Alperen Gündogan

Highlights

- Education
- Experience
- Projects
- Master thesis

Education

- Technical University of Munich, DE (2017-2020)
  - M. Sc. in Communication Engineering, high honors
  - DAAD Scholarship
- Istanbul Technical University, TR (2012 - 2017)
  - B. Sc. in Electronics and Communication Engineering, high honors
- Technical University of Ostrava, CZ (2015 - 2016)
  - Erasmus exchange

Working Experience

- Nomor Research (Apr 18 - July 20)
  - Working Student (Apr 18 – Aug 19)
    - Implementation of the latest 5G/NR standards into the 5G system simulator.
  - Internship (Aug 18 – Oct 18)
    - Design and implementation of 5G-V2X Communication
    - Protocol Stack design(PHY, MAC, RLC, PDCP, RRC layers) for V2X.
  - Master Thesis Project (Aug 19 – Mar 20)
  - Software/Research Engineer (Apr 20 – July 20)
    - Developing system and link-level standard-compliant simulation tools. Participating on research activities and actively taking part in 3GPP RAN1 standardization process.
    - Simulation automation
      - Docker orchestration.
      - Distributed job queue.

Projects

- Software Defined Networks (Summer 18)
  - Measurement-based QoS mechanisms

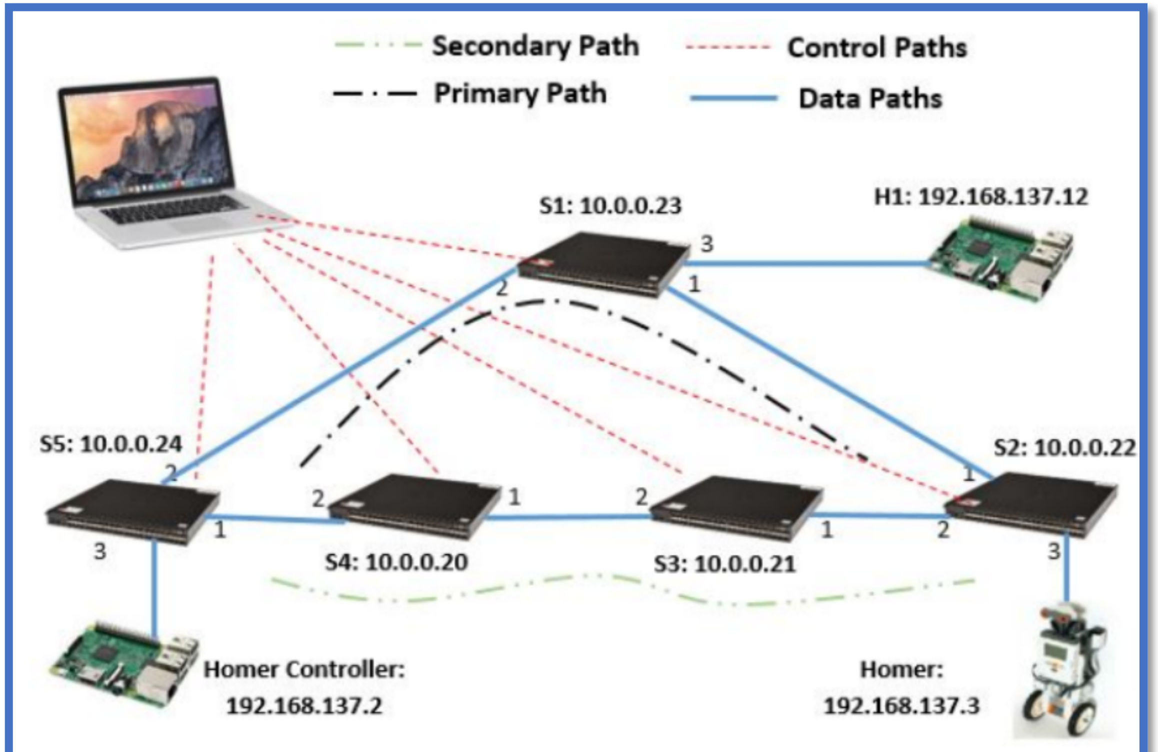
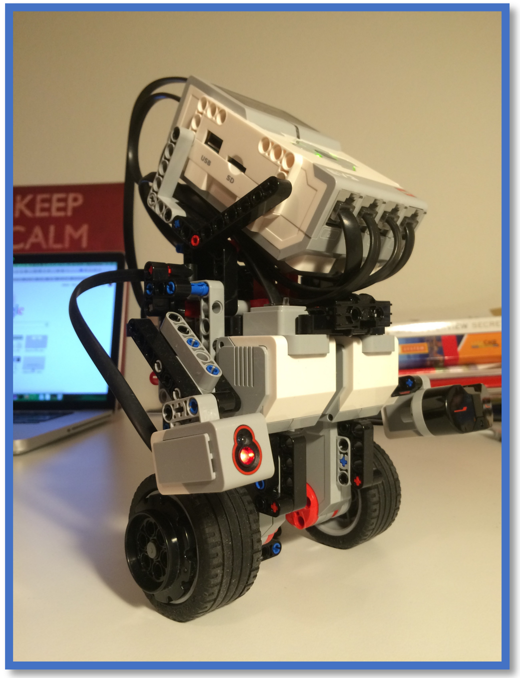


