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EDITORIAL

Focus on benchmarks for neuromorphic computing

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1. Introduction

Neuromorphic (brain-inspired) computing technology has been of interest to researchers since its origins in the work by a group at CalTech led by Carver Mead in the 1980s. More recently this interest has extended into the commercial domain with major industrial players such as IBM and Intel exploring the technology, and start-up companies commercializing neuromorphic solutions to applications such as inference in low-power edge systems through to datacentre-scale alternatives to GPUs for large language models and deep learning. With this growing commercial interest it is increasingly important to be able to compare and contrast the strengths and weaknesses of alternative neuromorphic offerings that range from the sub-threshold analogue circuits favoured by Mead's seminal work through novel device technologies such as memristors that offer physical in-memory compute capabilities, all the way up to large-scale many-core digital systems based upon conventional (and highly manufacturable) digital technologies. Such comparisons require benchmarks as the basis for comparison, but the sheer diversity of current neuromorphic technologies creates difficulties for prospective benchmarks.

This Focus Issue aims to pull together some early thinking on neuromorphic benchmarking. This comes in various forms, including comparing the same application on two different neuromorphic platforms and seeing which applications demonstrate a neuromorphic advantage over conventional solutions. The collected papers represent early perspectives on the neuromorphic benchmarking challenge but they are far from the last words on the matter—there is still a great deal left to do here!

2. The papers in the focus issue

The first paper [1] in the Focus Issue presents a biological spiking neural network model of a central pattern generator, an important neural mechanism that controls animal locomotion. This model is deployed in a simulated robot and is supported on both SpiNNaker and Loihi neuromorphic computing platforms. The paper describes the motivation for the work and the implementation using Nengo and the Neural Engineering Framework, and offers comparisons of the performance of the network on the two neuromorphic systems.

Nengo and the Neural Engineering Framework also feature in the second paper [2] that discusses the suitability of a neuromorphic approach for a human activity recognition system that could be implemented as an artificial intelligence of things application. It is proposed that such a system could be used as the basis for evaluating different neuromorphic technologies.

The third paper [3] raises the prospect of using neuromorphic technology to compute a wide range of applications outside the more common areas of biological modelling and AI. Here, applications such as graph algorithms, constrained optimization and signal processing are considered to be well-suited to neuromorphic implementations. The paper makes the case that the designers of future neuromorphic platforms should take into account the wider range of applications considered here.

The Intel neuromorphic deep noise suppression challenge presented in the fourth paper [4] in the Focus Issue is proposed as a widely-applicable problem that can be used to encourage innovative algorithms that

have the potential to demonstrate the benefits of neuromorphic solutions. The challenge is thrown open to the neuromorphic computing community.

The final paper [5] investigates the use of neuromorphic (spiking neural network) solutions to the problem of implementing closed-loop neuromodulation in brain–computer interfaces (BCIs) and finds that they perform better than conventional and artificial neural network solutions. BCIs offer the prospect of significant therapeutic benefits for individuals with disabilities, including the restoration of lost sensory, motor or cognitive functions. They impose significant constraints on the electronics in terms of real-time low-latency operation and size, thermal and energy limits.

3. Future outlook

There is a considerable amount of thinking around the global neuromorphic community into the development of neuromorphic benchmarks. One example is NeuroBench [6], which represents the collective ideas of nearly 100 co-authors into how best to structure and regularise appropriate benchmarks. Another example is benchmarking work supported by the EU Flagship human brain project (HBP) [7]; this paper focuses on comparisons of the two neuromorphic platforms (SpiNNaker and BrainScaleS) supported by the HBP with each other, with the GeNN framework running on CPUs or GPUs, and with conventional hardware platforms such as the Raspberry Pi. A third example is a benchmarking discussion paper [8] from Mike Davies, the leader of the Intel Loihi team.

There is clearly still a lot of work to be done in this area before a consensus emerges on appropriate ways to benchmark the very diverse hardware neuromorphic platforms that exist and will exist in the near future. Defining appropriate metrics as the basis for comparing these platforms is also difficult in the neuromorphic domain. Our hope is that this Focus Issue has contributed some concrete ideas into the process of building this consensus.

Data availability statement

No new data were created or analysed in this study.

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