Biologically Inspired Person Following Using FMCW Radar Data

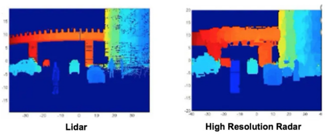

Fig. 1: Lidar vs. high resolution radar data. [1]

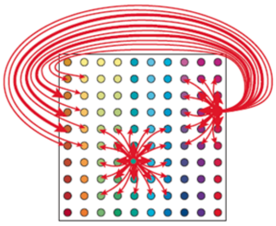

Fig. 2: Connections in an attractor network. [2]

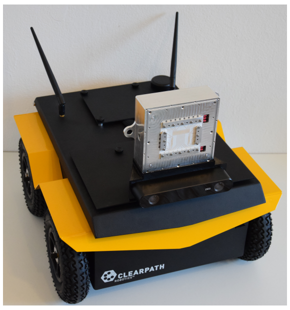

Fig. 3: Robot platform with FMCW radar.

Background

Although lidar sensors and vision systems are still the predominantly used sensors for automotive use cases, radar sensors receive more and more attention, mainly due to their robustness with regards to the weather. In contrast to lidars and cameras, radar sensors are able to detect objects even in problematic weather conditions like snowfall or fog and recent advances in FMCW radars increased the range/angle resolution significantly, as shown in Fig. 1, making it a viable alternative to lidar.

Detecting and tracking objects is a crucial task for autonomous vehicles in order to perform safe path planning and navigation in dynamic environments. This is commonly performed using either filter based algorithms [3] or artificial neural networks (ANNs) [4]. The resulting information is processed in order to e.g. avoid obstacles [5] or follow a person [6]. Most of these approaches, however, require extensive computational resources and with that electrical power, which is of course limited in autonomous vehicles.

Spiking neural networks (SNNs) are more biologically plausible networks than ANNs [7]. Unlike ANNs, these networks process data asynchronously and sparsely, namely through so called spikes - similarly to the mammalian brain. This potentially leads to highly efficient networks with a reduced energy consumption compared to ANNs by a power of ten when implemented on specialized *neuromorphic hardware* [8].

Task Description

Throughout this project you will be complementing an existing implementation of a spiking (continuous) attractor neural network (CANN) [9], as shown in Fig. 2, for object detection and tracking with an SNN for motor control using reinforcement learning (RL). CANNs are a popular tool for computational neuroscientists to model neuronal processes, such as associative memory or path integration [10], which is basically an egocentric tracking. The output of this network will serve as the input for an SNN using a reward modulated spike timing dependent plasticity (R-STDP) [11], [12] rule for learning to follow a tracked person. R-STDP has been already successfully implemented for similar tasks, like e.g. lane keeping [13].

The exact definition of the interaction between the two networks, as well as the definition of the learning rule and its inputs will be part of your work. The final network(s) will be evaluated on a real-world robotic platform (Clearpath Jackal) with a state-of-the-art high resolution FMCW radar as shown in Fig. 3.

During this project you will be

- doing an extensive literature research, specifically on spike encoding and R-STDP,
- familiarizing yourself with FMCW radar data,
- improving the existing implementation in Brian 2 and getting used to the framework,

Technical University of Munich

Faculty of Informatics

Chair of Robotics, Artificial Intelligence and Embedded Systems

Supervisor:
Prof. Dr.-Ing. Alois Knoll

Advisor:
Robin Dietrich, M.Sc.

Research project:
KI-ASIC

Type:
Masters Thesis, Guided Research

Research area:
Spiking Neural Networks, Signal Processing, Neuromorphic Engineering

Programming language:
Python

Required skills:
Python, Machine Learning, Signal Processing

Language:
Englisch/German

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For more information please contact us:

Phone: +49.89.289.17626

E-Mail: robin.dietrich@tum.de

Internet:
https://www6.in.tum.de/

- implementing an RL network in Python (using Brian 2) for person following,
- testing the system on a real-world robot and documenting your results.

Technical University of Munich

Faculty of Informatics

Chair of Robotics, Artificial Intelligence and Embedded Systems

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