Neuromorphic Computing in the Netherlands

WHITE PAPER

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Executive summary

This white paper – written by a team of experts from Radboud University, University of Groningen, Delft University of Technology, Eindhoven University of Technology, University of Twente, AMOLF, CWI and SURF – provides insight in the necessity and potential of neuromorphic computing for the Netherlands. Our aim is to create synergy between the expertise in both the public and the private parties in The Netherlands, and to put neuromorphic computing on the map as a key technology for energy-efficient computing.

Neuromorphic computing is a paradigm that draws inspiration from the structure and functioning of the human brain, in particular the co-location of data storage and data processing. This strongly reduces the amount of data transfer and therefore significantly increases the speed of computing while simultaneously reducing its energy consumption. It can, therefore, play a key role in data analysis in many fields. In addition, the development of expertise and neuromorphic data processing capabilities would limit the need to transfer privacy-sensitive data and would improve digital sovereignty.

Innovation in neuromorphic computing is dependent on developments in six key areas:

1. Materials
2. Devices
3. Circuit Design
4. Hardware Architecture
5. Algorithms
6. Applications

In the Netherlands, there is a strong and diverse academic community and multiple start-ups covering those areas of expertise. To consolidate and expand the already strong Dutch position in neuromorphic computing, it will be crucial to define a world-wide unique flagship on neuromorphic computing. This implies a transformation to a more concerted research effort and a cohesive community focused on a common goal. Therefore, our ambition beyond the white paper is to create a coalition 'Neuromorphic computing NL' and develop a roadmap for a collaborative effort towards future-proof energy-efficient computing.

Why do we need neuromorphic computing?

Information technology (IT) forms the backbone of the digital and knowledge-driven economy in the Netherlands. With the evolving digitalization, expansion of social media and artificial intelligence, this dependence has been rapidly growing to unsustainable levels. As a result, major problems emerge due to the associated energy costs and climate impact, which are particularly pressing in the Netherlands considering the limited physical space and power grid capacity available for data centers [Woo22]. Moreover, the evolving digitalization and its rapid expansion results in privacy and security issues, and leads to increasingly reliance on IT-expertise outside the Netherlands and even outside the EU, limiting sovereignty.

Neuromorphic computing has enormous potential for very fast and extremely energy-efficient data processing. It can, therefore, play a key role in data analysis in many fields, like for example in healthcare, sustainable food supply for the expanding world population, failure analysis of the power grid as well as for growth in key parts of the Dutch economy, such as for diagnosis of maintenance tasks in logistics. At the same time, neuromorphic computing allows applications such as evaluations of high-dimensional problems or cryptography that are simply impossible or too time and power consuming with standard approaches. In addition, the development of expertise and neuromorphic data processing capabilities would limit the need to transfer privacy-sensitive data and improves digital sovereignty.

What is neuromorphic computing?

Neuromorphic computing is a paradigm that draws inspiration from the structure and functioning of the human brain, in particular its small power consumption (~20 Watt), which is only a tiny bit as compared to the vast 50 million Watt consumed by supercomputers. The energy-efficiency of the human brain is enabled by doing data storage and data processing literally at the same place. This strongly reduces the amount of data transfer between spatially separated storage and processing components present in current digital hardware and, therefore, allows for massively parallel calculations. Hence, computations are completed very fast and data processing becomes extremely energy-efficient. The main goal of neuromorphic computing is to realize this potential for fast and energy-efficient information processing in non-biological yet brain-inspired computers.

