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Perspective

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The potential of multidimensional photonic computing

Ivonne Bente[1,7], Shabnam Taheriniya[2,7], Francesco Lenzini[3], Frank Brückerhoff-Plückelmann[1,2], Michael Kues[4], Harish Bhaskaran[5], C. David Wright[6] & Wolfram Pernice[1,2]

Abstract

The rapidly increasing demands on computational throughput, bandwidth and memory capacity fuelled by breakthroughs in machine learning pose substantial challenges for conventional electronic computing platforms. Historically, advancing compute performance relied on miniaturization to increase the transistor count on a given chip area and, more recently, on the development of parallel and multicore architectures. Computing platforms that process data using multiple, orthogonal dimensions can achieve exponential scaling on trajectories much steeper than what is possible with conventional strategies. One promising analog platform is photonics, which makes use of the physics of light, such as sensitivity to material properties and ability to encode information across multiple degrees of freedom. With recent breakthroughs in integrated photonic hardware and control, large-scale photonic systems have become a practical and timely solution for data-intensive, real-time computational tasks. Here, we explain developments in the realization of multidimensional computing platforms based on photonic systems. Moving to such architectures holds promise for low-latency, high-bandwidth information processing at reduced energy consumption.

Sections

[1]Physics Institute, University of Münster, Münster, Germany. [2]Kirchhoff-Institute for Physics, Heidelberg University, Heidelberg, Germany. [3]Consiglio Nazionale delle Ricerche, Istituto di Fotonica e Nanotecnologie (CNR-IFN), Milan, Italy. [4]Institute for Photonics, Leibniz University Hannover, Hannover, Germany. [5]Department of Materials, University of Oxford, Oxford, UK. [6]Department of Engineering, University of Exeter, Exeter, UK. [7]These authors contributed equally: Ivonne Bente, Shabnam Taheriniya. e-mail: wolfram.pernice@kip.uni-heidelberg.de

Introduction

The growing use of artificial intelligence and machine learning in technology is pushing the limits of computing for efficient real-time data processing and low-latency communication. As the computing landscape evolves to cater to the needs of an increasingly artificial-intelligence-enhanced society, the viability of future technology relies on incorporating sustainable and environmentally conscious alternatives. At present, the demand for higher computing power to train advanced artificial intelligence models in computer vision, natural language processing and multimodal computing (that is, combining language, speech and video) has grown faster than Moore's law scaling[1,2]. Specifically, large language models with billions of model parameters, such as OpenAI's GPT, Meta's Llama and Google's Gemini, present serious challenges for available computational resources[3–5]. The wide use of these models has widened the gap between the available computational capacity and the rapidly increasing volume of collected data that need processing. At the same time, meeting computational challenges steadily increases power consumption and carbon emissions[6,7], which is at odds with achieving carbon neutrality in the coming decades.

Given the current technological landscape, two prominent directions emerge to address future scaling needs in terms of hardware: first, the development of specialized hardware accelerators specifically designed to efficiently process large data sets characterized by their sheer volume rather than algorithmic complexity[8–11]. Second, specialized computing hardware directed at complex and computationally intensive tasks for which the underlying data sets are still of moderate size. These include molecular and atomic interaction simulations[12–15], cryptographic algorithm processing[16–21], climate[22,23] or financial modelling and risk analysis[24–28]. In the first case, classical computing schemes remain in use but are increasingly supplemented by specialized accelerators. These accelerators, such as graphical processing units (GPUs), tensor processing units (TPUs) and neural processing units, are specifically designed to efficiently handle arithmetic operations such as matrix–vector multiplications (MVMs). By working alongside traditional central processing units, they enhance the performance of artificial intelligence workloads, enabling more efficient and powerful computing. In the second case, non-classical machines that use quantum principles for computation are considered promising architectures to execute non-artificial intelligence complex algorithms. This is due to their natural ability to tackle complex problems beyond the reach of traditional classical hardware.

However, most current computing hardware does not benefit from a sustainable scaling strategy. Addressing future computational needs will require complementary architectures that offer improved scalability, energy efficiency and real-time processing capabilities. One promising route towards high-throughput systems is multidimensional photonic computing, which leverages light as an information carrier across multiple orthogonal degrees of freedom. This approach enables parallelism, compact encoding of complex operations and has the potential for fundamentally new modes of computation beyond the constraints of electronics.

This Perspective outlines how analog and quantum photonic systems can be used within a unified multidimensional framework to meet the growing demands of modern computation. Our focus is on quantum machine learning and quantum neural networks (QNNs) as illustrative examples of applications that are particularly well suited to photonic implementations.

To build this vision, we begin our discussion with the role of orthogonal degrees of freedom in photonic systems as a foundation for scalable and parallel information processing. We then make a distinction between data-heavy classical photonic computing, which excels at high-throughput tasks, and complexity-driven quantum computing, designed to tackle problems beyond the reach of classical systems. The complementary nature of these approaches suggests a promising path towards multidimensional, neuromorphic photonic quantum computing as a flexible and efficient architecture to meet future computational demands. Box 1 provides an overview of multidimensional photonic computing in relation to digital and analog approaches, explaining the key principles of each to offer an intuitive understanding of how this emerging paradigm operates.

Orthogonal degrees of freedom for photonic computing

Shifting focus from today's predominant fermionic information carriers in electronic circuits to bosonic information carriers, in particular photons, allows accelerated computational scaling. This is achieved by using superposition states of photons and by exploiting their orthogonal degrees of freedom to represent data. As orthogonal degrees of freedom cannot interact, replacing electrons with photons increases the capacity of each channel. This concept is already used in high-speed optical communication through techniques such as wavelength-division multiplexing (WDM)[29–31], in-phase and quadrature modulation[32–34], polarization division multiplexing[35] and spatial mode encoding[29], all of which contribute to highly parallelized signal processing.

In classical brain-inspired or neuromorphic photonic computing, the ability to integrate spectral, polarization and mode degrees of freedom at higher field intensities enables an increase in computational density. Although photonic devices may have a larger footprint compared with state-of-the-art digital transistors, the possibility to use multiple degrees of freedom within one device to increase the computational throughput offsets this limitation. This makes photonics an attractive choice for high-density computing applications.

