Multi-sensorial Real-time Localization for a Mobile Robot

PhD program - March 2003 – February 2007

Abstract: This work highlights a less common approach to the Autonomous robot navigation problem. Instead of providing the robot with an a-priori map or getting the robot to build its own map (SLAM), the robot is given a sequence of instructions that will take it to its goal. This poster presents two of the techniques that were employed 1) conversion of features into binary form 2)Using Hidden Markov Models (HMMs) to improve matching in the context of the reference sequence.

Keywords: Mobile Robot Localization, Multi-sensor integration, Binary feature integration, Reference Sequence Matching

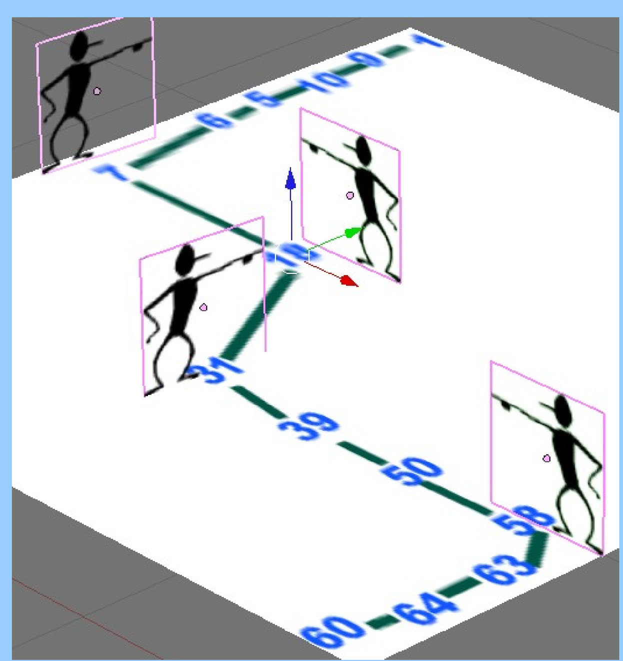
Mathematical techniques employed: Bernoulli mixture modeling, Hidden Markov Models

Problem Description

The robot is presented with a mission...to retrace a route.

➔The expected views and the required actions to keep the robot on the path must be communicated to the robot.

➔In the absence of a language, the robot is lead through the environment so that it can record the views that it will expect to find during the mission.



Methodology:

1) Place Recognition using Binary Features:

Features from each sensor are converted into binary variables and integrated into a single, binary, Feature Incidence Matrix (FIM).The features include Modified SIFT features from images (1) and multiple types of features from a 2D laser range scan (doors, walls, free-area, Hu moments) (2). The large dimensionality of the FIM is reduced by modeling it in terms of a Bernoulli Mixture and solved using the Expectation Maximisation method (3).

The integration of features from different sensors, by converting them into binary form, provides a robust and self-contained method for integrating features from dissimilar sensors (4).

2) Matching in the context of the reference sequence:

The reference sequence holds information not only because of the individual views but also as a result of the ordering of these views (5). The discontinuous nature of the HMM is taken in account by employing a profile-like HMM structure (6).

Using the Viterbi algorithm on the HMM, thus making use of the context of the reference sequence greatly improves the localization results (7).

3) Identifying criteria for better Reference Sequences:

The ability to localize within the reference sequence is only as good as the uniqueness of the views (including their context in the ref. seq.) and the ability of the robot to get to each view from the preceding one.

The concept of mutual information (8) is used to keep the views that will give the most robust reference sequence; given a set of behaviours and a set of sampled mission views

Publications:

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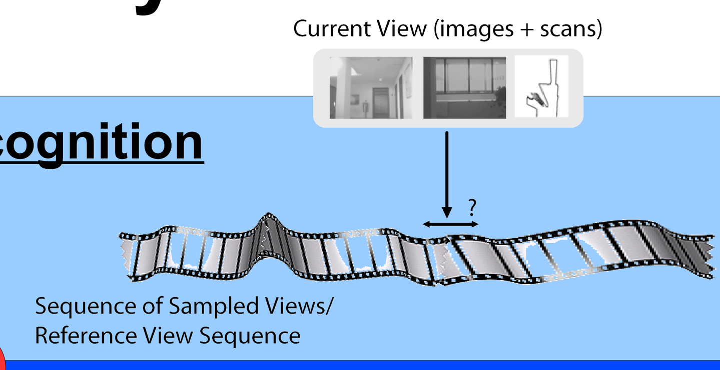
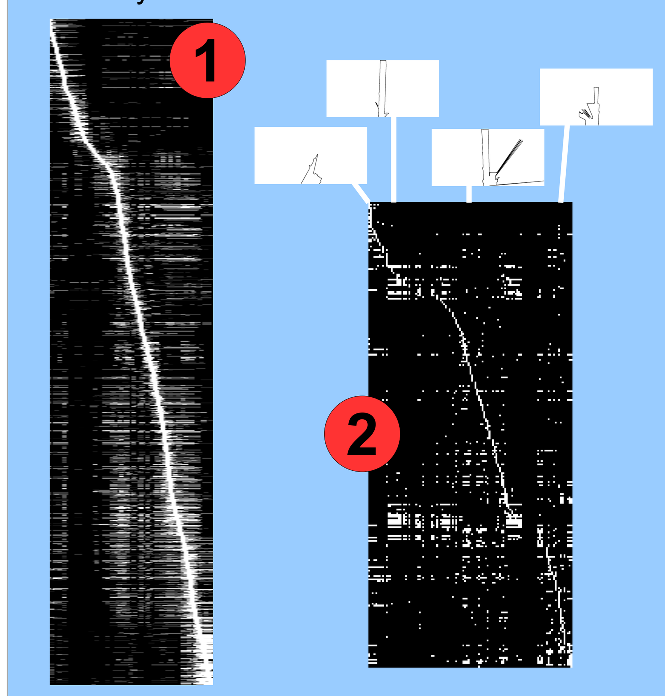
- Ferreira, F.; Santos, V. & Dias, J. A Low-level Framework for a Probabilistic Treatment of the Topological Description of a Robot Mission International Conference on Intelligent Robots and Systems, 2005
- Ferreira, F.; Santos, V. & Dias, J. Integration of Multiple Sensors Using Binary Features and a Bernoulli Mixture Model IEEE Conference on Multisensor Fusion and Integration, 2006

Part 1 – (Single view) Place Recognition





(3) Equation for Mix. model:

$$P(V^{obs}|\Theta) = \sum_{i=1}^{M} \alpha_i P_i(V^{obs}|\Theta_i)$$

Expectation step:

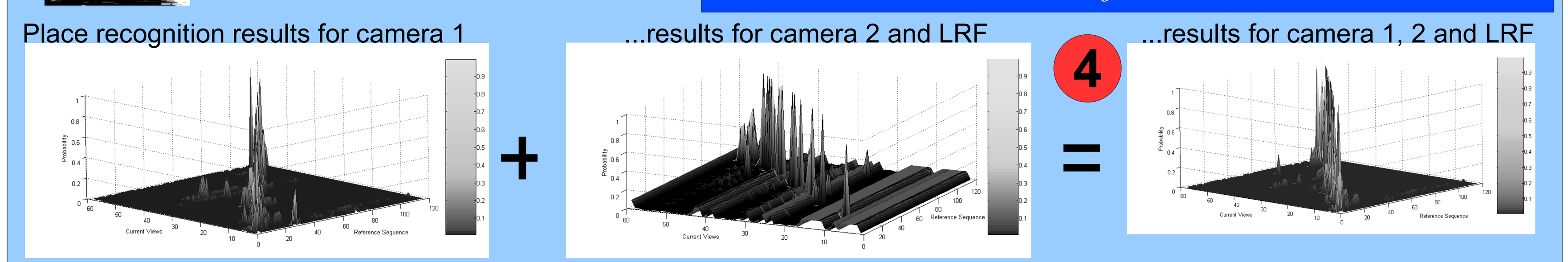
$$z_{ki} = \frac{\alpha_i P_i(V_k|\Theta_i)}{\sum_{j=1}^{M} \alpha_j P_j(V_k|\Theta_j)}$$

Maximisation step:

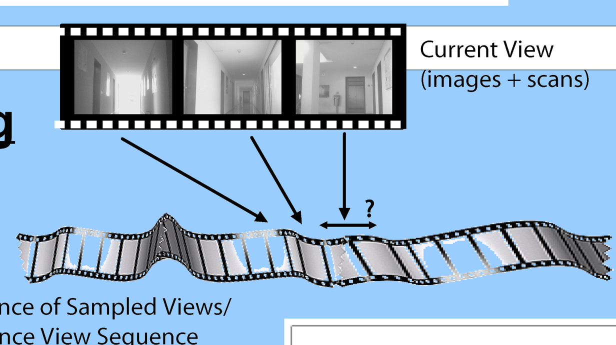
$$\Theta_i = \frac{\sum_{k=1}^{K} z_{ki} V_k}{\sum_{k=1}^{K} z_{ki}} \qquad \alpha_i = \frac{\sum_{k=1}^{K} z_{ki}}{K}$$

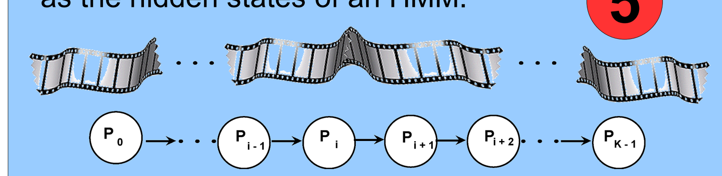
View Matching(k is matched View):

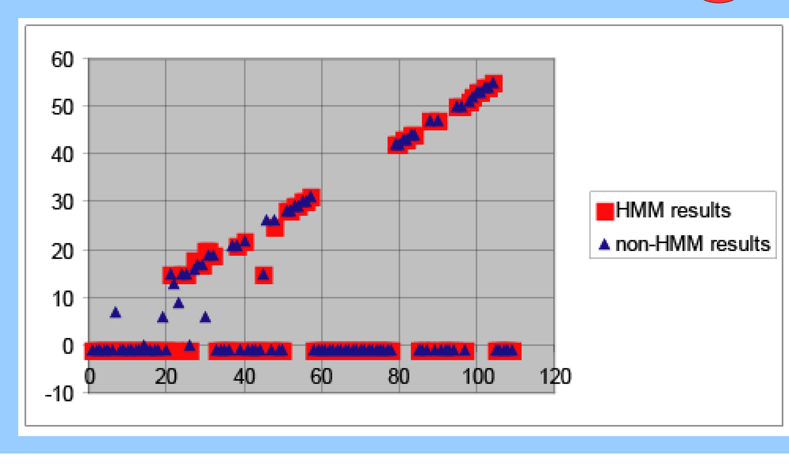
$$P(k|V^{obs}) = \frac{\sum_{j=1}^{M} P(k) z_{ki} \alpha_j P(V^{obs}|\Theta_j)}{\sum_{k=1}^{K} \sum_{j=1}^{M} P(k) z_{kj} \alpha_j P(V^{obs}|\Theta_j)}$$



Part 2 – Context Matching







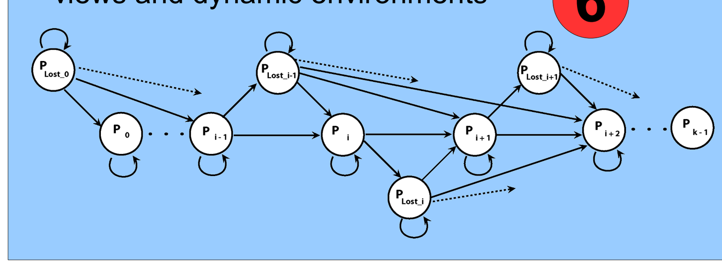
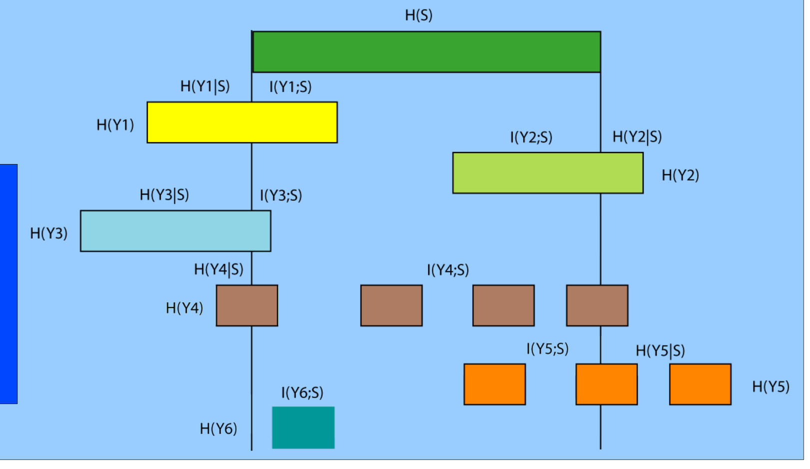