Neuromorphic computing includes several different aspects as illustrated in Figure 1 and briefly explained below:

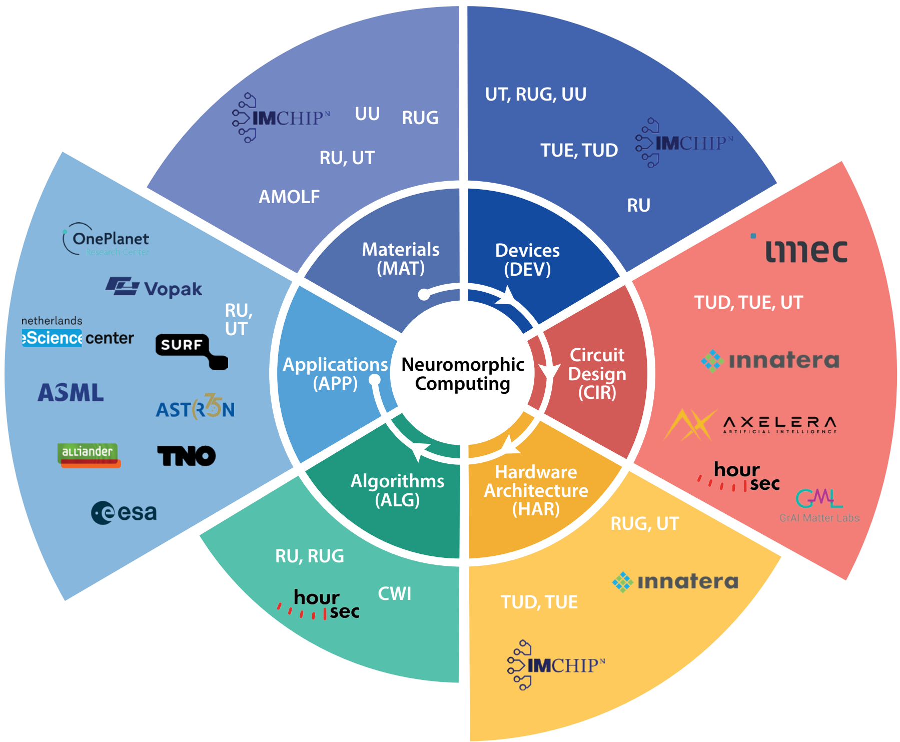


Figure 1: Overview of the key areas in neuromorphic computing (center ring) and distribution of expertise over the universities, knowledge institutions and national e-infrastructure service providers in NL. In applications, the potential list of companies is much larger, it is currently limited to those that had been consulted during compilation of the whitepaper. Outside applications, relevant startups based in NL are listed.

For neuromorphic computing, different **materials** are needed than those used for the transistors of digital computers. For example, materials with adaptive properties to mimic the synapses of the human brain. **Devices** are components with a given functionality. This can be a switch, a memory element and also a sensor or artificial neuron. Multiple devices have to be integrated for which neuromorphic **circuit design** is needed. Moreover, new **hardware architectures** have to be developed to realize a computing chip, featuring either fully neuromorphic or a combination of digital and neuromorphic circuits.

Algorithms of digital computers define the manner in which the computer is programmed and interacts with the environment. For digital computers there is a strict separation between software algorithms and hardware. For neuromorphic computing this seperation is less clear and they are often developed and designed together. Moreover, the way neuromorphic computers are programmed is different. They are essentially **learning machines**, just as the human brain, and they become better and better by training them with data.

Applications also play a special role in neuromorphic computing. It is not expected that neuromorphic computing will directly replace existing digital computers. It will rather have advantages for specific tasks that are highly demanding in terms of the amount of data, response time or the available energy. Especially tasks that involve pattern recognition and classification are very suited for neuromorphic computing. For example, fraud detection for credit card transactions in mobile payment terminals and image analysis by robots and on drones, with potentially huge business opportunities in, for example, health, logistics and food production.