Ultralow-latency photonic computation, which aligns with the growing demands of modern systems, is achieved by building on the vast bandwidth of optical carrier frequencies along with high modulation rates and short pulse durations. Simultaneously, temporal degrees of freedom can be used to reduce the need for physical components, enhancing efficiency and scalability[36] (Fig. 1a). Low energy consumption photonic computations in edge applications[37] have been demonstrated, making use of temporal accumulation for large vector representation[8,37,38] and photonic convolutional neural networks (CNNs)[39].

A complementary form of multiplexing uses the wavelength or frequency of the light. As photons do not interact with each other at the power levels required for analog computation, multiple signal carriers can be processed in parallel by encoding individual information on different wavelength channels (Fig. 1b). This approach enables parallel processing in linear photonic analog computation[8,40,41] and also allows the creation of highly entangled non-classical states for photonic quantum computation[42–44].

Spatial mode multiplexing with orthogonal free-space or waveguide modes enables parallel processing of analog data in physical systems that support multiple propagation modes (Fig. 1c). The abundance of spatial modes in free-space optics allows for highly parallel manipulation and processing of large input states. This parallel processing is

Box 1 | Multidimensional photonic computing

The evolution of computing systems reflects the increasing complexity of tasks and the demand for more efficient, scalable solutions. Traditional digital computing, which forms the backbone of modern information processing, relies on binary logic and sequential operations to handle deterministic problems with precision. However, as computational needs outgrow the capabilities of binary systems, alternative approaches such as analog and multidimensional computing become interesting. These approaches use continuous variables and orthogonal dimensions such as wavelength, space and polarization to achieve parallel processing and expanded representational capacity. In such architectures, the number of accessible states or computational pathways can provide additional opportunities for scaling to address the limitations of classical digital architectures. This progression illustrates a shift from simple binary systems to more advanced, integrated frameworks that are capable of addressing high-dimensional, complex challenges.

Digital computing

Digital computing, based on binary logic and the von Neumann architecture, encodes data as 0s and 1s and processes it sequentially, separating memory and processing units. This approach has driven technological progress with strengths in precision, scalability and efficiency for deterministic tasks. However, it faces challenges such as bottlenecks in data flow, physical limits to transistor miniaturization and inefficiencies in handling complex or high-dimensional data. Although essential for general-purpose tasks, digital computing increasingly serves as the foundation for advanced techniques designed to address modern computational complexities.

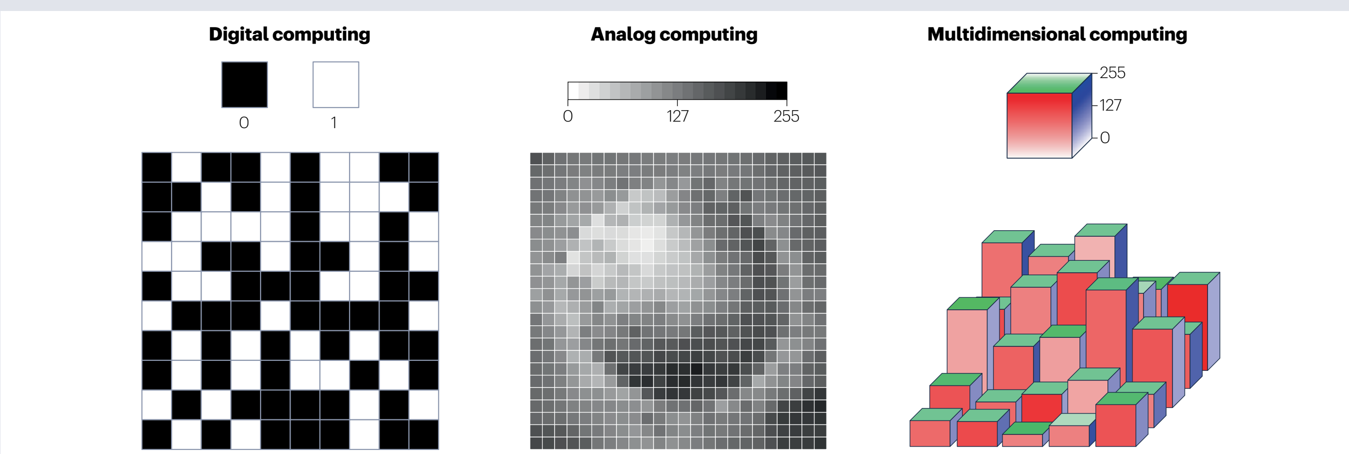
Analog computing

Analog computing refers to a computational paradigm that uses continuous variables to represent and process information, in contrast to digital systems that rely on discrete values. This concept incorporates a range of physical implementations, of which photonic computing is a prominent example in which light waves encode information through properties such as amplitude, frequency and phase. Analog computing offers advantages, including high-speed processing at the speed of light, energy efficiency compared with traditional electronics and natural parallelism suited to tasks such as signal processing and neural network simulations[145]. However, analog photonic computing faces challenges such as noise sensitivity, which can lead to instability and cause difficulty in achieving precision and scalability. Recent work indicates[146] that this is mainly due to complex correction mechanisms and the challenges of integrating analog systems with existing digital frameworks. Despite these challenges, analog optical computing is a promising solution for tasks that binary systems handle inefficiently.

Multidimensional computing

Multidimensional computing explores an additional approach to information processing by encoding and manipulating data across multiple orthogonal dimensions simultaneously. This concept is exemplified in photonic and quantum systems, in which bosonic information carriers, such as photons, use properties such as wavelength, polarization, spatial modes and temporal patterns to enable high-density data encoding. By leveraging orthogonal degrees of freedom, multidimensional systems enable the concurrent transmission and processing of multiple data channels. This approach aims to enhance computational density without increasing chip size in the long run. Although quantum systems leverage exponential scaling in Hilbert spaces to address problems that are intractable for classical architectures, photonic computing systems enable enhanced efficiency through the use of multiplexing techniques across orthogonal degrees of freedom[147].

