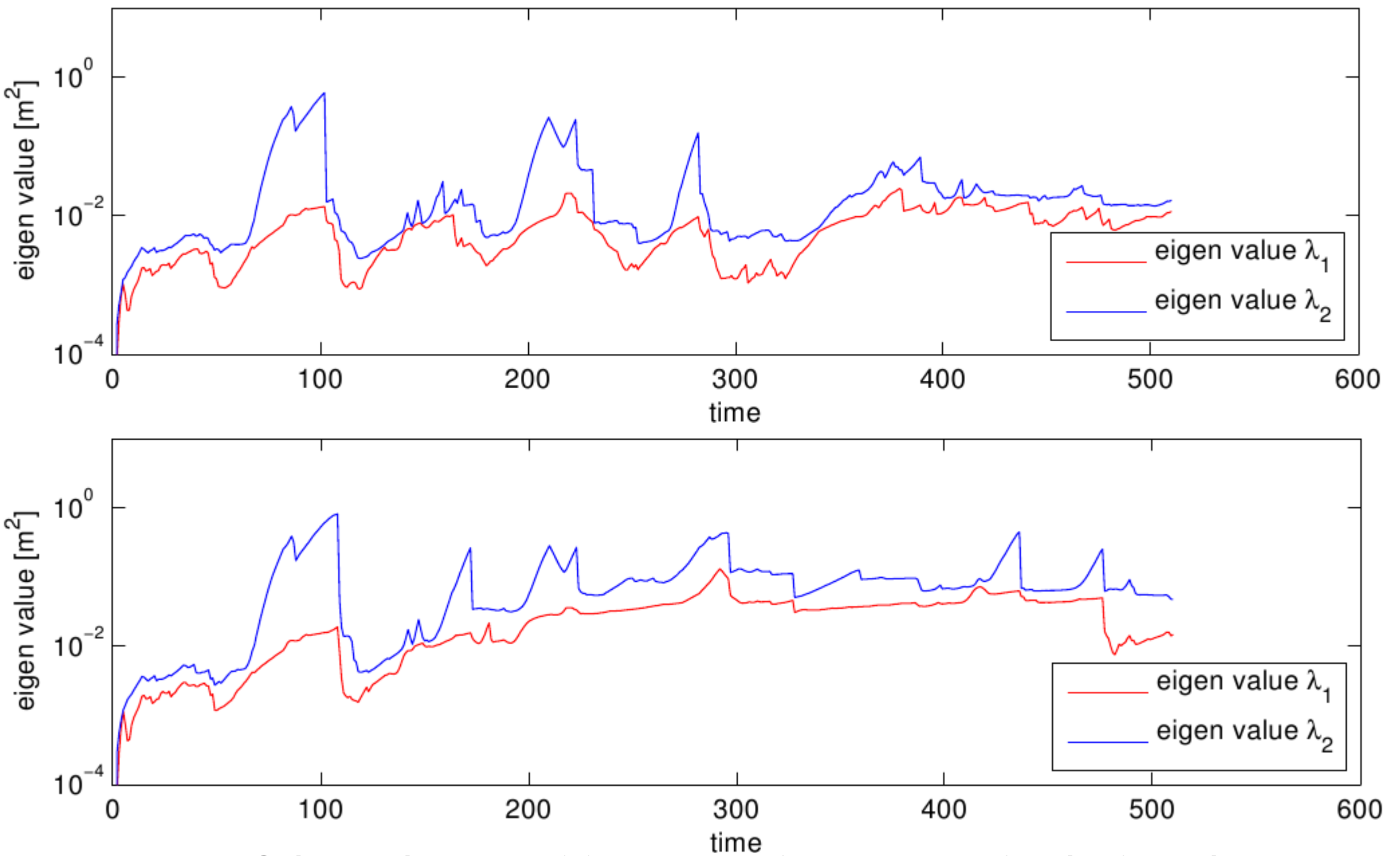
Results: Localization Quality



Eigenvalues of the robot position covariance matrix during the run without landmark limitation (top) and with restricted number of landmarks (bottom).