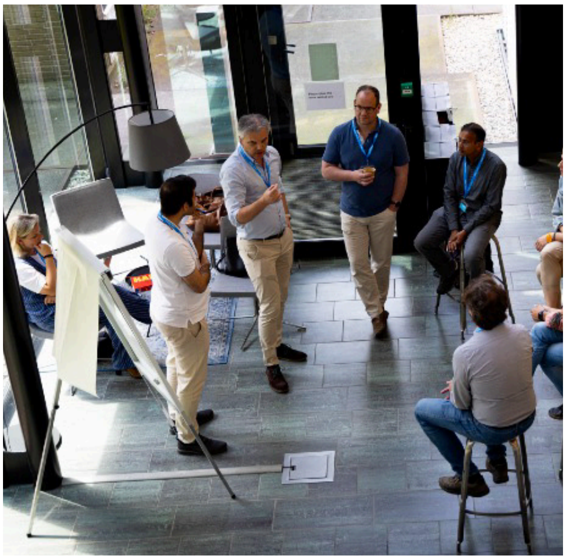
Specific tasks at data centers can benefit from neuromorphic computing as well, since the dependence of the computational cost on the complexity of the problem changes fundamentally by performing all required computations simultaneously in a neuromorphic hardware. As a result, certain large computations that are completely impossible on existing digital hardware, may become feasible with neuromorphic computing. This has applications in, for example, cryptography and for evaluations of high-dimensional problems.

What is the current position of the Netherlands?

The Netherlands offers a fertile ground for fostering significant societal and economic activity based on neuromorphic technologies [Con24]. The country boasts unique boundary conditions (Amsterdam Internet exchange point, strong datacenter industry) and an excellent ecosystem to foster technology transfer (TNO, IMEC) with several startups already entering the market (e.g. Innatera, AxeleraAI, GrAI Matter, IMChip, HourSec). Moreover, there is a strong and diverse academic community with several key actors (including CogniGron at the University of Groningen, MESA+/BRAINS at University of Twente, Radboud Neuromorphic Computing Initiative in Nijmegen, Hendrik Casimir and Artificial Intelligence Systems Institutes Eindhoven, Faculty of EEMCS at TU Delft, CWI, and AMOLF), which is key to sustain long-term innovation. These are also involved in a first collaborative national program, NL-ECO, and the collaborative academic platform Mission 10-X, that aim at energy-efficient computing and in which neuromorphic computing plays a key role. The specific distribution of expertise is shown in Figure 1 above. Furthermore, a summary of the key aspect of neuromorphic computing is provided in the appendices, in which leading scientists from Dutch research institutions describe the state-of-the-art and new developments.

Participants of the first Dutch neuromorphic computing ecosystem meeting at IMEC Eindhoven in June 2024.

What is the international neuromorphic computing landscape?



Many countries are currently investing in neuromorphic computing, both at fundamental and more applied levels [Meh22]. Key players in Europe are Switzerland (Institute for Neuroinformatics); Spain (IMS-CSIC); Germany (Aachen (NeuroSys [Lem23]), Juelich (Jülich Neuromorphic Computing Alliance (JUNCA)), Frankfurt (IHP-Microelectronics), Dresden (SpiNNAker 2, NAMLAB), Kiel (Neurotronics) and Muenster (Hybrain)); UK (Manchester, UCL, Cambridge [cam24]); and France (CEA-LETI, CNRS). In 2024, neuromorphic computing systems made their debut in the international high-performance computing landscape outside the EU. The Australian International Center for Neuromorphic Systems has announced Deep South, the world's largest neuromorphic supercomputer capable of 228 trillion synaptic operations per second. Furthermore, Japan (RIKEN-CCS) is exploring neuromorphic computing and in USA Intel has released Hala Point to utilize sparse connectivity and event activity, and major programs run at IBM (HERMES core, TrueNorth and Northpole chips), Stanford (Brains-in-Silicon) and Sandia National Labs.

What is the next step for neuromorphic computing in the Netherlands?

To consolidate and expand the already strong Dutch position in neuromorphic computing, it will be crucial to define a world-wide unique flagship on neuromorphic computing. This implies a transformation to a more concerted research effort and cohesive community focused on a common goal. To realize this goal we have to leverage the existing key expertise in neuromorphic computing and enhance connections between different levels of technological readiness. Simultaneously, such a common goal should benefit from already existing coalitions in semiconductors and emerging technologies like quantum, artificial intelligence and photonics (see info boxes) and conceptualize a technological integration perspective in which neuromorphic and other technologies can collaborate to address common challenges.