This approach surpasses the limitations of traditional binary computing, which struggles to scale owing to physical constraints outlined by Moore's law[148]. Multidimensional computing excels at high-dimensional tasks, such as artificial intelligence, machine learning and quantum simulations, by offering speed, flexibility and scalability[95–97]. Implementing such systems requires advanced technologies including integrated photonics, quantum processors and hybrid platforms, as well as sophisticated error correction to address noise and cross-domain integration challenges. Such demands may be met as multidimensional computing joins the computational landscape, offering potentially scalable solutions that support modern applications.



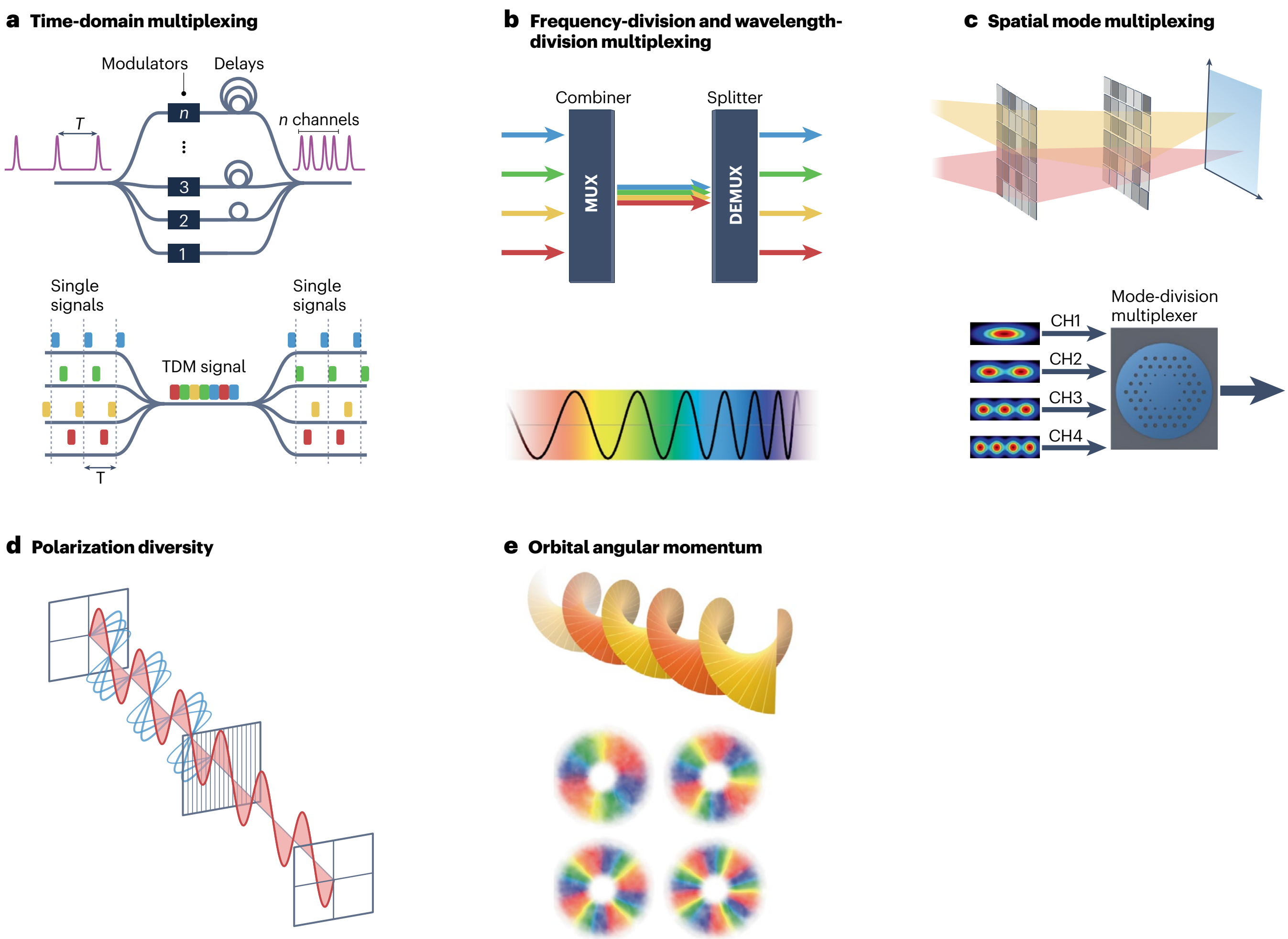


Fig. 1 | Degrees of freedom in optical computing. Schematic illustration of the different types of multiplexing used in optical computing. **a**, In time-division multiplexing (TDM), the incoming light of the same source and a fixed time interval T is split into n-channels, each channel is modulated and delayed, and in the end combined with the other channels such that the fixed time interval contains n signals (top). Using different light sources, each signal is transmitted on a different timestamp of a time interval and can be detected according to the timestamp afterwards (bottom). **b**, In frequency or wavelength-division multiplexing, several wavelengths (or frequencies) are combined by a multiplexer (MUX), transmitted or processed and then split up by a demultiplexer (DEMUX) into their separate wavelengths again. **c**, Spatial or mode-division multiplexing uses two states of orthogonal polarizations to transmit signals on the same frequency, with different modes providing a range of channels (CH). **d**, Polarization-division multiplexing uses two states of orthogonal polarization to transmit signals on the same frequency. **e**, In orbital angular momentum multiplexing, the orthogonal states of light are distinguished by the orbital angular momentum.

achieved through wavefront shaping with lenses, metasurfaces[45,46] or spatial light modulators[47,48]. In integrated and fibre-based systems, spatial multiplexing is realized by using different waveguides and multiple or multicore single-mode fibres as separate channels[8,29]. To support several orthogonal modes in multimode fibres, mode-division multiplexing is used together with multimode lasers[49], providing the necessary higher-order modes. In integrated photonic platforms for physical computation, waveguides carrying coherent or incoherent signals replace the traditional electrical wires. Transitioning from single-mode to multimode waveguide geometries supports the use of higher-order modes to encode information in orthogonal states. This approach has been successfully applied in mode-multiplexed MVM and CNNs[50,51].

As an intrinsic property of optical waves, polarization has long been used to encode orthogonal information across various fields (Fig. 1d), including optical communications[52], optical processors[53], quantum optics[54] and quantum information processing[55–57].