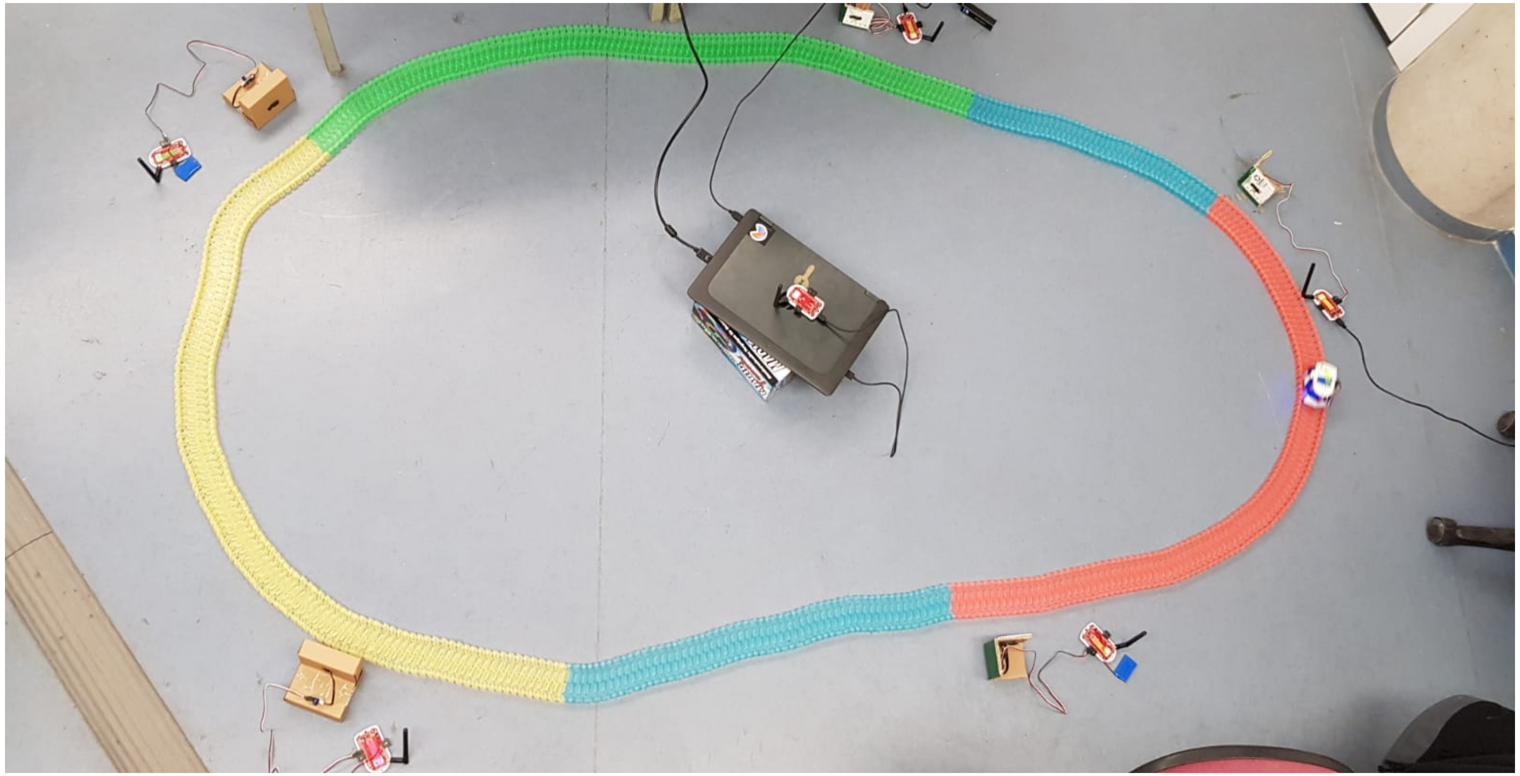
Fig. 2. Topology Setup of Our Application.