We recognize the recommendations of the survey by the Topsector ICT [con24] and emphasize that this whitepaper is a first important step to gather the full community in NL. To further develop a joint roadmap, we propose to form a coalition with all relevant parties and in close collaboration with the Topsector ICT and TNO formulate alignment with the National Technology Strategy. In addition, to strengthen the R&D position, we stress the importance of stable research funding and sustainable business climate for startup companies. Finally, valorization will be greatly accelerated by realizing publicly accessible neuromorphic infrastructure for testing and benchmarking the most promising applications, both in scientific and in societal and industrial applications.

ALIGNMENT WITH COMPLIMENTARY INIATIVES

Neuromorphic computing and Artificial Intelligence (AI)
Contemporary AI shows the potential of large parameterized models in real-world applications. In digital computers, power costs are staggering, both for training and public use of tools such as ChatGPT. However, the basic computations of AI can be realized potentially even faster on neuromorphic hardware and with extremely low power requirements. Therefore, processing can be done "at the edge", i.e. very close to where the data is produced.

Neuromorphic computing and Quantum technologies
Many societal challenges would benefit by leveraging the complementary strengths of neuromorphic and quantum computing. For example, the discovery of new pharmaceutical drugs: first, neuromorphic computing analyzes vast databases of chemical structures and biological data to identify interactions and provide a list of potential drug candidates. Next, quantum computing accurately simulates and optimizes molecular structures to enhance their therapeutic properties and shorten development times.

Neuromorphic computing and Photonics
The current development in photonic integrated circuits, together with novel functional materials, can provide multi-state modulation in the transmission of light, while maintaining the state after the power is turned off, allowing for both processing and memory, thus representing effective optical synaptic devices. When ultra-fast and high-bandwidth communication is required, in combination with local information processing, optical neuromorphic computing brings unique advantages.

Neuromorphic computing and Semiconductor technologies
Some neuromorphic circuits are already manufactured using standard semiconductor processes, demonstrating their viability in conventional CMOS technology. Upcoming materials and device structures, designed to be CMOS-compatible, will further support scalable, efficient integration. The near future likely lies in hybrid approaches that combine traditional semiconductor technology with novel neuromorphic components to maximize performance and adaptability.

Appendix 1: Key aspects of neuromorphic computing in the Netherlands

This appendix provides a summary of the key aspects of Neuromorphic Computing listed in Figure 1, featuring Materials, Devices, Circuits, Architectures, Algorithms and Applications. In addition, an example of optical neuromorphic computing is provided, exemplifying the link between neuromorphic computing and photonics.

Materials - Computing in Intelligent Matter

Further improvements within neuromorphic computing are feasible by addressing current limits stemming from scaling, reliance on external computing, and energy efficiency. Intelligent matter, capable of sensing, actuation, adaptation, and learning, is ideal for distributed, integrated information processing like in biological systems. It surpasses the memristive paradigm (see devices below) by embracing material complexity for comprehensive in-materia computing. This advancement is crucial for neuromorphic computing due to its parallelism and adaptivity, mimicking brain-like processes and boosting efficiency [Kas21]. Intelligent matter can scale effectively, supporting larger networks while maintaining low power consumption. Developing local, physically realizable learning rules [Jae23] is essential, addressing bottlenecks and driving the evolution of neuromorphic systems. Intelligent matter will be a key enabler of future neuromorphic systems.

Intelligent matter refers to a diverse class of complex material systems for information processing exploiting the intrinsic, often strongly nonlinear, physics or chemistry of materials. This is based on the bottom-up and distributive design of materials which themselves inherently exhibit the necessary computational behavior. This includes materials such as semiconductors, soft matter, metamaterials, and optical systems hosting light-matter interactions. Research has shown the integration of processing and memory down to the level of individual atoms [Kir21], as well as the ability to efficiently perform machine-learning tasks in a material [Che20]. There is also significant progress in the development of local learning rules, which are realizable in these physical systems. All these developments link to improving the energy efficiency of brain-like computations by providing new hardware solutions for neuromorphic computing beyond the memristive paradigm.

