Autonomous Navigation and Perception (086762)
Spring 2022 - Project

General

The purpose of this project is to get the student(s) closely familiar with state of the art approaches on one of the topics covered in (or related to) the course.

Note: The project is an excellent opportunity to investigate a potential topic/direction for research thesis. Those interested are encouraged to get in touch with the lecturer ***before*** choosing the project topic.

Guidelines and Requirements

1. Choose a topic from the table below.
   Doodle poll: Specify your preference [**link to Google Drive Doc**] (first-come first-served basis, please do not alter previously-made selections)
   Deadline: *April 27th 2022*, no extensions, better to decide earlier
2. Tasks (more details below)
   (a) Choose a topic and read paper(s) from the chosen topic.
   (b) (Partial) implementation as well as method's extension/generalization are encouraged and **required** to get full credit. We also encourage relevant online demonstrations using real sensors and robots.
   (c) Oral presentation of the topic during the last two weeks of the semester: 20 minutes, unless otherwise mentioned.
   (d) Submit a report that summarizes the paper(s) presented in class.
   Deadline: Submission is due July 21th 2022 (original Moed A final exam).

Written Report:

The report should summarize the material, as you comprehend it. The summary should highlight what you consider to be the main contribution of the paper(s), but should not be a "copy-paste" from the original paper(s). The basic structure of the report should typically be as follows:

1. *Introduction and overview*: Introduce the paper(s) topic. Describe how the paper fits in with the contents of this course, provide a brief background (literature review) and explain why the problem is important.
2. *Preliminary material and problem formulation*: Present a description of relevant notations and definitions, define mathematically the problem addressed by the paper(s), and summarize any preliminary mathematical material used in the paper(s).
3. *Main contribution*: A detailed discussion of the main results of the paper(s). This should include both a qualitative discussion and a mathematical presentation (i.e. show proofs, preferably in your own style).
4. *Implementation*: Demonstrate the main results of the paper(s) using simulation and/or real-world experiments. You are free to choose the programming language as well as using open source software. This also includes testing the approaches under different conditions than those originally assumed in the paper(s), as well as extending approaches to unsupported settings/scenarios.

5. *Discussion and Conclusions*: Summarize the report and provide some criticism: identify weak points, unrealistic assumptions or aspects that could be improved and suggest possible directions (or extensions) for future research.

The report **should not exceed 10-15 pages** in length. The usage of LaTex is highly recommended for writing the report. **Note**: to get full credit, items 4 and 5 should be addressed extensively.

Oral Presentation:

The oral presentation is complementary to the written report. The presentation should be in a "lecture" style format; i.e., you will present this in front of the class with the goal of "teaching" the main points of the paper(s). It is therefore should be well organized such that participants can easily understand the key concepts. Unless otherwise mentioned, the presentation should be around **20 minutes long**, with additional time allocated for questions (up to 5 minutes). The general format of the talk should mirror the structure of the written report. All team members should take **active** part in the presentation, e.g. for teams of two members, each member should talk about 10 minutes.

Topics & Papers

#	**Topic**	**Papers**
1	DESPOT: Online pomdp planning with regularization	[21]
2	FIRM: Sampling-based feedback motion planning under motion uncertainty	[1]
3	Incremental BSP	[5]
4	Data association aware BSP	[12]
5	GP motion planning via probabilistic inference	[11]
6	Monte-carlo planning in large pomdps (POMCP)	[15]
7	Rapidly-exploring random belief trees (RRBT)	[2]
8	BSP and active SLAM	[8]
9	Information-theoretic BSP in high dim. state spaces (rAMDL)	[10]
10	Active exploration + object detection	[20, 19]
11	Simplified decision making via belief sparsification	[4]
12	Belief Roadmap	[14]
13	Sampling-based informative planning	[7]
14	QMDP-Net	[9]
15	Stochastic Motion Planning under Partial Observability	[17]
16	Heuristic Search Value Iteration for POMDPs	[16]
17	POMDPs with continuous state, action, and observation spaces	[18]
18	Information Particle Filter Tree	[6]
19	Lets-drive: Driving in a crowd by learning from tree search	[3]
20	Active object classification via MCTS	[13]

Table 1: Reading material sorted by topic.

References

[1] A.-A. Agha-Mohammadi, S. Chakravorty, and N. M. Amato. FIRM: Sampling-based feedback motion planning under motion uncertainty and imperfect measurements. *Intl. J. of Robotics Research*, 33(2):268–304, 2014.

[2] A. Bry and N. Roy. Rapidly-exploring random belief trees for motion planning under uncertainty. In *IEEE Intl. Conf. on Robotics and Automation (ICRA)*, pages 723–730, 2011.

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