Finally, as an example of orthogonal states, the orbital angular momentum carried by light waves provides additional pathways for information encoding that are not used in conventional fermionic computation (Fig. 1e). Orbital angular momentum is predominantly used in free-space communication[58] and quantum applications[59–63], offering unparalleled opportunities to advance data encoding and processing.

These different multiplexing schemes are a crucial part of photonic computing devices. Implementing one or more of the multiplexing techniques shown in Fig. 1 increases the throughput of the photonic device by the number of channels that can be added.

Data-heavy versus complexity-driven architectures

Using these different orthogonal degrees of freedom in photonic platforms promises to change the landscape of classical and quantum photonic computing for data-heavy and complexity-heavy applications. This is needed because classical computing built on electronic circuits is constrained by fundamental physical and efficiency limitations, even though notable data throughput levels have been achieved. Yet with the push towards future exascale computing architectures, ultrahigh throughput is expected to become a critical component.

In the scope of multidimensional photonic computing, two development trajectories have emerged. One path lies in classical data-heavy information processing, as using photons for implementing arithmetic operations in analog computing systems enables single-shot operation at very high bandwidth and throughput. Mid-term and long-term scalability can be achieved by linear and nonlinear optical techniques, which enable brain-inspired or neuromorphic systems to emulate the analog computation functions of nervous tissue. Especially compelling is the combination of in-memory computing-based neuromorphic architectures and orthogonal degrees of freedom for data encoding.

The second path follows photonic quantum computing, which harnesses the large feature space available to this approach. For complexity-driven architectures, hyperdimensional computing (HDC) and quantum computing approaches offer viable scaling routes. Quantum computing capitalizes on the principles of quantum mechanics to execute intricate computations more effectively than classical systems, particularly in cryptography and complex simulation tasks. However, state-of-the-art quantum processors continue to face scalability challenges, including increasing the number of high-fidelity qubits while maintaining low error rates and sufficient coherence time. These limitations, along with the fragile nature of quantum operations, strongly impact data and signal reliability, particularly in large-scale and high-throughput applications.

The combination of these two computing paradigms on a photonic platform offers a promising way forward, aimed at maximizing data processing capabilities while minimizing environmental interaction and reducing thermal noise.

Data-heavy computation

Using photonic concepts promises to enhance computing capabilities for neuromorphic architectures. The term neuromorphic computing describes computing schemes or architectures that are inspired by brains and emulate biological neurons and synapses. As in a brain, neuromorphic computing can include the co-location of memory and processing, which is also termed in-memory computing. In the photonic domain, neuromorphic computing uses analog architectures, although this does not mean that neuromorphic hardware needs to be analog. Indeed, digital-based neuromorphic hardware is more mature[64]. Although neuromorphic computing focuses on realizing brain-like hardware, there are also neural networks, which implement brain-like computing schemes in software. Neural networks mimic biological brains and consist of layers of artificial neurons which are interconnected via weights and nonlinear activation functions. The weights can be represented by a matrix with which the inputs are multiplied, and the nonlinear activation function is applied to the result of the MVM. Merging neuromorphic computing with neural networks promises to better accelerate the MVMs, which are at the core of neural networks, making them faster and more energy-efficient. Photonic computing concepts aim to combine neural networks and neuromorphic computing both in hardware and in software.

Photonic computing concepts can be categorized according to the basic building blocks shown in Fig. 2. First, the overall design depends on the modulation scheme, which uses either amplitude or phase modulation to perform the calculation. Second, physically, the calculations are realized in free space, fibre or integrated optical schemes, but combinations of two or more are possible. Finally, the communication between the optical and electronic components is realized by an analog–digital or analog–analog interface. Adding to these basic building blocks, researchers look into the optimization of different details in the optical domain. These range from on-chip nonlinearity to deep neural networks, cloud computing, multiplexing, telecommunication, training and simulating physical systems, to integrating components. The integration of optical components often offers a more versatile usable chip with less chip area per calculation, which is more resource-efficient. In the following, we will give examples of how the basic building blocks from Fig. 2 are implemented in photonic applications and additionally, how they are combined with the various multiplexing techniques (Fig. 1) to enable multidimensional photonic computing.

Although optical telecommunication is already well established, especially for long-distance communication where current transatlantic transmission rates[65] are at 320 Tb s^{-1}, research on optical transceivers and frequency combs for optical communication is also relevant for photonic computing. Frequency combs provide equally spaced spectral lines over a certain frequency band, which can be used to encode multiple input parameters in photonic computing. Recent advances in the field that are important for optical communication and photonic computing include the integration of microcomb technology with an inverse-designed silicon photonic mode-division multiplexer[31], facilitating error-free transmission of 1.12 Tb s^{-1} through both mode-division and wavelength-division multiplexing. Additionally, a single microcomb ring can reach an optical data transmission rate of 1.84 Pb s^{-1} (equivalent to 230 Tb s^{-1}) by incorporating both spatial and wavelength multiplexing[29]. However, the speed of photonic computing is usually measured in terms of operations per second (OPS), which is not directly comparable to data transmission rates in terabit per second. Still, data transmission rates give a rough estimate of the data input rates that might be possible. The growing relevance of optical technologies for computing is further underscored by NVIDIA's recent announcement of co-packaged optics switches with GPUs[66,67], highlighting the growing importance of optical communication in short-distance communication.

