Biologically Inspired Spiking Clustering for Autonomous Driving

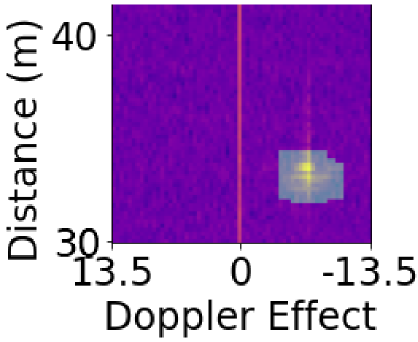

figure 1: FMCW range-doppler map with cluster. [1]

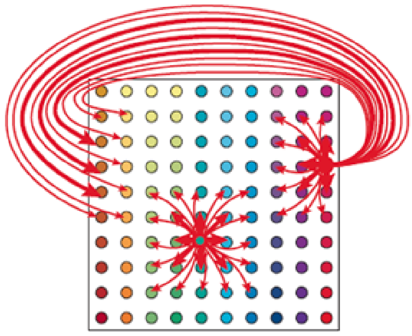

figure 2: Connections in an attractor network. [2]

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.

The clustering of FMCW radar data is typically performed after the object detection using CFAR. One of the most common methods to group the object points into clusters is DBSCAN [3]. Classic algorithms as well as deep learning based approaches for clustering, however, require an extensive amount of power, which is especially critical in automotive applications.

Spiking neural networks (SNNs) are the third generation of neural networks [4]. Unlike ANNs, these networks process data asynchronously and sparsely, namely through so called spikes. This is inspired by the mammalian brain, where neurons are connected with numerous synapses and communicate through spikes or action potentials. This potentially leads to highly efficient networks with a reduced energy consumption compared to ANNs by a power of ten [5].

Task Description

The objective of this thesis is to develop a spiking clustering algorithm that is able to cluster the data from a 2D range-doppler map, see figure 1. There already exist some spiking clustering implementations for other problems [6]–[8], which are mostly based on the idea of spiking rbf neurons [9], processing single data points at a time. This, however, might be impractical for the target case of online radar data processing in an autonomous vehicle. Another approach for data classification in 2D/3D space could be the use of (continuous) attractor networks [10], see figure 2.

Your task will it be to first search the literature for spiking and non-spiking clustering approaches. Afterwards you assess, which of the approaches is most suited for the given data. Finally, you implement a spiking neural network including neuron models, synapses, etc. and either train it or set the weights manually to perform clustering on range-doppler maps.

During the course of this project you will be

- doing an extensive literature research to find suitable approaches
- designing and developing a spiking neural network for clustering of 2D/3D data
- implementing the network in Python using (preferably) PyNN
- testing the system on neuromorphic hardware (SpiNNaker/Loihi)

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References

[1] A. Ouaknine, A. Newson, J. Rebut, F. Tupin, and P. Pérez, "CARRADA Dataset: Camera and Automotive Radar with Range-Angle-Doppler Annotations," *arXiv:2005.01456 [cs]*, 2021. arXiv: 2005.01456 [cs].

[2] *022118_0757_Howtorepres4.png (PNG Image, 602 × 649 pixels)*, https://www.cognav.net/wp-content/uploads/2018/02/022118_0757_Howtorepres4.png.

[3] M. Ester, H.-P. Kriegel, J. Sander, X. Xu, *et al.*, "A density-based algorithm for discovering clusters a density-based algorithm for discovering clusters in large spatial databases with noise," in *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*, ser. KDD'96, Portland, Oregon: AAAI Press), 1996, pp. 226–231.

[4] W. Maass, "Networks of spiking neurons: The third generation of neural network models," en, *Neural Networks*, vol. 10, no. 9, pp. 1659–1671, 1997.

[5] M. Davies, N. Srinivasa, T.-H. Lin, *et al.*, "Loihi: A Neuromorphic Manycore Processor with On-Chip Learning," *IEEE Micro*, vol. 38, no. 1, pp. 82–99, 2018.

[6] T. Natschläger and B. Ruf, "Spatial and temporal pattern analysis via spiking neurons," *Network: Computation in Neural Systems*, vol. 9, no. 3, pp. 319–332, 1998.

[7] S. M. Bohte, H. L. Poutre, and J. N. Kok, "Unsupervised clustering with spiking neurons by sparse temporal coding and multilayer RBF networks," *IEEE Transactions on Neural Networks*, vol. 13, no. 2, pp. 426–435, 2002.

[8] P. Lin, S. Chang, H. Wang, Q. Huang, and J. He, "SpikeCD: A parameter-insensitive spiking neural network with clustering degeneracy strategy," en, *Neural Computing and Applications*, vol. 31, no. 8, pp. 3933–3945, 2019.

[9] J. J. Hopfield, "Pattern recognition computation using action potential timing for stimulus representation," en, *Nature*, vol. 376, no. 6535, pp. 33–36, 1995.

[10] E. T. Rolls, "Attractor networks," en, *WIREs Cognitive Science*, vol. 1, no. 1, pp. 119–134, 2010.

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