

# IKO42360 Technical Report: Monte Carlo Localization (MCL)\*

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**Abstract**—You may or may not write an abstract. It is essentially a summary comprising of not more than 250 words.

## I. INTRODUCTION

This report guidance is not strict in the sense that you may *not only* add some point *but also* remove some point, yet you still obtain an optimal grade (if those addition and removal are reasonably justified). Feel free to ask TAs for any doubt.

- give some context or background
- state the problem
- state the objective
- give an overview about the method
- why choose a particular method
- give an overview about the experiment results
- outline the content

## II. THE ROBOT SIMULATION

- robot's specification?
- assumptions?

### A. Action Simulation

- assumptions?
- probability distribution?
- code listing

### B. Perception Simulation

- assumptions?
- probability distribution?
- code listing

## III. ACTION MODELS

- the theory: either odometry or velocity motion models
- assumptions, e.g. gaussian errors
- code listing
- experiment on motion model
- reproduce fig. 5.4, 5.9, 5.10 from [1]

## IV. PERCEPTION MODELS

- the theory: either beam model for range finders or feature-based measurement models
- assumptions, e.g. gaussian errors
- code listing
- tuning the intrinsic parameters
- experiment on perception model
- reproduce fig. 6.4, 6.5 from [1]

## V. KLD-SAMPLING MCL

### A. The standard MCL

- the theory
- code listing

### B. The KLD-sampling MCL

You may try other variants of MCL. If you do so, do not forget to change the title of this subsection and the section.

- the theory
- code listing

## VI. EXPERIMENTS AND RESULTS

### A. Setup

- what kind of map? assumptions?
- code listing for map constructions
- draw/illustrate the map!
- control commands? hardcoded? wall following?
- experiment design or procedure; the start state?
- evaluation metrics: errors, convergence time
- scope: localization problem type?
- is a live simulation available? excellent if one exists
- for each experiment (local, global and kidnapped-robot), reproduce fig. 8.3, 8.4, 8.7, 8.11, 8.13, 8.16, 8.17, 8.18, 8.19 from [1]. For some figures, replace “cell size” with “number of particles”

### B. Local Localization

- result, comparison: standard vs. variant
- analysis

### C. Global Localization

- result, comparison: standard vs. variant
- analysis

### D. Kidnapped-robot Problem

- result, comparison: standard vs. variant
- analysis

## VII. RELATED WORK

Discuss or review in-depth *one* related work. Each team is initially assigned different paper. This can be changed to any paper of your choice; preferably it is published in major robotics conferences, such as ICRA, IROS, RSS. For you, we have collected: [2], [3], [4], [5], [6], [7]

- what is the problem that they tackled?
- how is the proposed solution/method?
- how good is their solution? any comparisons?
- what are the limitations of their work?
- what future work or open problems do they mention?
- your opinions about the work

\*Team TA, compiled on 27/05/2014 at 9:11pm

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## VIII. CONCLUSIONS

- re-state the problem, goal briefly
- highlight the (proposed) method
- convey the results, mention the advantages of using the (proposed) method and current limitations
- some lessons-learned, some open problems

## APPENDIX

The answer to Problem 2 is explained here.

- re-state the problem, goal briefly
- formulate the  $MDP = (S, A, P_{sa}, R, \gamma)$
- code listing
- plot the values of  $V^*$  on the grid map
- plot the optimal policy  $\pi^*$  on the grid map
- analysis

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- [6] Y. Fu, S. Tully, G. Kantor, and H. Choset, “Monte carlo localization using 3d texture maps,” in *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on*, Sept 2011, pp. 482–487.
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