TECHNISCHE UNIVERSITÄT MÜNCHEN
Human-centered Assistive Robotics
UNIV.-PROF. DR.-ING. DONGHEUI LEE

April 22, 2021

ADVANCED SEMINAR (AUTONOMOUS SYSTEMS)

Overview of Course

Procedure

The advanced seminar course consists of the following events, which will be announced on TUMonline:

1. *Kick-off Meeting* – presentation of potential individual topics by supervisors and description of the schedule for the advanced seminar.
2. *Report Submission* – submission of the final report, final presentation, and electronic copies of all publications that were read or reviewed during the advanced seminar.
3. *Final Presentation* – each participant will present their findings of their advanced seminar.

Please note that *participation in all events is a requirement for successful completion of the advanced seminar*. Participation will be documented by means of an attendance list.

Timeline

Event	Date	Time & Venue
Kick-off Meeting	23.04.2021	10:00 – 11:00 (Online)
Submission of Final Report and Materials	12.07.2021	15:00 (Room 5006*)
Final Presentation	16.07.2021	10:00 – 11:30 (Online or Room 5016@2906*)

* – Rooms 5006 and 5016@2906 are located on the fifth floor in Karlstr. 45, 80333 München.

Note: A Zoom link will be provided for online meetings. The final presentation *may* be conducted in person, should the COVID situation allow it.

Final Report: Submission Protocol

As partial fulfillment of the course's requirements, a printed copy of your report and a CD containing required materials have to be submitted by 12.07.2021 (no later than 15:00). Thus, the presentation must be finished by the deadline. These items must be delivered to Room 5006 (fifth floor of Karlstr. 45 building) to the course organizer. The final report should be about 10 pages (excluding the title page, table of contents, and bibliography) and must be written using LaTeX (we recommend using *Overleaf*). Your supervisor will provide you with the template for the presentation and the report. The second page of the report has to contain the assigned topic sheet. The report should only be stapled two times on the left side (no spiral or adhesive binding).

The CD must contain the following materials: 1) your final presentation, 2) your final report, and 3) any and all relevant scientific material. The CD should be composed of two directories: *Documents* and *Presentation*. In the documents directory, either a Microsoft word document or all Latex files (including images) should be present as an archived .ZIP file. In addition, a .PDF copy of your report should be present in this directory. The presentation directory should contain a PowerPoint presentation, which is either in a native PowerPoint format (e.g., .PPT) or a .PDF format. All relevant (electronic) references have to be saved on the CD as a .ZIP file entitled "References".

Final Presentation

The duration of the final presentation is *10 minutes maximum*. You may ask your supervisor or organizer to provide you with a PowerPoint template for your presentation. After the presentation, a 5 minute discussion will take place in which everyone should actively participate. Your contribution to the discussion will be considered for thee final grade. It is compulsory to attend all presentations.

Literature Review

The literature review should be carried out independently. Your supervisor will support you by providing appropriate reference books, scientific papers, and other pertinent materials. To facilitate your introduction to the topic, your supervisor will also provide a list of introductory articles along with a problem definition.

Role of Supervisors

The supervisor is the reference person in case of any inquiries. You and your supervisor should agree on the specifics of the topic and identify expectations. The supervisor will support you in technical matters, final report preparation and proofreading, and presentation of the results. If desired, students can practice their presentations prior to the final presentations in order to get some feedback on presentation style and content. Your supervisor may also provide you with access to the workstations available for students and can introduce you to the computer programs or platforms required to complete the seminar project.

Note: It is necessary that the written report and the final presentation are submitted to the supervisor *at least 1 week before the deadline*.

Grading

Your grade for the advanced seminar is based on the template attached below. This assessment template contains various criterion related to the preparation of the advanced seminar, the final report, final presentation, and participation during the discussion session that follows each presentation.

Please note the following:

Item	Criteria Description	Grade
	Preparation Phase	
1	**Introduction**: understanding and overview given the difficulty of the task	—
2	**Contribution**: creativity, innovation, initiative, self-organization, decisiveness	—
3	**Organization**: organization, time management, persistence and diligence	—
4	**Scientific Work**: rigor, systematic approach, analysis of results	—
	Final Report (Documentation)	
5	**Formatting**: structure, completeness, sources, formatting, and graphic design	—
6	**Didactics**: style, expression, comprehension, conciseness of pictures and diagrams	—
7	**Scientific Content**: technical correctness, discussion and evaluation of results	—
	Participation	
8	**Discussion**: active participation in discussion during presentations	—
	Final Presentation	
9	**Technical Content**: scientific content, classification and evaluation, discussion	—
10	**Presentation**: presentation style, adherence to time, clear slides and videos, etc.	—

Regulations for Absence

There are strict regulations concerning unexcused absence from the advanced seminar. *Unexcused absence in any of the advanced seminar events will lead to failure in the course.* In case of illness, a doctor's certificate must be presented. Overlap with other courses is not a sufficient excuse, as a decision must be made in favor of one course at the beginning of the semester.