Video: Visual SLAM in everyday environments

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Conclusions

The proposed approach covers the operational area with landmarks in such a way that a minimum localization quality is achieved in the whole map.

Our approach to handle the problem of an ever growing number of landmarks is a further step towards lifelong operation.

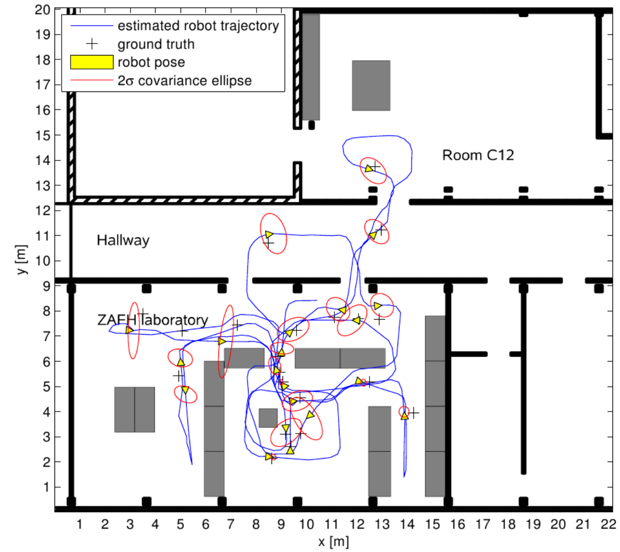
Suitability for daily use as mandatory in service robotics

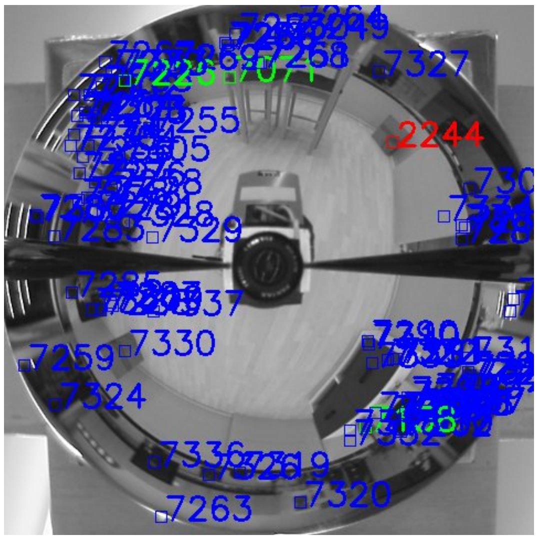
The approach can be used with all kinds of feature-based EKF SLAM approaches.

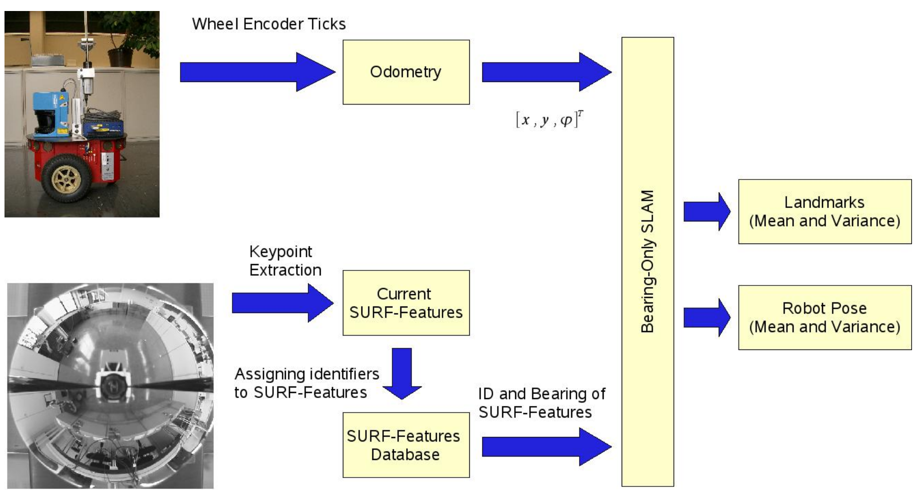
Future Work

We will focus on evaluating further approaches for landmark rating.

