Invitation to the Oral Examination – Department [CE]

For the occasion of his examination for a Doctoral Degree,

Etienne Müller

will present his/her dissertation entitled/on

Optimizing the Conversion of Continuous-Valued Networks to Spiking Neural Networks

on **15th November 2024** at **15:00 h (3:00 p.m.)**

Attendance to the presentation is open to the public. The presentation will be in German.

The candidate, all members of the Examination Committee, and authorized examiners of the TUM School of CIT are invited to the presentation and subsequent oral examination.

The presentation and subsequent examination will take place in hybrid format –

online via **Zoom**

https://tum-conf.zoom-x.de/j/64549356811?pwd=xaluEbYgj3JaOxaiZwVahvZEx9Ltit.1

Meeting-ID: 645 4935 6811
Kenncode: 633699

Examination committee:
Chair: **Prof. Alin Albu-Schäffer**
First Examiner: **Prof. Alois Knoll**
Second Examiner: **Prof. Markus Diesmann, Jülich FZ, Uniklinik RWTH Aachen**

Abstract:

Deep learning has significantly advanced the field of Artificial Intelligence (AI) in the past decade, with powerful parallel computing hardware and new approaches in artificial neural networks (ANNs) enabling the creation of very deep architectures that frequently exhibit superhuman performance. Despite this success, energy consumption can be problematic in various contexts, such as large server applications with independent power generation, advanced driver assistance systems in cars with limited battery capacity, and small embedded systems with restricted power budgets.
One potential solution to this issue is neuromorphic computing, which is inspired by biological neurons and has the potential to reduce energy consumption through the use of spiking neural networks (SNNs). SNNs communicate with short all-or-nothing pulses rather than the continuous-valued activation functions used in traditional ANNs. While numerous approaches have been proposed for training SNNs, none have achieved performance comparable to ANNs trained with highly optimized gradient descent-based learning algorithms. As a result, the current state-of-the-art involves taking pre-trained ANNs and converting them into SNNs.
This thesis aims to analyze and compare the properties of ANNs and SNNs, review and optimize existing conversion approaches, and enable the development of more effective and efficient neuromorphic systems. We focus on the three fundamental encoding

techniques: rate coding, population coding, and temporal coding. Through our analysis, we developed optimization techniques for increasing inference speed and approximating hyperparameters in rate-coded networks to construct the deepest SNN to date with more than 100 layers, providing the basis for a spiking transformer network. Furthermore, we propose a novel approach for sparse, low-energy computation in temporal-coded networks and demonstrate previously infeasible time-series processing through population coding by exploiting the inhomogeneities of analog neuromorphic hardware. By thoroughly exploring the possibilities for conversion between ANNs and SNNs, we hope to make significant progress toward enabling the widespread adoption of neuromorphic computing and reducing the energy consumption of AI systems.

Mailing list:

Members of the examination committee & doctoral candidate

Garching, 31th October 2024