Vision-Aided Navigation (086761) - Fall 2019
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 poll**]
   Deadline: by lecture #5 (*November 24th 2019*, 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 is encouraged and **required** to get full credit.
   (c) We also encourage relevant online demonstrations using real sensors and robots. In some cases, students will be able to use robots from the Autonomous Navigation and Perception Lab (ANPL). If interested, contact us for more details.
   (d) Oral presentation of the topic: 20 minutes, unless otherwise mentioned.
   (e) Submit a report that summarizes the paper(s) presented in class.
   Deadline: Submission is due last lecture

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 pages** in length. If submitted electronically, please convert to .pdf format. The usage of LaTex is highly recommended for writing the report.

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	Assigned to	Presentation date
	VAN/SLAM			
1	VAN I	[13, 19]		
2	VAN II	[20]		
3	SLAM review	[4]		
4	Qualitative mapping	[23]		
5	Bundle adjustment	[16, 22]		
	Data association and multi-robot SLAM			
6	Multi-Robot SLAM	[15]		
7	Multi-robot data association + SLAM	[12, 11]		
8	Communication Planning for multi-robot SLAM	[8]		
9	Data association + SLAM I	[7]		
10	Data association + SLAM II	[21, 2]		
11	Distributed (object-level) Mapping	[5]		
	Belief space planning (BSP), active SLAM, active exploration			
12	BSP	[25, 3]		
13	BSP and active SLAM	[10]		
14	BSP + factor graphs	[17]		
15	Data association + BSP	[24]		
16	Active exploration + object detection	[28, 27]		
17	Active object detection	[1]		
18	Efficient BSP via sparsification	[9, 6]		
	Deep learning (DL) perspective			
19	DL based camera localization & inference	[14, 18]		
20	Deep semantic localization & odometry	[26]		

Table 1: Reading material sorted by topic.

References

[1] N. Atanasov, B. Sankaran, J.L. Ny, G. J. Pappas, and K. Daniilidis. Nonmyopic view planning for active object classification and pose estimation. *IEEE Trans. Robotics*, 30:1078–1090, 2014.

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[3] 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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