The challenges and opportunities in computing in intelligent matter are based on exploiting the full materials properties themselves for computational functionality. This is largely based on linking material platforms and techniques from various fields of research, with concepts in neuroscience, computer science and artificial intelligence and supported by key experts from RU, UT, RUG, UU and AMOLF. The opportunities are to create intrinsic self-learning and ultimately autonomous functionality in materials, without the reliance on external computing or software. These ideas are linked to creating integrated neurons and synapses in material systems, and developing physically realizable learning rules, as well as developing computationally specific functionality that exploits the energy efficiency and other advantages of the given material platforms.

Devices - Memristors

Efficient massively parallel information processing requires basic computer elements that can provide adaptable connections in the form of variable resistances. If these resistances can be stored after the power is turned off, both information processing and storage can be performed at the same location. This in-memory computing avoids the data transfer that accounts for most of the energy consumption in data centers. Devices presenting these features are known as memory resistors (memristors) or memristive devices [Str08, Was09, Pre15, Bur17,Kam24]. They can be miniaturized as much as transistors in current computers and can be fabricated in existing chip fabs.

Driven by the computing demands of the AI revolution and the associated interest of industry (HP labs, IBM research, IMEC), various memristive devices have been realized at Dutch and foreign labs [Cai19]. Features that are sought in memristors are: wide range of adaptable resistance, high speed, long retention, low operation energy, high endurance and high reproducibility. The diversity in complex material processes (magnetic, electric, structural, and/or chemical) underlying memristive behavior unites materials scientists with different backgrounds. The further involvement of device engineers, computer scientists and AI experts forms a thriving scientific landscape. However, the ideal material has not been found yet.

In search of the ideal memristor predictability is a key issue. Materials displaying both permanent resistive memory and adaptability often rely on the interplay between physical phenomena, whose combined effects are challenging to control. In times when control at the atomic scale is commonplace, the next materials frontier lies on harnessing that complexity. The need to explore new materials can be challenging in industrial settings and is leading to exciting new synergies between academic and industrial labs, supported by key experts from UT, RUG, RU, UU, TUE and TUD as well as by IMChip. Moreover, memristors need to be co-designed as part of novel computer architectures and programmed in ways that are very different from those of digital computers.

Circuits - Neuromorphic Circuit Design

Existing digital computing technology has been successfully used to build neuromorphic circuits that mimic the fundamental dynamic properties of their biological counterparts, such as neurons and synapses, with a high degree of precision, reliability, and detail. These systems are particularly suited for the implementation of specific sensory-motor/decision mappings or functionalities, thus paving the way for the construction of neuromorphic behaving agents and edge computing systems. Furthermore, they are particularly suitable for building efficient brain-machine interfaces.

Current research spans from realizing neuromorphic circuits for bio-inspired synaptic-plasticity circuits to neuromorphic circuits capable of integrating emerging technologies and neuromorphic devices [Iel19, Var22] in fully-fledged computing architectures. So far, neuromorphic circuits have seamlessly integrated into sensory-processing architectures, addressing low power, low latency, and reduced data rates [Yao24]. Additionally, various neuromorphic hardware now support doing calculations with networks of artificial spiking neurons, including BrainScale-2 [Peh22], SpiNNaker [FB20], NeuroGrid [Ben14], TrueNorth [Ako15], Tianjic [Den20], Loihi [Dav18], ODIN [Fre19], PRIME [Chi16], DYNAP-SE2 [Ric24], and µBrain [Stu21]. These systems emphasize power efficiency by embracing brain-inspired computing principles via event-based computation and co-location of memory and processing.

Recent AI achievements pose two key challenges: the increasing computing power needed for AI models and the memory bandwidth mismatch, known as the von Neumann bottleneck. Researchers explore neuromorphic circuit designs to tackle these challenges. This approach, however, comes with one drawback, namely, the cost and reduced scalability of fully custom designed neuromorphic circuits. To counter this, a parallel route supported by key experts at RUG, TUD, TU and Innatera explores the integration of these systems with conventional computing machines. In other words, all the levels of the computing stack should be co-engineered with neuromorphic circuits to become usable for real-world applications.

