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## Efficient Spiking and Artificial Neural Networks for Event Cameras

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# Propositions

accompanying the dissertation

## Efficient Spiking and Artificial Neural Networks for Event Cameras

by

**Alexander KUGELE**

1. The ANN-to-SNN conversion approach generalizes to temporally changing event camera data, such that the SNN after conversion is still more energy- and parameter-efficient than the ANN (Chapter 4).
2. The streaming rollout translates to a synaptic delay when using it on converted or trained SNNs, which makes execution more efficient (Chapter 4 and 5).
3. Hybrid SNN-ANNs process event camera data more efficiently than comparable ANNs and SNNs while achieving a similar performance on the benchmark task (Chapter 5).
4. A memory mechanism is needed to remember past information when processing event camera data, even in the absence of occlusions (Chapter 6).
5. Excluding objects with a low event count when training a neural network on event camera data improves performance on test data, even if the test data contains objects with low event count (Chapter 6).
6. The amount of publications in deep learning hinders proper reviewing and reproduction.
7. The time for a project is always underestimated.
8. It is important to know when to stop a project, but it is equally important to not give up too early.
9. Communication is key when working together on a project.

These propositions are regarded as defensible, and have been approved as such by the promotor Prof. Dr. E. Chicca.