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I have fully read and acknowledge the above information and guidelines for the advanced seminar course.

Matriculation Number: ______________________

Full Name (First Name, Last Name): ______________________

Date, Place: ______________________

Signature: ______________________

TECHNISCHE UNIVERSITÄT MÜNCHEN
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April 18, 2021

A D V A N C E D S E M I N A R
for
Student's name, Mat.-Nr. 0815

A survey of self-supervised learning for robot's perception

Problem description:

Self-supervised learning focuses on learning the representation based on the input data itself, rather than relying on the manually labelled data [2]. For example, if there are N images of various objects, one can transform (i.e., random color jittering, random crop,...) a single image in a various way. Then, if one can get two differently transformed images from the single image, they can be labelled as a positive pair, while two transformed images from different two images can be labelled as a negative pair. Based on this self-supervised learning approach, a neural network based models can employ lots of data for training without the manual labels, and learn the representation of data without biases inside human labels. These self-supervised learning(SSL) based approaches are also deeply discussed in the field of robotics [4, 3], and the aim of this seminar is to conduct a survey of SSL-based methodologies in robotics. In addition, one would be encouraged to conduct survey about SSL-based methodologies in the research of computer vision and reinforcement learning [1, 5], so that one's idea of how to apply SSL-based methods to robotics can be fully discussed with the supervisor.

Bibliography:

[1] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. *arXiv preprint arXiv:2002.05709*, 2020.

[2] Virginia R de Sa. Learning classification with unlabeled data. In *Advances in neural information processing systems*, pages 112–119, 1994.

[3] Ashvin Nair, Dian Chen, Pulkit Agrawal, Phillip Isola, Pieter Abbeel, Jitendra Malik, and Sergey Levine. Combining self-supervised learning and imitation for vision-based rope manipulation. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pages 2146–2153. IEEE, 2017.

[4] Pierre Sermanet, Corey Lynch, Yevgen Chebotar, Jasmine Hsu, Eric Jang, Stefan Schaal, Sergey Levine, and Google Brain. Time-contrastive networks: Self-supervised learning from video. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1134–1141. IEEE, 2018.

[5] Andy Zeng, Shuran Song, Stefan Welker, Johnny Lee, Alberto Rodriguez, and Thomas Funkhouser. Learning synergies between pushing and grasping with self-supervised deep reinforcement learning. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 4238–4245. IEEE, 2018.

Supervisor: Dr. Hyemin Ahn

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TECHNISCHE UNIVERSITÄT MÜNCHEN

Human-centered Assistive Robotics

UNIV.-PROF. DR.-ING. DONGHEUI LEE

April 18, 2021

A D V A N C E D   S E M I N A R
for
N.N., Mat.-Nr. XXXXXXX

Stability of first order DS for motion generation and learning of robotic tasks

Problem description:

Dynamical Systems (DS) have recently emerged as a powerful tool for motion generation and task modeling, lending themselves well to machine learning frameworks. Beyond simple motions, they have also been used for modeling robotic catching of flying objects, hybrid force-motion control , human intent estimation and task adaptation, and incremental learning of robotic skills, to name a few. One of the main important features that DS possess is their ability to generate stable motions with guaranteed convergence to a point attractor or a limit cycle. This becomes possible by making use of intuitive and well known concepts in control theory such as Lyapunov functions [2] where often the stability requirements are incorporated a-priori as constraints during the learning phase, where the learning is formulated as an optimization problem. On the other hand, other works force the stability constraints on the fly while the robot is executing the motion, for instance by using Contraction theory [3], or Energy tanks [1]. In this seminar, the aim is to understand and review the different methods used for ensuring the stability of first order DS, used in the context of motion generation and learning of robotic tasks.

- Understand the concept of DS and their use for generating stable motions.
- Review the different existing methods used for ensuring the stability of DS.

