



Neuromorphic Computing in Nederland

WHITE PAPER



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Samenvatting

Dit white paper – geschreven door deskundigen van de Radboud Universiteit, Rijksuniversiteit Groningen, Technische Universiteit Delft, Technische Universiteit Eindhoven, Universiteit Twente, AMOLF, CWI en SURF – biedt inzicht in de noodzaak en het potentieel van neuromorphic computing voor Nederland. Ons doel is synergie te creëren tussen de expertise en infrastructuur van publieke en private partijen in Nederland en neuromorphic computing op de kaart te zetten als sleuteltechnologie voor energiezuinige dataverwerking.

Neuromorphic computing is een paradigma geïnspireerd op de structuur en werking van het menselijk brein, waar dataopslag en dataverwerking op dezelfde plek plaatsvinden. Dit vermindert de noodzaak van dataoverdracht aanzienlijk en verhoogt daarmee de verwerkingssnelheid, terwijl het energieverbruik juist drastisch wordt gereduceerd. Daarmee kan neuromorphic computing in verschillende sectoren een sleutelrol spelen bij de analyse van grote hoeveelheden data. Daarnaast zal de ontwikkeling van kennis over en toegang tot neuromorphic computing de noodzaak beperken om privacygevoelige data over te dragen en zo een positieve bijdrage leveren aan de digitale soevereiniteit.

Innovatie in neuromorphic computing is afhankelijk van ontwikkelingen op zes kerngebieden:

1. Materialen
2. Componenten
3. Circuitontwerp
4. Hardware-architectuur
5. Algoritmes
6. Toepassingen

Met een sterke, diverse academische gemeenschap en meerdere startups is Nederland heel actief op het gebied van neuromorphic computing. Om deze sterke uitgangspositie te consolideren en uit te bouwen, is het cruciaal om een 'moonshot' op het gebied van neuromorphic computing te definiëren. Dit moet resulteren in een beter gecoördineerde onderzoeksinspanning en een sterker verbonden ecosysteem. Het is daarom onze ambitie om een 'Neuromorphic computing NL' coalitie te creëren en een roadmap te ontwikkelen voor een gezamenlijke inspanning richting toekomstbestendige, krachtige en energiezuinige computing.



Waarom neuromorphic computing?

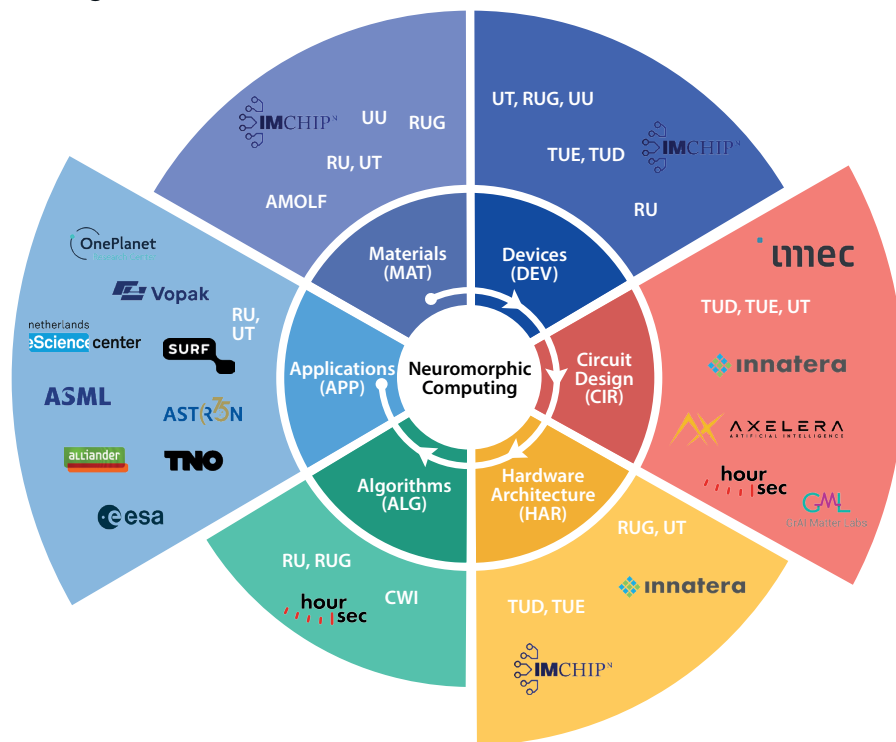
Informatietechnologie (IT) vormt de ruggengraat van de digitale en kennis-gedreven economie in Nederland. De snelle ontwikkelingen in digitalisering en de groei van sociale media en kunstmatige intelligentie leiden tot hoge energiekosten en een grote klimaatimpact, wat vooral voor Nederland nijpend is gezien de beperkte fysieke ruimte en netwerkcapaciteit voor datacentra [Woo22]. Bovendien leidt de evoluerende en snel toenemende digitalisering tot privacy- en veiligheidsproblemen en tot een toenemende afhankelijkheid van IT-expertise buiten Nederland en zelfs buiten de EU, met ernstige consequenties voor onze soevereiniteit.