Focusing on neural networks and optimization solutions, several studies aim to enhance the computing capabilities of photonic technologies by making use of one or more multiplexing techniques. One technique integrates WDM on a silicon photonic chip using a microring weight bank approach[40], which closely resembles a continuous-time recurrent neural network to replicate its behaviour in a photonic system. Another proposal for a large-scale brain-inspired photonic computer for classifying video-based human actions uses spatial mode multiplexing while modulating the optical phase[68]. Applying WDM technology to design scalable circuits for photonic neural networks can simulate the behaviour of basic integrate-and-fire neurons[69]. Incorporating an on-chip frequency comb (providing several wavelengths) and a photonic tensor core achieved 4 T-OPS in

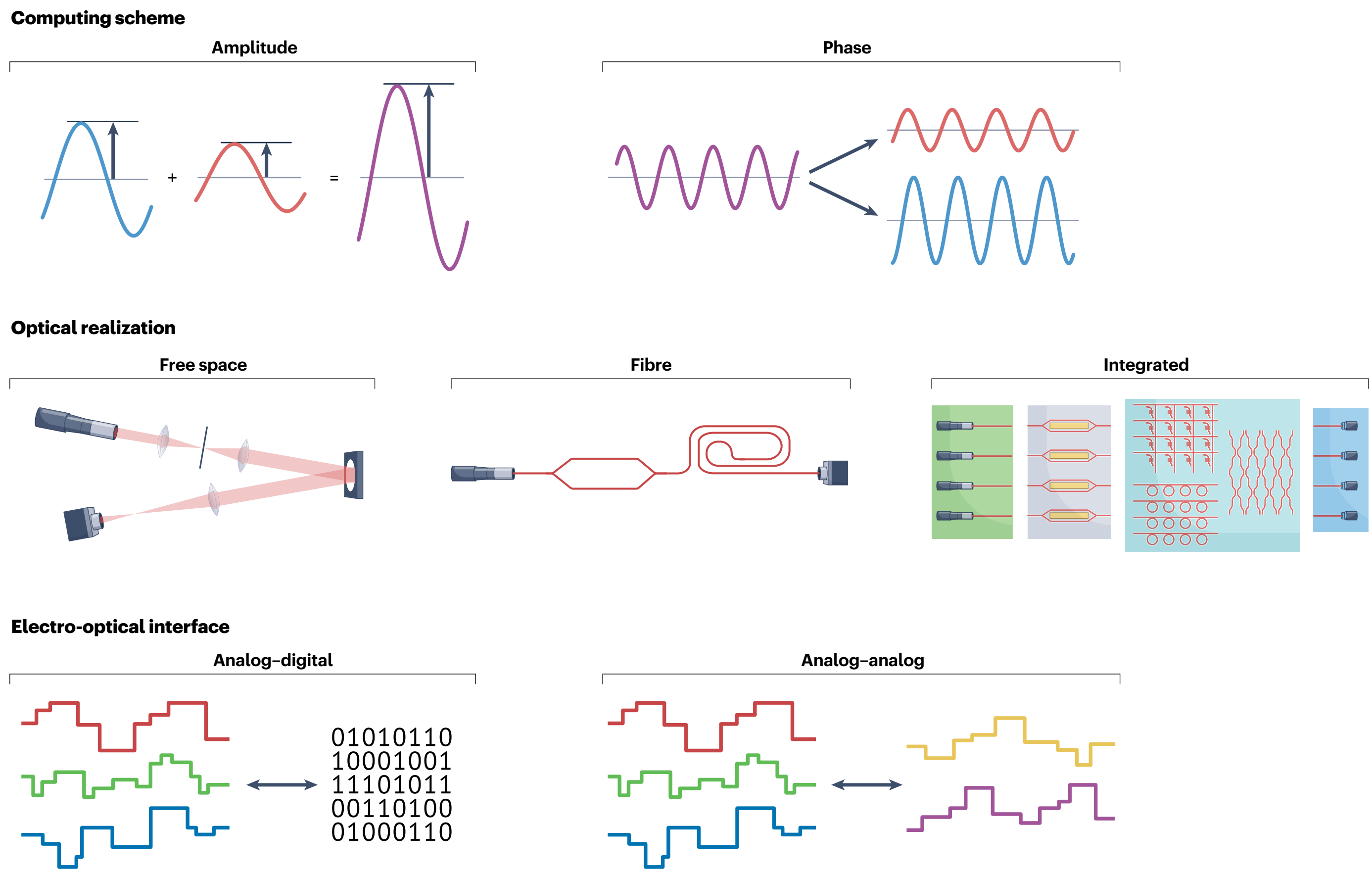


Fig. 2 | Overview of basic building blocks for neuromorphic photonic computing approaches and platforms. In photonic computing, the light needs to be modulated to carry information. This information is encoded in the light by amplitude or by phase modulation. The modulation scheme substantially predefines the architecture of the photonic computing scheme. The modulation is most commonly realized in free space, fibre or integrated photonic components, but a combination of fibre and integrated components is also used. Furthermore, the photonic components need an electro-optical interface, which is either analog–digital or analog–analog, for their control, modulation or readout.

a specialized application-specific processor[41]. A large-scale photonic CNN using time-division multiplexing is a first step towards improving the speed and scalability of photonic neural networks, but spatial division multiplexing and WDM could enhance system throughput[39]. More recently, it was shown that photonic convolutional processing can be enhanced by decreasing the optical coherence of the input light[70]. This concept also enables progress towards probabilistic photonic computing[71].

Thus far, many photonic computing approaches demonstrate shallow neural networks consisting of only one layer. This has been addressed by a reconfigurable diffractive processing unit that uses spatial modulation and temporal multiplexing, supporting millions of neurons[72]. This unit can adapt to various types of neural networks, such as diffractive deep neural networks, diffractive networks in networks and diffractive recurrent neural networks. Integrated trainable diffractive optics have also been shown, which can process vision and audio data at 217.6 T-OPS[73]. Another proposal to realize deeper neural networks uses an optical computing network that sends weight data from cloud-based smart transceivers across long distances (86 km) to edge devices that leverage WDM to efficiently perform image recognition with minimal power consumption[74].

Although in most optical neural network (ONN) approaches nonlinearity is handled by software, there are efforts to realize it directly on-chip. An initial demonstration used coherent homodyne multiplication to realize a phase-encoded detection-based optical nonlinearity. This novel ONN approach based on a vertical cavity surface emitting laser (VCSEL) architecture uses time multiplexing to model systems with tens of billions of neurons[75]. Having the nonlinearity directly on-chip combined with the detection can have advantages such as low latency, as shown in this example. Integrated photonic nonlinearity can add to the latency owing to additional electro-optical conversions, whereas material-based nonlinearities can be wavelength-dependent and require additional compensation when multiple wavelengths are used. More details on integrated nonlinearities can be found in ref. 76.