Architectures - Brain-inspired Adaptive Hardware Architectures

Brains are not only extremely energy efficient and able to perform complex tasks, but also exhibit remarkable degrees of resilience. There are many unique brain features that enable this: fused computation-and-memory, enormous parallelism, analog event-driven processing, and fault tolerance. Inspired by at least some of these features, computer engineers are building revolutionary computing architectures to achieve extreme energy efficiency and adaptivity that can address many societal challenges related to computing "at the edge", i.e. very close to the sensors that produce the data.

Two main directions that can be seen as the state of the art: i) bringing computing in memory (or close), and ii) ultimate customization of reconfigurable hardware resources. On the former, many ongoing projects in academia and industry exist that fall into the two major classes: Computing near Memory and Computing in Memory (data stays in the memory while being processed). The state of the art explores both traditional technologies as well as emerging device technologies to realize such architectures.

Emerging brain-inspired adaptive hardware architectures face several challenges that need solutions to realize their full potential, including: a) energy efficiency versus accuracy, b) manufacturing variability and technology non-idealities, c) scalability, d) models of computing and online learning, e) programming and execution models, f) design tools and methods, g) resilience, h) self-healing, i) standards and interoperability. These challenges are addressed by both academic experts (TUD, TUE) and startups (AxelaraAI, HourSec).

Neuromorphic Algorithms

Once novel materials are available for building brain-like neural systems, ways to 'program' them are needed. However, one cannot just type program instructions into a neural network to solve task A or B. Neural systems are learning systems, and if they are to perform a task, one must train them. Current software algorithms, such as those behind the deep learning revolution in AI are digitally simulated. Instead, for energy-efficient computing training procedures are needed that adapt the hardware physics directly, without the energy-costly detour through digital simulation [Ahm21].

The basis of biological learning processes is to adapt the strength of synaptic connections between neurons. Much current work in neuromorphic computing focuses on memristors, which can be directly used as adaptable electronic synapses. Different physical sorts of memristors display different phenomena of adaptivity. Much work is spent on characterizing and harnessing them for synaptic adaptation processes known from brains, in particular spike-timing dependent plasticity. Other important strands of algorithm research concern re-formulations of the digital learning rules used in deep learning to spiking analog neural networks, and methods to compute with large random neural networks known as reservoir computing.

Further developments in algorithms are to learn more from the brain – biological brains exploit a multitude of dynamical-adaptive mechanisms, many of which remain to be discovered (collaboration with neuroscientists). In addition, neuromorphic systems need to scale from single-effect demonstrators to large, hierarchically organized multi-module architectures that can solve complex tasks (collaboration with cognitive scientists and computer architecture engineers). Furthermore, formal models of computing in self-organizing physical systems need to be developed for a systematic engineering of hardware and software (collaboration with theoretical computer scientists and mathematicians). These interdisciplinary efforts are supported by world-wide leading experts in neuromorphic algorithms from RU, RUG and CWI.

Applications

Already today, digital neuromorphic hardware shows promising advantages in consumer hardware such as smartphones and laptops, delivering a 2-3 times longer battery life. In these situations, dedicated neuromorphic coprocessors are designed in digital hardware and combined with conventional general-purpose processors. This hybrid scenario is generally expected for emerging neuromorphic hardware. This makes the application development itself challenging, since niche applications must be identified and benchmarked, with potentially many failures and hurdles for integration with existing computational workflows. It will be key to develop an ecosystem in which such testing cycles can be closed quickly such that a small set of most promising applications emerge soon and can form the basis for a neuromorphic computing industry to scale up. Broadly speaking, the most promising applications are expected for situations for which fast processing is needed (short latency or high throughput) and for which the available energy budget is limited.