Questions?







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References

[1] Bailey, T. (2003). Constrainted Initialisation for Bearing-Only SLAM, Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 1966-1971, Taipei, Taiwan

[2] G. Dissanayake, H. F. Durrant-Whyte, and T. Bailey, “A Computationally Efficient Solution to the Simultaneous Localisation and Map Building (SLAM) Problem”, in IEEE International Conference on Robotics and Automation (ICRA), 2000, pp. 1009–1014.

[3] Herbert Bay, Tinne Tuytelaars and Luc Van Gool, “SURF: Speeded Up Robust Features”, in Proceedings of the ninth European Conference on Computer Vision, 2006.

Landmark quality measures:

Shannon Information
Fisher Information
Information Content (Dissanayake)

covariance matrix

$$cov(L)=\begin{bmatrix}\sigma_{xx}^2 & \sigma_{yx}^2 \\ \sigma_{xy}^2 & \sigma_{yy}^2\end{bmatrix}$$

Information content by Dissanayake[2]:

$$I_L=\frac{1}{\sigma_{xx}^2}+\frac{1}{\sigma_{yy}^2}$$

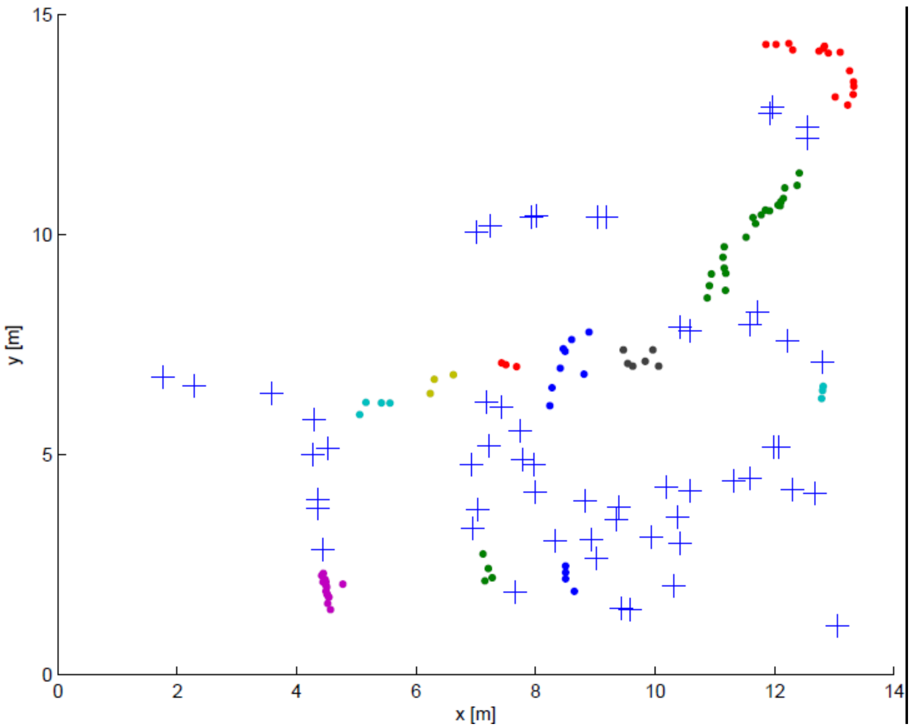
DBSCAN

density bases clustering algorithm

The algorithm typically constructs clusters around local dense maxima, separated by regions of low density.

does not need to know the number of clusters in advance

only two parameters: *MinPts* and *Eps*



JCBB (Joint Compatibility Branch and Bound)
indistinguishable features
$O(1.53^n)$
take into account „joint probabilities“

kd-tree based method
distinguishable features
$O(n \log(n))$