Neuromorphic configurations, using both linear and nonlinear optical techniques, make use of the functions of analog computation, pushing the limits of data processing speed. These photonic neuromorphic architectures, which combine high-speed data transmission with formidable computational capabilities, are crucial for the future of exascale computing and underscore the importance of ultrahigh throughput. A photonic convolutional accelerator that uses a combination of time, wavelength and spatial multiplexing[8] has reached a processing speed of 11 T-OPS. This method encodes convolutional kernel weights into microcomb lines as optical power, simplifying data processing by transmitting temporal input data through kernel wavelength channels and combining the optical signals in a photodetector. In a related work, a video image processor using a Kerr microcomb and wavelength, spatial and polarization multiplexing techniques achieved a computing speed of 21.4 T-OPS[9]. These efforts share the goal of reaching peta-OPS speeds and expanding the functional range by incorporating polarization and additional spatial dimensions. In these examples, the combination of several multiplexing techniques enables ultrahigh throughput, exemplifying the benefits of multidimensional computing.

A key challenge for most ONNs is the opto-electronic interface. The photonic platforms offer low-latency data traffic, and the electronic input is needed to drive and readout active components. Optimizing this interface is crucial to obtain fast and efficient performance. An all-analog chip combining electronic and optical computing[11] could greatly reduce energy consumption by optimizing the opto-electronic processing interface. The chip integrates optical analog computing based on spatial light multiplexing, which manages data processing and feature extraction, and electronic analog computing, which handles the final result calculations. This architecture supports digital post-processing and achieves an energy reduction by three orders of magnitude compared with conventional electronic architectures. In another approach based on the first proposed ONN[77], researchers from Microsoft and Cambridge introduced an analog iterative machine that uses spatial-division multiplexing[78] to speed up optimization problems in combined opto-electronic analog hardware. The analog iterative machine reportedly surpasses existing quantum hardware in solving optimization problems at room temperature with unprecedented accuracy.

Further optimization of ONNs can be achieved by co-designing physical systems for computation[79] and with training algorithms such as physics-aware training[80], which considers imperfections from fabrication or noise during the forward pass of the training. Additionally, systems with no clear mathematical isomorphism between the physical layer and conventional artificial neural network can be trained by simulating the backward pass while the physical system processes the forward pass simultaneously. Although this is an example of a model-based approach, other approaches based on reinforcement learning[81] or simulated annealing[82] are model-free. An extensive review on computing with physical (photonic) systems and efficient optimization of those can be found in ref. 83.

Merging multiplexing techniques with advanced photonic elements aims to enable powerful architectures for accelerating artificial intelligence and optimization problems to complement complementary metal-oxide-semiconductor-based central processing units, GPUs and TPUs. Each of the studies discussed earlier addresses different problems in the field, such as using an on-chip nonlinearity, optimizing the electro-optical interface, improving speed or energy efficiency and integrating more components on-chip. In an optimal chip, all these issues have to be optimized at the same time to guarantee optimal performance of the photonic computing architectures.

Digital state-of-the-art TPUs such as Google TPU v4 with 275 T-FLOPS (floating-point OPS)[84] (~190 W, ~1.4 T-FLOPS per watt) and digital neuromorphic hardware such as IBM True North with 58 giga-synaptic-OPS[85] (or 400 giga-synaptic-OPS per watt), and analog electronic neuromorphic hardware such as IBM Hermes with 63.1 T-OPS (or 9.76 T-OPS W^{-1})[86], show the computation speeds that need to be achieved by photonic systems while keeping the energy consumption low.

Latencies of photonic computing approaches lie in the range of 30 ps to 8.1 µs (refs. 8,11,41,73,75). Note that some of these times describe the optical latency only, whereas others include the whole system processing time. In some works, the energy efficiency is given in OPS per watt, ranging from 0.4 T-OPS W^{-1} to 74.8 P-OPS W^{-1} (refs. 10,41,72,73,75) for the whole system efficiency, whereas other works report the energy per operation, ranging from 40 aJ per OP to 4.38 nJ per OP[11,74,75,87]. Another important metric is the compute density, especially for integrated photonic accelerators, which ranges from 1.2 T-OPS mm^{-2} to 447.7 T-OPS mm^{-2} (refs. 41,73,87) or 1,758 T-FLOPS mm^{-2} (ref. 10). Several articles discuss these metrics in more detail[10,41,83,88–94].

Complexity-driven computation

Advanced machine learning and computational models that effectively realize abstract mappings and manage complex data structures use the concept of HDC for complexity-driven computation. Such approaches naturally map to multidimensional computing ideas by operating in a high-dimensional abstract space. By focusing on encoding information in hyperdimensional vectors and using content-addressable memory platforms, HDC improves the support for advanced machine-learning algorithms including support vector machines. HDC is particularly notable within computational architectures owing to its inherent robustness against uncertainties, often introduced by hardware, which makes HDC particularly suited to analog systems. For example, by using the electronic in-memory approach, an encoder and associative memory outperforms 65 nm complementary metal-oxide-semiconductor technology in terms of energy efficiency[95]. In another development, novel attention mechanism that stores unrelated items in the key memory as uncorrelated hyperdimensional vectors enhances the performance of the controller[96]. This advance enables the HDC in CNN controllers. Additionally, a proposed neuro-vector-symbolic architecture combines deep neural networks and vector-symbolic architectures[97]. This integration creates a synergistic system that co-designs a visual perception frontend and a probabilistic reasoning backend, leading to improvements in the overall computational architecture.

With the proposed potentials in mind, various solutions to the challenges in HDC have been discussed[98], starting with optical interconnects that offer higher bandwidth and lower energy consumption to facilitate data transfer between processors and memory. Opting for passive optical components such as optical interference units and optical nonlinear units enables efficient operations with negligible optical power consumption. Hybrid optical–electrical structures take advantage of the speed and efficiency in optical components alongside the control capabilities of electronic elements[98].