Examples of applications in various economic and public sectors:

- Monitoring and anomaly detection of the **electrical power grid** relies on state-estimations of the whole grid, which are based on computing-intensive calculations. Faster and more energy-efficient state estimation will enable more effective control of the power grid. This is increasingly important in view of the rapid grid expansion needed to realize sustainability goals.

- Integration of neuromorphic hardware with drones enables literally on-the-fly image processing and pattern recognition, with great security advantages (limited or no transfer of privacy-sensitive data to external computers) and numerous potential applications: in the **public sector** (searching for victims of natural disasters) in **food production** (inspecting plants) as well as for maintenance planning in **logistics** (inspection of tanks, trains, airplanes).

- In **healthcare**, brain-computer interfacing, neuroprostheses, and implantable neuronal interventions towards mitigating depression and epilepsy are foreseen [Qi23]. Using internal signal processing that mimics information encoding in the brain helps to smoothen the connection between brain signals and neurotechnologies as well as reduces power consumption [Moh23].

- Monitoring of atomic-scale deviations occurring during **chip manufacturing** requires large-scale computations. Neuromorphic technologies would enable to speed up this process and will make it possible to develop future technologies – up until closer integration of computers and human brains. The latter is currently being commercialized by companies like Neuralink and Phosphoenix.

- Large-scale **research** infrastructures rely critically on abundant and affordable compute resources. For example, the Larger Hadron Collider and the European Low Frequency Array (LOFAR) operate at data volumes of over 100,000,000 GB/year, while climate modeling features even a factor 5-10 higher data volumes. Still many problems like large scale simulations of quantum materials are not even feasible with the existing infrastructures. Collaborative research by RU, UT, SURF and IBM, as well as in collaboration with Astron, indicate that neuromorphic computing can reach 1000 times lower energy consumption and over 10 times faster calculations [Kos23].

Example: Optical neuromorphic computing

Many applications such as Internet of Things (IoT), autonomous driving and zero-energy sensors require super-GHz bandwidth, low latencies and a small energy-footprint. Optical neuromorphic computing transfers its well-known high-bandwidth and low-energy interconnect credentials to the field of neuromorphic computing [Sha21,Xu21,McM23]. The negligible energy overhead for moving data encoded in light within photonic processors enables unprecedented energy-efficient parallel computation [Bai23,Men23], while wave diffraction and light scattering inherently realize fully connected and recurrent neural networks [Wet20,Hu24].

Metaphotonic structures can perform dedicated mathematical operations on data encoded as images in 2D wavefronts. Nanostructured diffractive surfaces perform analog processing with light, such as Fourier transforms, convolutions, spatial differentiation and integral equation solving [Hu24,Cor19, Cor23], scenarios exploited at AMOLF. High performance photonic chip technologies [Bog20,Smi14] are also investigated with great success at TU/e. Deep neural network models are mapped on photonic integrated chips for ultra-low latency parallel computation [Shi22,Shi23], while ultra-low energy consumption is targeted by exploiting brain-inspired approaches based on spiking laser networks on chip [Put23a,Put23b] and on electro-optical spiking nodes using resonant tunneling diodes [Hej23, Zha23].

Fundamental limits, bounded by reciprocity, linearity and passivity, result in a reduced range of operations executable in diffractive `through chip' wave-based computing. Reconfigurability, tailored optical nonlinearities and gain are crucial for complex nonlinear analog computations and diffraction-based neural networks. When mapping optical computing engines on-chip, built-up losses limit scalability, while the accumulated noise and signal degradation reduce the overall system resolution. For both approaches, efficiency and accuracy are key challenges for cascadable operation. Schemes of heterogeneous material integration will enable next generation neuromorphic photonics, supported by TU/e, AMOLF and IMEC.