Table 1: Comparison of results showing Place-recognition failures with and without using HMMs.

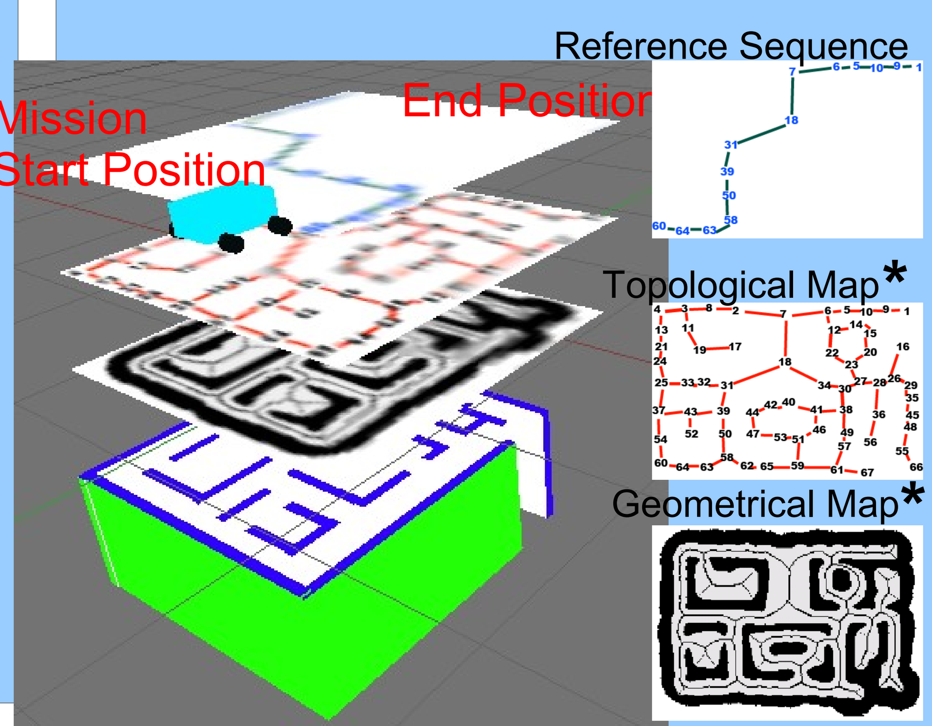
Mission Number	Reference Sequence	No-HMM failure.	HMM failure.
1	6	5	2
2	6	2	2
3	6	5	1
4	6	6	1
5	6	3	3
6	6	3	0

Part 3 – Creating better Sequences



(8) Keep Views whose mutual information is high enough. The distributions take into account the total probability of detecting the View (X is the hidden Place in the environment, the Ys correspond to the view).

$$H(X|Y_1, Y_2) = H(X) - I(Y_1; X) - I(Y_2; X)$$



Comparison with methods that use complete maps:

+ the ref. seq. can be sufficient for certain tasks (no prior mapping req.)

+ the ref. seq. could be an effective method for communication (users/robot, robot/robot).

+/- Does not substitute Mapping.

- The ref. seq. contains the least information and may perform worse than a complete map in certain environments.

*Thrun, S. Learning Metric-Topological Maps for Indoor Mobile Robot Localization Artificial Intelligence, 1998, 99, 21-71

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* was a recipient of a PhD fellowship of the University of Aveiro between Mar 2003 and Feb 2006

* is a recipient of a research scholarship under the BACS project (FP6-IST-027140) at the Faculty of Science and Technology, University of Coimbra from Sep 2006

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