Bibliography:

[1] C. Blocher, M. Saveriano, and D. Lee. Learning stable dynamical systems using contraction theory. In *2017 14th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI)*, pages 124–129, 2017.

[2] S. Mohammad Khansari-Zadeh and Aude Billard. Learning stable nonlinear dynamical systems with gaussian mixture models. *Trans. Rob.*, 27(5):943–957, October 2011.

[3] M. Saveriano. An energy-based approach to ensure the stability of learned dynamical systems. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pages 4407–4413, 2020.

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TECHNISCHE UNIVERSITÄT MÜNCHEN
Human-centered Assistive Robotics
UNIV.-PROF. DR.-ING. DONGHEUI LEE

April 14, 2021

A D V A N C E D   S E M I N A R

Sample-Efficient Reinforcement Learning for Robotic Applications

Problem description:

Current robotic applications of reinforcement learning (RL) are mostly based on on end-to-end deep reinforcement learning algorithms due to their capability of handling high-dimensional input data (e.g. images) and of automatically identifying relevant features for the execution of robotic tasks [5]. However, despite the remarkable initial success for robot control [4], these techniques requires an impractical large number of training instances and an unreasonable amount of time to produce adequate behaviours. The focus of this survey is to identify RL approaches that tackle this low sample efficiency of current deep RL methods [1, 3, 2].

Bibliography:

[1] A. Agostini and E. Celaya. A Competitive Strategy for Function Approximation in Q-learning. In *Proceeding of the 22nd International Joint Conference on Artificial Intelligence (IJCAI'11)*, pages 1146–1151. AAAI Press, 2011.
[2] Jacob Buckman, Danijar Hafner, George Tucker, Eugene Brevdo, and Honglak Lee. Sample-efficient reinforcement learning with stochastic ensemble value expansion. In *Advances in Neural Information Processing Systems*, pages 8224–8234, 2018.
[3] Todd Hester and Peter Stone. Texplore: real-time sample-efficient reinforcement learning for robots. *Machine learning*, 90(3):385–429, 2013.
[4] Sergey Levine, Peter Pastor, Alex Krizhevsky, Julian Ibarz, and Deirdre Quillen. Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. *The International Journal of Robotics Research*, 37(4-5):421–436, 2018.
[5] Niklas Wahlström, Thomas B Schön, and Marc Peter Deisenroth. From pixels to torques: Policy learning with deep dynamical models. *arXiv preprint arXiv:1502.02251*, 2015.

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TECHNISCHE UNIVERSITÄT MÜNCHEN
Human-centered Assistive Robotics
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April 20, 2021

A D V A N C E D   S E M I N A R

Review about action recognition for robot learning

Problem description:

Learning from Demonstration has gathered big attention in state of the art of robot programming [1]. Hereby, it is often beneficial to transfer the observed behavior not directly to the robot but in the form of so called skills or actions. These skills consider the robot's and environmental constraints during execution. There exist already some references that review this topic to some extent [4, 3, 2]. However, the aspect of robot learning is not always considered and some reviews might no longer be up to date.

In detail, do a literature survey on the mentioned topic and consider these research questions in your advanced seminar:

- How are the skills observed (vision & motion markers, kinesthetic teaching, force sensors, demonstration tool)?
- Which methods are used to recognize/classify the skill?
- Analyze how these skills are considered in a robot learning problem
- Do such skills relate to meaningful robot operations?
- Which of these approaches could be used in an industrial robot programming setup?

From these research questions, we will derive a structure for your review report.

Bibliography:

[1] S. Calinon and D. Lee. Learning control. In P. Vadakkepat and A. Goswami, editors, *Humanoid Robotics: a Reference*. Springer, 2018.
[2] Volker Krüger, Danica Kragic, Aleš Ude, and Christopher Geib. The meaning of action: A review on action recognition and mapping. *Advanced robotics*, 21(13):1473–1501, 2007.
[3] Lei Wang, Du Q Huynh, and Piotr Koniusz. A comparative review of recent kinect-based action recognition algorithms. *IEEE Transactions on Image Processing*, 29:15–28, 2019.
[4] Zhongxiang Zhou, Rong Xiong, Yue Wang, and Jiafan Zhang. Advanced robot programming: a review. *Current Robotics Reports*, pages 1–8, 2020.