Appendix 2: Neuromorphic experts in the Netherlands

AFFILIATION	NAME	ALG	APP	CIR	DEV	HAR	MAT
Amolf	Femius Koenderink				x		x
	Marc Serra Garcia					x	
	Martin van Hecke						x
	Nachi Stern	x					x
	Said Rodriguez				x		x
Astron	Chris Broekema		x			x	
AxeleraAI	Bram Verhoef		x			x	
Centrum Wiskunde & Informatica	Sander Bohte	x	x				
Hoursec	Alexandra Pinto		x			x	
Innatera	Amir Zjajo		x	x		x	
Radboud Universiteit	Alex Khajetoorians						x
	Andrey Bagrov	x					x
	Bert Kappen	x					x
	Johan Kwisthout	x	x				
	Johan Mentink	x	x				x
	Mahyar Shahsavari	x	x				
	Marcel van Gerven	x	x				
	Paul Tiesinga	x	x				
	Peter Korevaar						x
	Theo Rasing						x
	Ton Coolen	x	x				
	Wilhelm Huck		x				x
Rijksuniversiteit Groningen	André van Schaik		x	x			
	Bart Besselink				x		
	Bart Kooi				x		x
	Beatriz Noheda				x		x
	Dirk Pleiter		x			x	
	Elisabetta Chicca			x			
	Erika Covi			x	x		x
	Farhad Merchant		x	x			
	Herbert Jaeger	x					
	Maria Loi				x		x
	Matthew Cook	x					
	Niels Taatgen	x					
	Tamalika Banerjee		x		x		x
Technische Universiteit Delft	Anteneh Gebregiorgis			x		x	
	Charlotte Frenkel			x			
	Christos Strydis		x			x	
	Georgi Gaydadjiev			x		x	
	Guido de Croon	x					
	Heba Abunahla			x	x		x
	Moritz Fieback			x	x		
	Mottaqiallah Taouil			x	x		
	Rajendra Bishnoi		x	x			
	Said Hamdioui			x		x	
	Wouter Serdijn			x			
Technische Universiteit Eindhoven	Aida Todri-Sanial			x	x		
	Andrew Nelson					x	
	Eugenio Cantatore			x			
	Federico Corradi	x		x			
	Henk Corporaal			x		x	
	Manil Dev Gomony					x	
	Marco Fattori			x			
	Martijn Heck				x	x	
	Patty Stabile				x	x	
	Sander Stuijk			x		x	
	Victor Calzadilla					x	
	Weiming Yao					x	
	Yoeri van der Burgt				x		x
Universiteit Twente	Amir Yousefzadeh		x	x		x	
	Christian Nijhuis				x		x
	Hans Hilgenkamp				x		x
	Sander Smink				x		x
	Wilfred van der Wiel				x		x
Universiteit Utrecht	Marjolein Dijkstra				x		x
	René van Roij				x		x

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Colophon

Core team
Johan Mentink (RU, coordinator)
Theo Rasing (RU)
Dominique Kösters (RU)
Isabel Rijk (RU)
Hans Hilgenkamp (UT)
Sander Smink (UT)
Beatriz Noheda (RUG)
Georgi Gaydadjiev (TUD)
Said Hamdioui (TUD)
Sagar Dolas (SURF)
Irene Bonati (SURF)

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Authors key aspects and info boxes

Materials
Wilfred van der Wiel (UT)
Alex Khajetoorians (RU)

Devices
Beatriz Noheda (RUG)
Hans Hilgenkamp (UT)

Circuits
Elisabetta Chicca (RUG)
Federico Corradi (TUE)

Algorithms
Sander Bothe (CWI)
Herbert Jaeger (RUG)

NC and Artificial Intelligence (AI)
Lambert Schomaker (RUG)

NC and Quantum technologies
Aida Todri-Sanial (TUE)
Heike Riel (IBM)

Architectures
Georgi Gaydadjiev (TUD)
Said Hamdioui (TUD)

Applications
Johan Mentink (RU)
Isabel Rijk (RU)

Optical neuromorphic computing
Femius Koenderink (AMOLF)
Patty Stabile (TUE)

NC and Photonics
Martijn Heck (TUE)
Patty Stabile (TUE)

NC and Semiconductor technologies
Wilfred van der Wiel (UT)