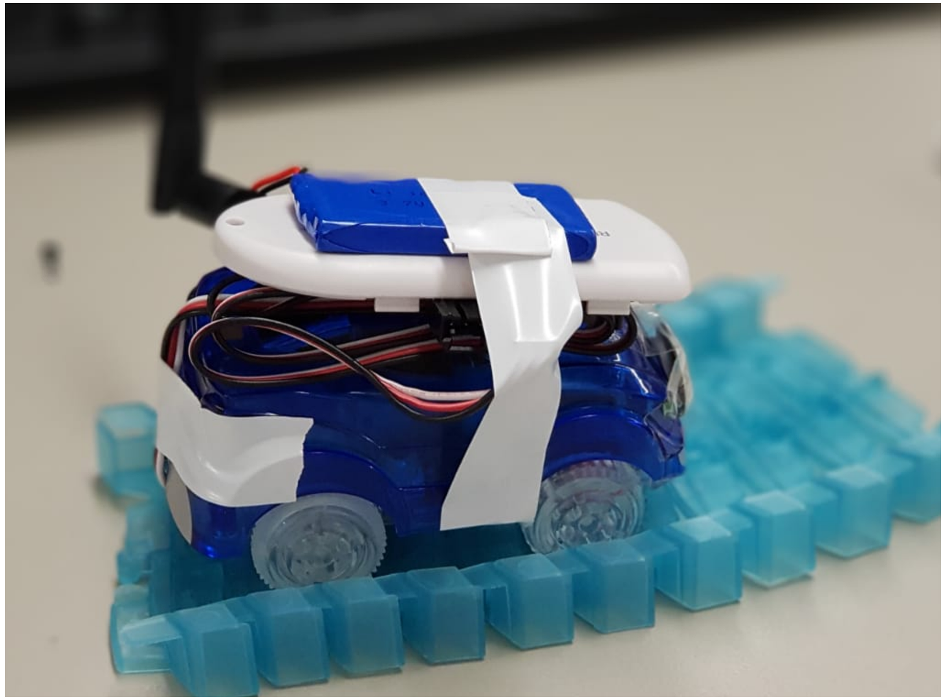


Source: https://github.com/gundoganalperen/

Projects

- Wireless Sensor Networks (Winter 18)
  - Intelligent Transportation System with Wireless Sensor Networks





Source: https://github.com/gundoganalperen/

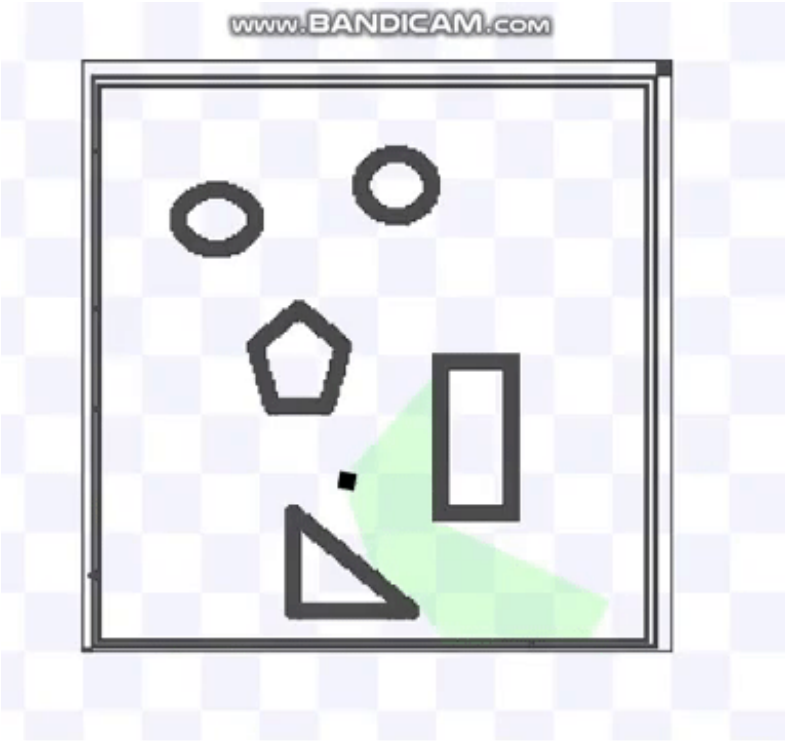
Projects

- Research Proposal (Winter 18)
  - Deep Reinforcement Learning based Resource Management for Cellular Vehicle-to-Vehicle Communication(C-V2V)