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TECHNISCHE UNIVERSITÄT MÜNCHEN
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April 21, 2021

A D V A N C E D   S E M I N A R

Review of grasping technologies for bin picking applications in industrial scenarios

Problem description:

Picking random objects in not-known positions is still a complex task for robotic applications in industrial scenarios [1]. As a matter of facts, market ready systems for solving this issue (e.g. Keyence® Robot Vision) can be come expensive. Therefore, if this task need to be implemented in Small Medium Enterprises (SMEs), which represent the 99% of the European businesses [2], it could become difficult for the companies. Fortunately, other solutions which rely on new developments in Artificial Intelligence (AI) and grasping strategies based on object shape detection can be employed. These leverage different sensors and open-source AI algorithms based on Neural Networks (NN) to detect objects and then generate point where gripping can happen [1].

In order to understand which are the best technologies for solving this task in an affordable way which can be used by SMEs an analysis of the actual technologies is necessary. Therefore, in this advanced seminar you will research, analyse and propose some methodologies for the bin picking. This will compromise diving into research papers and code repositories for bin picking applications. Your tasks will be as follows:

- Literature research
- Evaluate and identify the main components necessary for bin picking
- Description and comparison of different methods for bin picking
- Summarizing the findings on a report

Bibliography:

[1] Fujita, M. and Domae, Y. and Noda, A. and Garcia Ricardez, G. A. and Nagatani, T. and Zeng, A. and Song, S. and Rodriguez, A. and Causo, A. and Chen, I. M. and Ogasawara, T, "What are the important technologies for bin picking? Technology analysis of robots in competitions based on a set of performance metrics", Advanced Robotics, 2019, pp. 1-15, DOI: 10.1080/01691864.2019.1698463.

[2] European Union, "Unleashing the full potential of European SMEs", Publications Office of the European Union, Luxembourg, 2020, ISBN: 978-92-76-16912-3.

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TECHNISCHE UNIVERSITÄT MÜNCHEN
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April 22, 2021

ADVANCED SEMINAR

Exploring Conventions to Define a Robot's Knowledge System

Problem description:

At the intersection of robotics and AI, designing a knowledge representation is an important issue to address, as it ultimately reflects how knowledge should be acquired, retained, and used by a robotic system for problem solving. There are many ways of defining a robot's knowledge base, such as classical approaches and solvers (PDDL [1, 2]), semantic graphs, ontologies and networks (e.g. OWL/RDF [3]), probabilistic graphical models (e.g. Bayesian networks and Markov models [4]), cognitive architectures [5] (e.g. ACT-R, Soar, CLARION, ICARUS, etc.), or more implicit representations from unsupervised learning (e.g. deep learning with neural networks).

Your task is to compile a literature review that addresses the following:

- What are the conventional platforms, languages, or methods that are used to program the knowledge representation of a robot? What are some examples of works that have used these approaches within the *last decade*?
- How is the grounding of semantic knowledge to a robot's actions and perceptions of the environment conventionally handled?
- What improvements, if any, can be made to facilitate the acquisition of knowledge in a way that is more natural to the human learning process?

Feel free to discuss any additional approaches that were not explicitly described in this prompt!

Bibliography:

[1] Drew McDermott, Malik Ghallab, Adele Howe, Craig Knoblock, Ashwin Ram, Manuela Veloso, Daniel Weld, and David Wilkins. PDDL - The Planning Domain Definition Language, 1998.
[2] Malte Helmert. Concise finite-domain representations for pddl planning tasks. *Artificial Intelligence*, 173(5-6):503–535, 2009.
[3] Steffen Staab and Rudi Studer, editors. *Handbook on Ontologies*. International Handbooks on Information Systems. Springer, 2004.
[4] Daphne Koller and Nir Friedman. *Probabilistic graphical models: principles and techniques*. MIT press, 2009.
[5] Iuliia Kotseruba and John K Tsotsos. 40 years of cognitive architectures: core cognitive abilities and practical applications. *Artificial Intelligence Review*, 53(1):17–94, 2020.

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TECHNISCHE UNIVERSITÄT MÜNCHEN

Human-centered Assistive Robotics

UNIV.-PROF. DR.-ING. DONGHEUI LEE

April 14, 2021

A D V A N C E D   S E M I N A R

Activity Detection and Prediction of Risk of Falling - A Systematic Review

Problem description:

Falls are the second cause for injury deaths worldwide with highest mortality in elderly ($>$ 65 years). In the context of improving postural control during static and dynamic balance wearable devices have been developed and investigated [5] and provide a good opportunity for the application in everyday life [4]. However, to provide reliable feedback in situations of increased risk of falling or adapt the level of assistance, the correct detection of the current posture [1] and activity [3] and the detection [2] and prediction of postural instability is crucial to define the threshold when feedback should be given.