Concurrently, as quantum systems can naturally exploit a multidimensional space for physical computing, it makes them exceptionally suitable for implementing tasks that are typical in machine learning and artificial intelligence, such as performing linear operations on large sets of data[99] or mapping data into a high-dimensional feature space[100,101]. Over the past decade, this has motivated the growth of a new research field known as quantum machine learning[102]. At present, quantum machine learning can be broadly classified into two main categories – quantum basic linear algebra subroutines (qBLAS) and QNNs.

qBLAS are quantum algorithms designed to efficiently execute subroutines based on linear algebra operations, such as inverting linear systems of equations[99]. Using only n logical qubits, qBLAS can

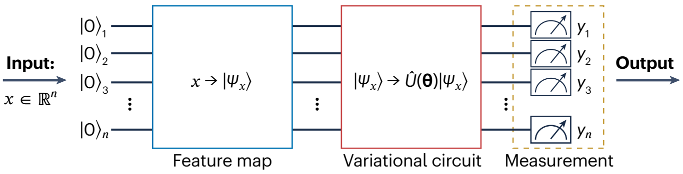


Fig. 3 | Configuration of a quantum neural network. An input vector consisting of n real numbers is mapped into a quantum state consisting of n qubits. The state is evolved with a parametrized unitary transformation. At the output of the circuit, the value of each qubit is measured and classically post-processed to calculate a cost function. Figure adapted from ref. 116, Springer Nature Limited.

process a large data set with 2^n dimensionality and provide an exponential speed-up in various machine-learning tasks[103–105]. Despite their notable potential, these algorithms are subject to several limitations[106]. The most prominent limitation, referred to as the input problem, consists in the loading of 2^n data entries into n quantum bits. This task can only be efficiently performed with the aid of a quantum random access memory[107]. Although photonic implementations for small-scale systems have been already demonstrated[108], scaling up to larger sizes remains a challenge. Moreover, the implementation of qBLAS strictly requires a large-scale fault-tolerant quantum processor, which – despite recent advances in this direction[109,110] – will likely require a substantial amount of time before it can be effectively deployed.

QNNs are variational quantum circuits based on a set of parametrized quantum gates[111]. Unlike qBLAS, they can be implemented in a noisy-intermediate scale quantum processor, which is a medium-sized quantum computer, typically consisting of a few hundred of modes and gates, able to show quantum computational advantage without the requirement of performing (or with only limited) quantum error correction[112]. When handling classical data sets, QNNs can perform most of the tasks assigned to classical neural networks and address the input problem described previously by establishing a direct (one-to-one) or nearly direct (close to one-to-one) correspondence between the input data entries and the physical modes of the network. However, unlike the case of qBLAS, it is an open question whether they can provide a genuine advantage over classical systems[113–115]. As noted in ref. 102, there are compelling reasons to believe that this should be the case. Indeed, if a quantum processor can generate outputs that are computationally difficult for classical systems to reproduce, it is also reasonable to assume that it could identify patterns in data that a classical computer might miss. For example, in supervised learning tasks (Fig. 3), a first set of quantum gates is used to map the input data into an exponentially large, but sparse, feature Hilbert space.

The mapped data can be directly classified in the feature Hilbert space with an additional set of parametrized quantum gates, whose values – in close analogy with classical neural networks – are optimized to minimize a cost function[100,101]. Preliminary results suggest that these systems can enable a higher capacity, that is, they are able to approximating a larger number of functions, as well as faster training than their classical counterparts[116]. Interestingly, a classical simulation of a QNN consisting of a sizeable number of modes quickly becomes a computationally intractable problem. Thus, a proper benchmarking of such hypotheses will require the physical implementation of these architectures.

Moving forward towards the implementation of QNNs in near-term quantum photonic processors, two main approaches are currently under study: discrete-variable and continuous-variable optical quantum computing. In discrete-variable quantum computing, the information is encoded in discrete degrees of freedom of a single photon, such as its orthogonal polarization states, or its alternative propagating paths. For this approach, challenges ahead include the development of deterministic single-photon source and deterministic two-photon entangling gates, for which nonlinearities at the single-photon level (currently unavailable with conventional nonlinear optical media) are strictly required. A particularly promising direction is the use of quantum dots embedded in waveguides or optical cavities. These systems are already a leading platform for the realization of highly efficient single-photon emitters[117–119] and, as recently demonstrated, can also be used for mediating nonlinear interactions between single-photon wavepackets[120–123]. Alternatively, within the narrower framework of quantum reservoir computing[124], the required nonlinearity could be achieved through photonic quantum memristors, which can be more easily implemented in current photonic platforms by combining programmable interferometers with single-photon detectors[125].

Continuous-variable quantum optics is an analog approach to optical quantum computing, in which the information is encoded in operators with a continuum spectrum of eigenvalues, namely, the amplitude and phase quadratures of the electric field[126]. As a main advantage, the required quantum states – squeezed states of light – can be generated on-demand by parametric down-conversion, whereas deterministic entangling operations can be performed using beam splitters. Additionally, the information encoded in the states is read-out by homodyne detection with conventional photodiodes. Essentially, when implementing this set of operations (known as Gaussian operations), continuous-variable QNNs can maintain all the benefits of classical photonic systems, including high bandwidth, low-energy consumption and operation at room temperature. Furthermore, similar to classical photonic systems, they can be scaled-up to larger dimensions by leveraging either frequency[127] or temporal[128] degrees of freedom. Combined with the possibility of generating squeezed

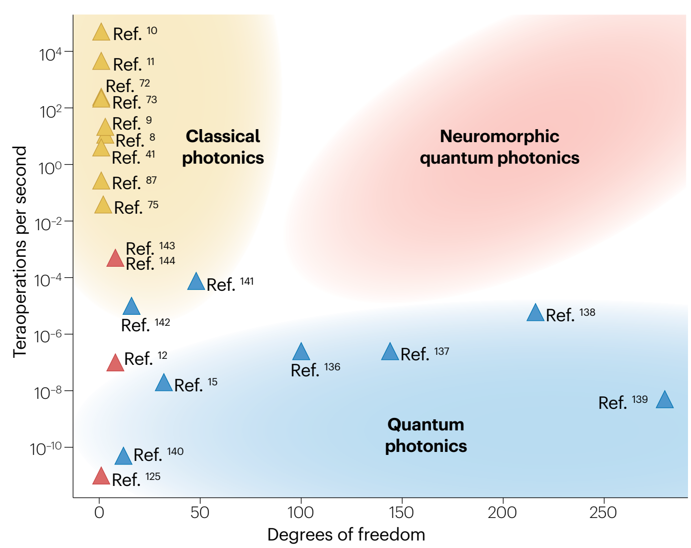


Fig. 4 | Perspective for neuromorphic quantum photonics. Joining the capabilities of classical photonic processing with quantum photonics opens up the field of neuromorphic quantum photonics. This combines the high data throughput of photonic neural networks with the ability of quantum networks to process information in a high-dimensional Hilbert space.

light on-demand and creating entanglement deterministically, this property gives continuous-variable systems a potential for scalability. Indeed, using a limited number of components interfaced with optical delay lines, it is already possible to generate ultra-large cluster states multiplexed in the time domain characterized by very large depth[109] (86.4 billions of entangled modes).