- Training about AI
  - Machine Learning for Communications
  - Approximate Dynamic Programming and Reinforcement Learning
  - Applied Reinforcement Learning
  - Neural Networks and Deep Learning (Coursera)
  - Improving Deep Neural Networks: Hyperparameter tuning, Regularization and Optimization (Coursera)

Projects

- Applied Reinforcement Learning (Summer 19)
  - LIDAR based Obstacle Avoidance with Reinforcement Learning using Turtlebot



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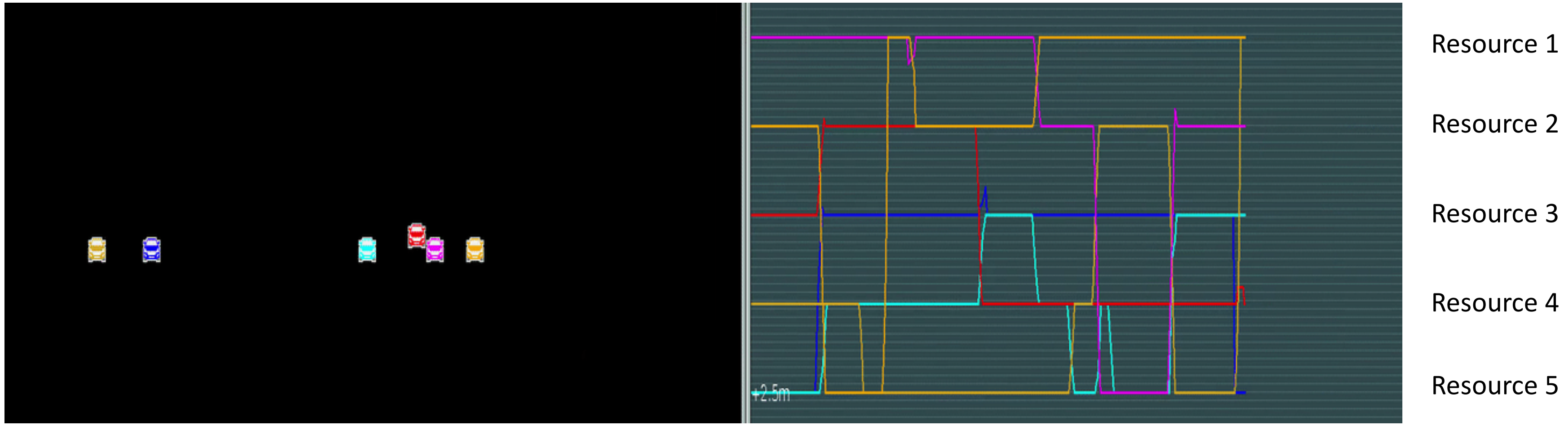
Master Thesis

- Distributed Resource Allocation with Multi-Agent Deep Reinforcement Learning for 5G-V2V Communication
  - Autonomous resource allocation in the absence of a base station. Each vehicle is a learning agent.
  - Goal: Perform joint/cooperative behavior in a distributed fashion to utilize packet reception ratio.
  - Research Status
    - Workshop “Machine learning in the context of communication networks” at TUM (21.02.2020)
      - https://mlkuvs.lkn.ei.tum.de
    - Mobihoc 2020 (submitted)
    - IEEE Transactions on vehicular communication (Expected)



Distributed Resource Allocation for 5G-V2X Communication with Multi-agent Reinforcement Learning

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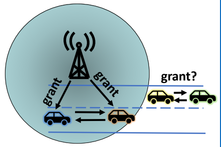
Motivation

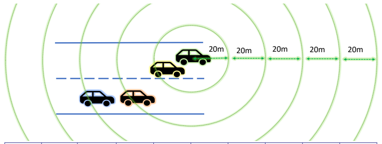
- Millions of death from car accidents[1].
- **Vehicle-to-everything(V2X) Communication**
  - Presence of base station can not be guaranteed.
- **Distributed radio access technologies**
  - Cellular-V2X(C-V2X)
    - **Spatial-Local observation for decisions**
    - Based on Carrier Sensing



- **Problem: Near** vehicles are likely to select the **same** resources[2].
- *Far vehicles use the same resources with multi-agent reinforcement learning(MARL) in congestion scenario.*

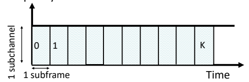
System Model

- N users have to select one of K resources where $K \leq N$.
- If m_j>1 users select a resource only the closer transmitter will be decoded.
- **State Space**
  - Each vehicle i, at time-step t, observe $s_t^i = (a_{t-1}^i, v_t^i)$ with previous action and view-based positional distribution $v_t^i = f(positions, B, R)$ (intuition:[3]). Piggyback positions with periodic safety messages.