Tasks:

- Perform a systematic search for existing approaches for recognizing and predicting different activities and postures of daily life as well as detecting and predicting the time point of instability
- Document your procedure
- Provide an overview of existing approaches
- Evaluate existing approaches
- Provide an approach for defining when to give feedback by combining the best approaches for recognising the current activity and posture during various static and dynamic situations and for predicting the time point of increased risk of falling

Bibliography:

[1] C. M. El Achkar, C. Lenbole-Hoskovec, A. Paraschiv-Ionescu, K. Major, C. Buela, and K. Aminian. Classification and characterization of postural transitions using instrumented shoes. *Medical Biological Engineering Computing*, 56(8):1403–1412, Dec 2018.

[2] M. C. Kilby, M. Solobounov, and K. M. Newell. Postural instability detection: Aging and the complexity of spatial-temporal distributional patterns for virtually contacting the stability boundary in human stance. *Plos One*, 9(10), 2014.

[3] F. Labarrire, E. Thomas, L. Calistri, V. Optasanu, M. Gueugnon, P. Ornetti, and D. Laroche. Machine learning approaches for activity recognition and/or activity prediction in locomotion assistive devices-a systematic review. *Sensors*, 20:6345, 11 2020.

[4] C. Z. Ma, A. H. Wan, D. W. Wong, Y. P. Zheng, and W. C. Lee. A vibrotactile and plantar force measurement-based biofeedback system: Paving the way towards wearable balance-improving devices. *Sensors (Basel)*, 15:31709–22, 2015.

[5] D. W. Ma, C. Z.and Wong, W. K. Lam, A. H. Wan, and W. C. Lee. Balance improvement effects of biofeedback systems with state-of-the-art wearable sensors: A systematic review. *Sensors (Basel)*, 16:434, 2016.

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TECHNISCHE UNIVERSITÄT MÜNCHEN
Human-centered Assistive Robotics
UNIV.-PROF. DR.-ING. DONGHEUI LEE

April 19, 2021

A D V A N C E D   S E M I N A R

Online Anomaly Detection and Skill Transition in Robotic Tasks

Problem description:

One of the main goals of autonomous systems is to robustly achieve a task at hand even in unknown environments or when unmodeled perturbations occur. This is especially challenging during robotic manipulation tasks with complex object interactions. Manually designing rules to determine whether the recorded multi-modal sensor information indicates a valid or invalid skill execution can be very hard or intractable. That is why Learning from Demonstration (LfD) plays an important role, when transferring task knowledge from humans to robots. Current LfD approaches use different strategies to encode the demonstrated task knowledge [4], [3] and rely on an online decision making system to decide when and to which successive behavior to switch in order to recover from an erroneous execution or to initiate a new skill [1], [2]. Online anomaly detection and flexible skill transition are key factors for achieving reliable task performance under challenging conditions and should be further investigated in this seminar:

- Carry out literature research on online anomaly detection and skill transition
- Compare the advantages and drawbacks of different strategies for handling anomalies regarding e.g. their detection mechanisms, generalization capabilities to new environments and underlying task representations
- Develop own ideas for flexibly handling anomalies

Bibliography:

[1] Thomas Eiband, Matteo Saveriano, and Dongheui Lee. Intuitive programming of conditional tasks by demonstration of multiple solutions. *IEEE Robotics and Automation Letters*, 4(4):4483–4490, 2019.

[2] Daniel Kappler, Peter Pastor, Mrinal Kalakrishnan, Manuel Wüthrich, and Stefan Schaal. Data-driven online decision making for autonomous manipulation. In *Robotics: Science and Systems*, 2015.

[3] Scott Niekum, Sarah Osentoski, George Konidaris, Sachin Chitta, Bhaskara Marthi, and Andrew G Barto. Learning grounded finite-state representations from unstructured demonstrations. *The International Journal of Robotics Research*, 34(2):131–157, 2015.

[4] Daehyung Park, Michael Noseworthy, Rohan Paul, Subhro Roy, and Nicholas Roy. Inferring task goals and constraints using bayesian nonparametric inverse reinforcement learning. In *Conference on Robot Learning*, pages 1005–1014, 2020.

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