Neuromorphic computing heeft de potentie om zeer snelle en extreem energiezuinige dataverwerking mogelijk te maken. Het kan daarom op veel gebieden een sleutelrol spelen in data-analyse, zoals in de gezondheidszorg, duurzame voedselvoorziening voor de groeiende wereldbevolking, storingsanalyse van het elektriciteitsnet en de logistiek. Tegelijkertijd maakt neuromorphic computing toepassingen mogelijk, zoals berekeningen van hoog-dimensionale problemen en cryptografie, die simpelweg onmogelijk of te tijd- en energie-rovend zijn met de huidige computers. Daarnaast zal de toegang tot neuromorphic computing de noodzaak beperken om privacygevoelige data over te dragen, wat onze digitale soevereiniteit verbetert.

Wat is neuromorphic computing?

Neuromorphic computing is een paradigma geïnspireerd op de structuur en werking van het menselijk brein, met name het lage energieverbruik (~20 Watt), wat slechts een fractie is vergeleken met de 50 miljoen Watt die supercomputers verbruiken. De energie-efficiëntie van het menselijk brein is mogelijk omdat dataopslag en -verwerking letterlijk op dezelfde plek plaatsvinden. Dit zorgt voor veel minder dataoverdracht dan in huidige digitale hardware en maakt parallelle dataverwerking op grote schaal mogelijk. Hierdoor worden berekeningen veel sneller en wordt dataverwerking extreem energiezuinig. Het hoofddoel van neuromorphic computing is dit potentieel voor snelle en energiezuinige informatieverwerking te realiseren in niet-biologische, brein-geïnspireerde computers.

Neuromorphic computing omvat verschillende kernaspecten, zoals weergegeven in Figuur 1 en hieronder kort toegelicht:



Figuur 1: Overzicht van de kerngebieden in neuromorphic computing (binnenste ring) en verdeling van expertise over de universiteiten, kennisinstellingen en nationale aanbieders van e-infrastructuur in Nederland. Bij toepassingen zijn alleen de bedrijven genoemd die zijn geraadpleegd tijdens het opstellen van het white paper, het potentieel is uiteraard veel groter. Buiten toepassingen zijn relevante Nederlandse startups weergegeven.

Voor neuromorphic computing zijn andere **materialen** en **componenten** nodig dan die gebruikt worden in digitale computers. Bijvoorbeeld materialen met aanpasbare eigenschappen om de synapsen van het menselijk brein na te bootsen. Componenten zijn onderdelen met een bepaalde functionaliteit. Dit kan een schakelaar zijn, een geheugenonderdeel maar ook een sensor of kunstmatig neuron. Aangezien meerdere componenten moeten worden geïntegreerd is er ook neuromorf **circuitontwerp** nodig. Bovendien moeten nieuwe **hardware-architecturen** worden ontwikkeld om een computerchip te realiseren, met volledig neuromorfe of een combinatie van digitale en neuromorfe circuits.

Algoritmes van digitale computers bepalen de manier waarop de computer wordt geprogrammeerd en communiceert met de omgeving. Bij digitale computers is er een strikte scheiding tussen software-algoritmes en hardware. Bij neuromorphic computing is deze scheiding minder duidelijk en worden ze vaak samen ontwikkeld en ontworpen. Bovendien worden neuromorfe computers anders geprogrammeerd. Het zijn in essentie **machines die leren**, net als het menselijk brein en ze worden beter door ze te trainen met data.

Neuromorphic computing heeft specifieke **toepassingen**. De verwachting is niet dat bestaande digitale computers direct worden vervangen. Neuromorphic computing zal eerder voordelen hebben voor specifieke taken die zeer veeleisend zijn qua hoeveelheid data, reactietijd of beschikbare energie. Vooral taken op het gebied van classificatie en patroonherkenning zijn zeer geschikt voor neuromorphic computing. Denk aan fraudedetectie bij creditcardtransacties en beeldanalyse door robots en drones, met potentieel grote economische voordelen, bijvoorbeeld in de gezondheidszorg, logistiek en voedselproductie.