v_t^i										
	0.0	0.0	0.33	0.33	0.33	0.0	0.0	0.0	0.0	0.0

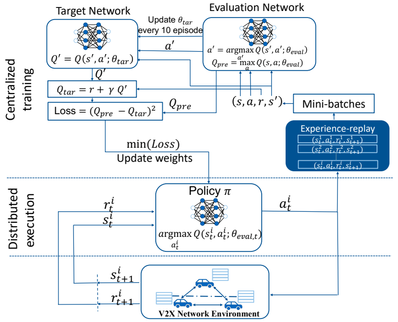
- **Action Space**
  - $a_t^i \in \{1, 2, \ldots K\}$, $i \in \{1, 2, \ldots N\}$ where $K < N$ is the number of resources.



- **Reward Design**
  - Cooperative. N_c^i ≔vehicles perform the same action with the user i.

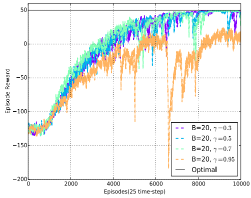
$$r_t^i(a_t^i, s_t^i) = \begin{cases} 1, & N_c^i = 1 \\ \left.\begin{matrix} 0 & \text{if } dist(i,k) \text{ farthest} \\ -N_c^i & \text{else} \end{matrix}\right\} & N_c^i = 2 \quad r_t^i(a_t^i, s_t^i) = r_t^i(a_t^i, s_t^i) + \frac{\sum_{i=1}^{n} r_t(i)}{n} \\ -N_c^i, & N_c^i > 2 \end{cases}$$

- **Goal**: Maximize the discounted return $R_t = \sum_{l=0}^{H} \sum_{i=0}^{N} \gamma^l \, r_{t+l}^i(a_{t+l}^i, s_{t+l}^i)$
- **Double Deep Q Network(DQN) with Long-Term-Short-Memory(LSTM) input layer and $\in -greedy$ policy.**

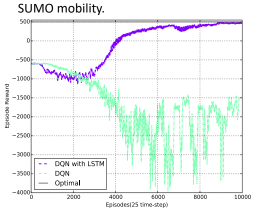


Evaluations

N=4, K=3, 100m highway, velocities={18,36,45,54}kmph



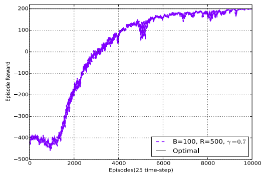
N=20, K=20, 500m highway,~35kmph, SUMO mobility.

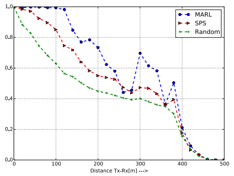


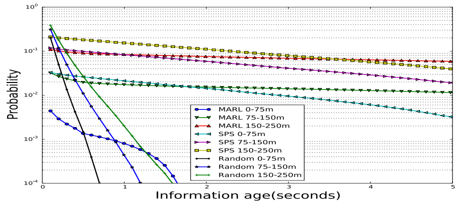
- The proposed approach converges to the desired policy!
- Higher discount factor ($\gamma \geq 0.95$) degrades learning performance.
- LSTM enables learning for the desired policy.

Network Simulations[4]

- Scenario: N=12, K=10, 500m highway, ~35 kmph, SUMO mobility.







- The average packet reception ratio(PRR) over time for the proposed MARL approach is **0.7864** whereas the average PRR for SPS is **0.6913.**

Conclusions

- In congestion, vehicles sacrifice communication with far vehicles in order to provide higher PRR and lower information age(IA) for near vehicles.
- Limitations:
  - Tested only in one direction. Directional resource pools.
- Contributions:
  - Fully distributed resource allocation based on view-based positional distributions of vehicles.
  - Train the policy in simulation and deploy it in real vehicles.
- Future works:
  - Evaluation of different mobility and environment scenarios.
  - Scaling the algorithm for larger scenarios.

References

[1] World Health Organization. Global status report on road safety 2018. Technical report, Genf, Schweiz, 2018.
[2] Nomor Research. Comparison of V2X based on 802.11p, LTE and 5G. White paper, Munich, Germany, April 2019
[3] Foerster, J.N., de Witt, C.A.S., Farquhar, G., Torr, P. H., Boehmer, W., & Whiteson, S. (2018). Multi-agent common knowledge reinforcement learning. arXiv preprint arXiv: 1810.11702.
[4] Realtime Network Simulator(RealNeS), Nomor Research. http://nomor.de/services/simulation/system-level-simulation/

Questions?