Vision-Aided Navigation (086761) - Fall 2021
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 23rd 20*21, 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 February 3rd 2022 (original Moed A final exam).

Written Report:

The report should summarize the material, as you comprehend it, and importantly, provide some criticism and potentially extend formulation to overcome limitations or address more general settings. 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. **Ideally**, include a mathematical derivation/formulation that extends or overcomes a limitation(s) of the original paper(s).

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	Assigned to	Presentation date
	VAN/SLAM			
1	VAN I	[16]		
2	VAN II	[17]		
3	Qualitative mapping	[20]		
4	Bundle adjustment	[13]		
5	Bundle adjustment + scale constraint	[19]		
6	Exactly Sparse Variational Inference	[2]		
	Data association and single/multi-robot SLAM			
7	Multi-robot data association + SLAM	[11]		
8	Data association + SLAM I	[9]		
9	Data association + SLAM II	[18, 3]		
10	Data association + (Semantic) SLAM III	[24]		
11	Distributed (object-level) Mapping	[6]		
12	Distributed multi-robot semantic SLAM	[25]		
	Belief space planning (BSP), active SLAM, active exploration			
13	BSP	[22, 4]		
14	BSP and active SLAM	[10]		
15	BSP + factor graphs	[14]		
16	Data association + BSP	[21]		
17	Active exploration + object detection	[27, 26]		
18	Active object detection	[1]		
19	Simplified decision making in the belief space	[7]		
	Deep learning (DL) perspective			
20	DL based camera localization & inference	[12, 15]		
21	Deep semantic localization & odometry	[23]		
22	Semantic perception and SLAM	[8]		
23	Driving in a crowd by learning from tree search	[5]		

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.

[2] Timothy D Barfoot, James R Forbes, and David Yoon. Exactly sparse gaussian variational inference with application to derivative-free batch nonlinear state estimation. *Intl. J. of Robotics Research*, 2020.

[3] S. Bowman, N. Atanasov, K. Daniilidis, and G. Pappas. Probabilistic data association for semantic slam. In *IEEE Intl. Conf. on Robotics and Automation (ICRA)*, pages 1722–1729. IEEE, 2017.

[4] 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.

[5] Panpan Cai, Yuanfu Luo, Aseem Saxena, David Hsu, and Wee Sun Lee. Lets-drive: Driving in a crowd by learning from tree search. In *Robotics: Science and Systems (RSS)*, 2019.

[6] Siddharth Choudhary, Luca Carlone, Carlos Nieto, John Rogers, Henrik I Christensen, and Frank Dellaert. Distributed mapping with privacy and communication constraints: Lightweight algorithms and object-based models. *Intl. J. of Robotics Research*, 36(12):1286–1311, 2017.

[7] Khen Elimelech and Vadim Indelman. Simplified decision making in the belief space using belief sparsification. *Intl. J. of Robotics Research*, 2021. Accepted, ArXiv: https://arxiv.org/abs/1909.00885.

[8] Y. Feldman and V. Indelman. Spatially-dependent bayesian semantic perception under model and localization uncertainty. *Autonomous Robots*, 2020.

[9] D. Fourie, J. Leonard, and M. Kaess. A nonparametric belief solution to the bayes tree. In *IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS)*, 2016.

[10] V. Indelman, L. Carlone, and F. Dellaert. Planning in the continuous domain: a generalized belief space approach for autonomous navigation in unknown environments. *Intl. J. of Robotics Research*, 34(7):849–882, 2015.

[11] V. Indelman, E. Nelson, J. Dong, N. Michael, and F. Dellaert. Incremental distributed inference from arbitrary poses and unknown data association: Using collaborating robots to establish a common reference. *IEEE Control Systems Magazine (CSM), Special Issue on Distributed Control and Estimation for Robotic Vehicle Networks*, 36(2):41–74, 2016.

[12] Alex Kendall, Matthew Grimes, and Roberto Cipolla. Posenet: Convolutional networks for real-time 6-dof camera relocalization. In *Intl. Conf. on Computer Vision (ICCV)*, 2015.

[13] K. Konolige and M. Agrawal. FrameSLAM: from bundle adjustment to realtime visual mapping. *IEEE Trans. Robotics*, 24(5):1066–1077, 2008.

[14] D. Kopitkov and V. Indelman. No belief propagation required: Belief space planning in high-dimensional state spaces via factor graphs, matrix determinant lemma and re-use of calculation. *Intl. J. of Robotics Research*, 36(10):1088–1130, August 2017.

[15] D. Kopitkov and V. Indelman. Robot localization through information recovered from cnn classificators. In *IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS)*. IEEE, October 2018.

[16] S. Leutenegger, S. Lynen, M. Bosse, R. Siegwart, and P. Furgale. Keyframe-based visual-inertial odometry using nonlinear optimization. *Intl. J. of Robotics Research*, 2014.

[17] T. Lupton and S. Sukkarieh. Visual-inertial-aided navigation for high-dynamic motion in built environments without initial conditions. *IEEE Trans. Robotics*, 28(1):61–76, Feb 2012.

[18] Beipeng Mu, Shih-Yuan Liu, Liam Paull, John Leonard, and Jonathan How. Slam with objects using a nonparametric pose graph. In *IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS)*, 2016.

[19] V. Ovechkin and V. Indelman. Bafs: Bundle adjustment with feature scale constraints for enhanced estimation accuracy. *IEEE Robotics and Automation Letters (RA-L)*, 3(2):804–810, 2018.

[20] Jennifer Padgett and Mark Campbell. Probabilistic qualitative mapping for robots. *Robotics and Autonomous Systems*, 98:292–306, 2017.

[21] S. Pathak, A. Thomas, and V. Indelman. A unified framework for data association aware robust belief space planning and perception. *Intl. J. of Robotics Research*, 32(2-3):287–315, 2018.

[22] S. Prentice and N. Roy. The belief roadmap: Efficient planning in belief space by factoring the covariance. *Intl. J. of Robotics Research*, 28(11-12):1448–1465, 2009.

[23] N. Radwan, Valada A., and Burgard W. Vlocnet++: Deep multitask learning for semantic visual localization and odometry. *IEEE Robotics and Automation Letters (RA-L)*, 2018.

[24] V. Tchuiev, Y. Feldman, and V. Indelman. Data association aware semantic mapping and localization via a viewpoint-dependent classifier model. In *IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS)*, 2019.

[25] V. Tchuiev and V. Indelman. Semantic distributed multi-robot classification, localization, and mapping with a viewpoint dependent classifier model. *IEEE Robotics and Automation Letters (RA-L)*, 5(3):4649–4656, 2020.

[26] WT Teacy, Simon J Julier, Renzo De Nardi, Alex Rogers, and Nicholas R Jennings. Observation modelling for vision-based target search by unmanned aerial vehicles. In *Intl. Conf. on Autonomous Agents and Multiagent Systems (AAMAS)*, pages 1607–1614, 2015.

[27] Javier Velez, Garrett Hemann, Albert S Huang, Ingmar Posner, and Nicholas Roy. Modelling observation correlations for active exploration and robust object detection. *J. of Artificial Intelligence Research*, 2012.