Aangezien de rekenkosten van een complex probleem drastisch verminderd kunnen worden door alle vereiste berekeningen parallel uit te voeren, kan neuromorphic hardware ook in datacentra een groot verschil maken. Hierdoor kunnen bepaalde grote berekeningen die absoluut onmogelijk zijn op bestaande digitale hardware, haalbaar worden met neuromorphic computing. Dit heeft toepassingen in bijvoorbeeld cryptografie en voor berekeningen van hoog-dimensionale problemen zoals weersvoorspellingen en klimaatmodellen.

Wat is de huidige positie van Nederland?

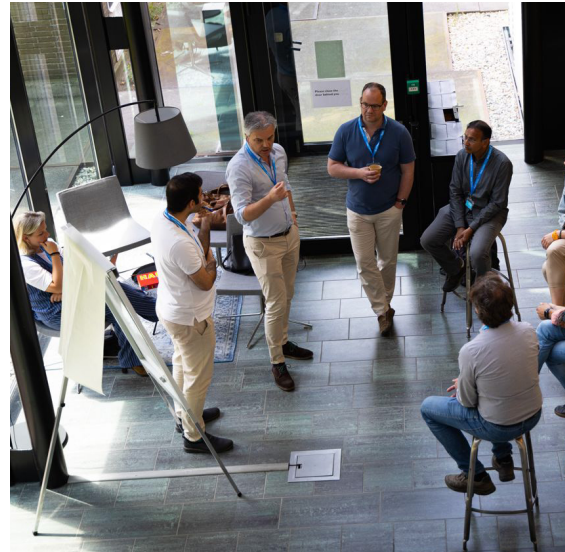
Nederland biedt een vruchtbare bodem voor het bevorderen van maatschappelijke en economische activiteit gebaseerd op neuromorfe technologieën [Con24]. We beschikken over unieke randvoorwaarden (Amsterdam Internet Exchange, sterke datacenterindustrie) en een uitstekend ecosysteem voor technologieoverdracht (TNO, IMEC) met verschillende startups die de markt al hebben betreden (bijvoorbeeld Innatera, AxeleraAI, GrAI Matter, IMChip, HourSec). Bovendien is er een sterke en diverse academische gemeenschap met verschillende belangrijke spelers (waaronder CogniGron bij de Rijksuniversiteit Groningen, MESA+/BRAINS bij Universiteit Twente, Radboud Neuromorphic Computing Initiative in Nijmegen, Hendrik Casimir en Artificial Intelligence Systems Institute Eindhoven, Faculteit EEMCS bij TU Delft, CWI en AMOLF), wat essentieel is voor lange-termijninnovatie. Genoemde instellingen zijn ook betrokken bij het eerste nationale programma, NL-ECO en het gezamenlijke academische platform Mission 10-X, gericht op energiezuinige computing waarin neuromorphic computing een sleutelrol speelt. De specifieke verdeling van expertise is weergegeven in Figuur 1 hierboven. Appendices 1 en 2 geven een samenvatting van de kernaspecten van neuromorphic computing, waarin vooraanstaande wetenschappers van Nederlandse onderzoeksinstituten de huidige status en de nieuwste ontwikkelingen beschrijven.

Deelnemers aan de eerste Nederlandse neuromorphic computing ecosysteembijeenkomst bij IMEC Eindhoven in juni 2024.



Het internationale neuromorphic computing landschap

Veel landen investeren momenteel in neuromorphic computing, zowel op fundamenteel als toegepast niveau [Meh22]. Belangrijke spelers in Europa zijn Zwitserland (Institute for Neuroinformatics); Spanje (IMS-CSIC); Duitsland (Aken (NeuroSys [Lem23]), Jülich (Jülich Neuromorphic Computing Alliance), Frankfurt (IHP-Microelectronics), Dresden (SpiNNaker 2, NAMLAB), Kiel (Neurotronics) en Münster (Hybrain)); VK (Manchester, UCL, Cambridge [cam24]); en Frankrijk (CEA-LETI, CNRS). In 2024 maakten neuromorfe computersystemen hun debuut in het internationale high-performance computing landschap buiten de EU. Het Australische International Center for Neuromorphic Systems kondigde toen Deep South aan, 's werelds grootste neuromorfe supercomputer die 228 biljoen synaptische operaties per seconde kan uitvoeren. Verder verkent Japan (RIKEN-CCS) neuromorphic computing en in de VS heeft Intel Hala Point uitgebracht en lopen er grote programma's bij IBM (HERMES core, TrueNorth en Northpole chips), Stanford (Brains-in-Silicon) en Sandia National Labs.



Wat is de volgende stap voor neuromorphic computing in Nederland?