Nevertheless, to realize a continuous-variable QNN, Gaussian operations alone are insufficient. As with discrete-variable systems, they must be complemented with a strong optical nonlinearity (for example, self-Kerr interaction), having an analogous role to the nonlinear activation functions in classical neural networks. Although achieving sufficiently strong nonlinearities with available material platforms has so far been out of reach, the recent progress in the performance of photonic integrated circuits implemented in $\chi^{(2)}$-nonlinear materials is bringing nonlinear optics close to a regime where this might be feasible[129,130]. Particularly, recent theoretical results suggest that in a continuous-variable setting, non-Gaussian operations with sufficient strength could be implemented using existing technology[131–135]. Although this will only be possible upon the solution of several engineering challenges – first of all, the realization of photonic circuits with a propagation loss coefficient substantially below the current state of the art – such an achievement could open the unique perspective of realizing a quantum processor operating at high bandwidth and in a room-temperature environment, in which all the benefits of classical and quantum photonic systems can be combined.

Towards multidimensional neuromorphic photonic quantum computing

Integrating classical photonic processing with quantum photonics opens up possibilities for developing multidimensional neuromorphic quantum photonics. This combination leverages the high data throughput of photonic neural networks alongside the capability of quantum networks to process information within a high-dimensional Hilbert space.

Figure 4 shows a graphical overview of the current state of the art in quantum and classical photonic systems (the detailed performance characteristics of the depicted systems are listed in Table 1). Classical photonic computing shows very high operation speeds up to 50 P-OPS[10], whereas the degrees of freedom used are in the single-digit regime. By contrast, quantum photonic systems operate with up to 300 degrees of freedom at relatively low speed. Here, we use the term degrees of freedom to express the complexity of classical photonic computing and (neuromorphic) quantum photonic computing. Classical photonic computing considers the number of different multiplexing techniques implemented, whereas (neuromorphic) quantum photonic computing works with the number of realized modes. Gaussian boson samplers, which exploit the deterministic generation of squeezed states of light, have demonstrated quantum computational advantage in three distinct experiments[136–138]. However, because these systems lack full circuit programmability, they are limited to producing photon number distributions that are computationally difficult to sample classically, without solving any problem of practical relevance. Thus, despite their computational complexity, these systems remain data-wise shallow.

Although electronic analog computing has already proven capable of processing large data with low latency and high energy efficiency[86], current classical photonic processors excel primarily n performing linear operations. Despite their ability to process large data efficiently, it can be argued that they are computation-wise shallow.

Table 1 | Performance characteristics of existing photonic processors, as reported in refs. 8–12,15,41,72,73,75,87,125, 136–144

Author	Ref.	Degrees of freedom	Teraoperations per second
Classical neuromorphic photonics			
Xu et al. (2021)	8	3	11.322
Feldmann et al. (2021)	41	1	4
Chen et al. (2023)	11	1	4.6×10^{3}
Ashtiani et al. (2022)	87	1	0.27
Xu et al. (2024)	10	1	50×10^{3}
Zhou et al. (2021)	72	1	240.1
Chen et al. (2023)	75	3	0.0384
Tan et al. (2023)	9	2	21.386
Cheng et al. (2024)	73	1	217.6
Quantum photonics			
Madsen et al. (2022)	138	216	6×10^{-6}
Zhong et al. (2020)	136	100	2.5×10^{-7}
Bluvstein et al. (2024)	139	280	5×10^{-9}
Zhong et al. (2021)	137	144	250×10^{-9}
Maring et al. (2024)	140	12	50×10^{-12}
Yu et al. (2023)	15	32	20×10^{-9}
Wang et al. (2019)	141	48	76×10^{-6}
Carosini et al. (2024)	142	16	10×10^{-6}
Neuromorphic quantum photonics			
Spagnolo et al. (2022)	125	1	10×10^{-12}
Bao et al. (2023)	143	8	500×10^{-6}
Arrazola et al. (2021)	12	8	100×10^{-9}
Vigliar et al. (2021)	144	8	500×10^{-6}

Table 1 lists the details of the performance characteristics reported in the plotted references.

Continuous-variable QNNs offer a potential solution to bridge these two regimes by simultaneously leveraging temporal or frequency degrees of freedom alongside the intrinsic nonlinearity of emerging photonic integrated platforms. This approach enables the development of large-scale ONNs that retain the benefits of classical photonic systems while expanding their capabilities, potentially unlocking novel functionalities in artificial intelligence.

Multidimensional photonic computing offers attractive perspectives by leveraging the unique properties of light for faster processing speeds and greater energy efficiency, thereby addressing two of the key challenges in modern computing: performance bottlenecks and power consumption. Encoding information not only in the intensity of light but also in other properties such as phase, polarization and wavelength allows parallel processing in multiple dimensions. This expands the computational capacity beyond what is achievable with traditional, 1D electronic circuits. Photonics is the natural platform for ONNs and optical quantum computing – two fields that are highly promising for solving complex problems in machine learning, cryptography and large-scale simulations. By enabling more complex and dense data encoding and transmission, multidimensional photonic computing could revolutionize fields that require massive computational power. The ability to process information at light speed, with low energy consumption and high scalability, makes it a highly attractive technology for the future of computing. Ongoing advances will further explore new aspects of light–matter interactions, especially by introducing suitable nonlinearities, integrated circuit quality and room-temperature operations, to unlock more efficient avenues into the inherently probabilistic operation modes enabled by multidimensional photonic systems, ultimately offering increasingly adaptive approaches to information processing beyond the capabilities of conventional deterministic architectures while joining the capabilities of classical neuromorphic and quantum photonic computing.

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