Om de reeds sterke Nederlandse positie in neuromorphic computing te consolideren en uit te breiden, is het cruciaal om een 'moonshot' op dit gebied te definiëren. Dit impliceert een transformatie naar een meer gecoördineerde onderzoeksinspanning en -gemeenschap gericht op één doel. Om dit doel te realiseren moeten we de bestaande expertise in neuromorphic computing benutten en de verbindingen tussen verschillende technologische ontwikkelingsniveaus versterken. Hierbij kunnen we profiteren van bestaande coalities op het gebied van halfgeleiders en opkomende technologieën zoals quantum computing, kunstmatige intelligentie en fotonica (zie infokaders) en gezamenlijk een perspectief ontwikkelen om gemeenschappelijke uitdagingen aan te pakken.

We erkennen de aanbevelingen van het rapport van de Topsector ICT [con24] en benadrukken dat dit white paper een eerste belangrijke stap is om de volledige gemeenschap in Nederland samen te brengen. Om een gezamenlijke roadmap verder te ontwikkelen, stellen we voor om een coalitie te vormen met alle relevante partijen en in nauwe samenwerking met de Topsector ICT. Daarnaast benadrukken we het belang van een stabiele onderzoeksfinanciering en een duurzaam vestigingsklimaat voor startups voor het versterken van de R&D-positie. Tot slot zetten we in op valorisatie door het realiseren van een publiek toegankelijke neuromorfische infrastructuur voor het testen en benchmarken van de meest veelbelovende toepassingen in de wetenschap, industrie en maatschappij.

AFSTEMMING MET COMPLEMENTAIRE INITIATIEVEN

Neuromorphic computing en kunstmatige intelligentie (AI)

De energiekosten van AI die draait op digitale computers is enorm, zowel voor het noodzakelijke leren als het publiek gebruik van toepassingen zoals ChatGPT. Met neuromorphic hardware kunnen de basisberekeningen van AI potentieel veel sneller worden uitgevoerd met een extreem laag energieverbruik. Daardoor kan verwerking 'on the edge' (ter plekke, in specifieke computerchips) plaatsvinden, zeer dicht bij waar de data wordt geproduceerd.

Neuromorphic computing en quantumtechnologieën

Bij veel maatschappelijke uitdagingen kunnen we profiteren van de complementaire sterktes van neuromorphic en quantum computing. Bijvoorbeeld bij de ontdekking van nieuwe geneesmiddelen: eerst analyseert de neuromorfe computer enorme databanken van chemische structuren en biologische data om interacties te identificeren en potentiële kandidaat-geneesmiddelen te selecteren. Vervolgens simuleert en optimaliseert de quantumcomputer nauwkeurig moleculaire structuren om hun therapeutische eigenschappen te verbeteren en ontwikkeltijden te verkorten.

Neuromorphic computing en fotonica

De huidige ontwikkeling in fotonische geïntegreerde schakelingen, gecombineerd met nieuwe functionele materialen, kan de transmissie van licht over meerdere toestanden verdelen, die behouden blijven nadat de stroom is uitgeschakeld. Hiermee kan licht voor zowel dataverwerking als dataopslag gebruikt worden en kunnen effectieve optische synaptische componenten gerealiseerd worden. Optische neuromorphic computing biedt unieke voordelen wanneer ultrasnelle communicatie met een hoge bandbreedte in combinatie met lokale informatieverwerking vereist is.

Neuromorphic computing en halfgeleidertechnologieën

Sommige neuromorfe circuits worden al geproduceerd met behulp van standaard halfgeleiderprocessen, wat hun levensvatbaarheid in conventionele CMOS-technologie aantoont. Nieuwe materialen en componenten die CMOS-compatibel zijn, zullen een schaalbare en efficiënte integratie verder ondersteunen. Daarom is de verwachting dat in de nabije toekomst traditionele halfgeleidertechnologie zal worden gecombineerd met nieuwe neuromorfe componenten, om zo computingprestaties en flexibiliteit te maximaliseren.

Appendix 1: Kernaspecten van neuromorphic computing in Nederland

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 μ Brain [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 cascable operation. Schemes of heterogeneous material integration will enable next generation neuromorphic photonics, supported by TU/e, AMOLF and IMEC.

Appendix 2: Neuromorphic computing experts in Nederland

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
	Chris Broekema		x			x	
Astron	Bram Verhoef		x			x	
AxeleraAI	Sander Bohte	x	x				
Centrum Wiskunde & Informatica	Alexandra Pinto		x			x	
Hoursec	Amir Zjajo		x	x		x	
Innatera	Alex Khajetoorians						x
Radboud Universiteit	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
	André van Schaik		x	x			
Rijksuniversiteit Groningen	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
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	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		
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	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	
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