This is an accepted manuscript.
Cite this article:
Lamata, L. Memristors go quantum. Nat. Photon. (2022). https://doi.org/10.1038/s41566-022-00975-3

INTEGRATED OPTICS

Memristors go quantum

Lucas Lamata

A photonic quantum memristor is experimentally demonstrated, paving the way to neuromorphic quantum computing.

Every undergraduate student in electronic engineering learns about the basic building blocks of electric circuits, namely, the inductor, capacitor, and resistor. In 1971, Leon Chua proposed a new circuit element, complementary to the previous three: the memristor [1]. A memristor is a device whose resistance has memory, i.e. it stores information about its past states, and thus the name "memristor", or memory-resistor. The concept of memristor devices has evolved in the past few decades and has been extensively studied both in theory and experiments [2]. Memristors are expected to provide a new paradigm for computing, in terms of physical neural networks and neuromorphic computing. Being this concept basically from classical physics, it was not until very recently that a quantum version was proposed and analysed. A quantum memristor is a device that exhibits both quantum coherence and, in its classical limit, memristive behaviour. This concept was introduced by Pfeiffer *et al*. [3] and proposals for implementations with quantum platforms were subsequently analysed, leveraging on quantum photonics [4] and superconducting circuits [5].

Now, writing in *Nature Photonics*, M. Spagnolo *et al*. [6] have experimentally realized a photonic quantum memristor, showing both its coherent and memristive behaviour.

The motivation to introduce this element is to elucidate whether one may harness both the advantages of quantum computing and the memory characteristics of the memristor. Quantum benefits include much faster computation via quantum parallelism and genuine quantum properties such as entanglement, while the memory behaviour is a nonlinear feature enabling quantum neuromorphic computing beyond purely unitary evolution, which is linear. Pfeiffer *et al*. [3] suggested to attain the two functions via a combination of a quantum two-level system, weak measurements, and feedback. The two-level system provides the quantum behaviour, while the measurement and feedback, in turn, enable the nonlinear memristive behaviour. Two different quantum platforms were later studied for implementing this idea, namely, superconducting circuits [5] and quantum photonics [4]. In the latter case, the quantum memristor is based on a tuneable beam splitter, where the outcome of one of the output ports determines the reflectivity of the beam splitter itself. This feedback mechanism provides the memory and nonlinear behaviour, while the photonic degrees of freedom provide the quantum coherence. Spagnolo *et al*. [6] now implement experimentally an enhanced version of this proposal in an integrated photonic chip.

Quantum photonics is a widely studied quantum platform, both theoretically and experimentally [7]. Employing photons for encoding quantum information is appealing because photons can propagate to long distances with no decoherence, which makes them well suited for communication networks. However, current drawbacks of photonic quantum computing include difficulty in producing single photons on demand, detectors with far from ideal fidelities and limitations in achieving nonlinear behaviour, as quantum photonics behaves mostly linearly. The first two aspects, the single-photon sources and detectors, are constantly improving, e.g., with quantum dot single-photon sources and superconducting detectors. The third aspect, the nonlinear behaviour, united to coherent properties and network structure, is what a quantum memristor based on quantum photonics could enable. The demonstration of a photonic quantum memristor by Spagnolo *et al*. [6] may represent a basic building block for neuromorphic quantum computing. This may evolve into a novel quantum computing paradigm, largely unexplored, that could share connections and common speedups with the field of quantum machine learning, when compared to classical machine learning [8,9].

The authors adapted the proposal of [4]to make it more suitable for a real experiment, and implemented it on an integrated quantum photonics chip. The device consists of a dual rail encoding with an integrated waveguide system connected to a single photon source and detector. The memristive behaviour is implemented, as envisioned in [4], via a tuneable beam splitter, where the outcome of one of the output ports is fed onto the reflectivity of the beam splitter itself (pictured in figure 1(a)). This feedback mechanism produces the nonlinear behaviour that may be employed as a useful resource for neuromorphic quantum computing. The tuneable beam splitter is created, as customary in integrated waveguide photonics, via a Mach-Zehnder interferometer whose arms come very near to each other at two nearby points, allowing tunnelling and therefore quantum superposition of the two paths, as shown in figure 1(b). The reflectivity of the beam splitter, represented by the probability of photon crossing between different modes, is tuned by a thermal phase shifter. The shifter is controlled externally by connecting one of the output waveguides via an optical fibre to a microcontroller, which directly handles the phase shifter, as shown in figure 1(b). State preparation and state tomography are also included in the chip, before and after the quantum memristor section, respectively. This allows for a detailed analysis of the performance of the device. All the waveguides are fabricated via laser writing on a glass substrate.

The authors also speculate on possible performance improvement brought about by a network of quantum memristors for machine learning tasks, such as an image classification problem. They carry out numerical simulations of a neural network that employs purely classical resources, and compare it to a network that uses just three quantum memristors.

The numerical results show that with only this limited amount of quantum memristors, a significant gain in resources can be achieved. Indeed, about 1000 images would be needed for training the network with the quantum memristors, as opposed to the classical case, which would require more than one order of magnitude more images. In addition, the quantum-based network could classify images with an accuracy of 95%, while the classical counterpart would only achieve 71% accuracy. Even though it is hard to compare neural networks to each other, be it classical or quantum, these results point to a possible quantum advantage by employing quantum memristors in machine learning.

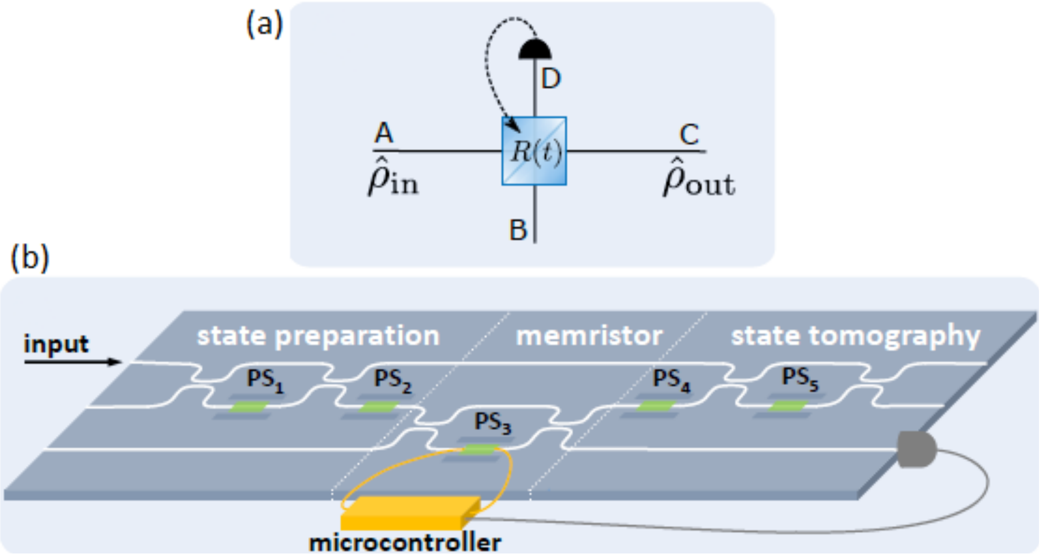

Figure 1. (a) Basic concept of a quantum memristor. A is the input port, while C and D are output ports. The measurement at port D is used to update the reflectivity R(t). (b) Scheme of the integrated quantum photonic chip consisting of a state preparation, a memristor and a state tomography section. The tuneable beamsplitter is implemented in the central section as a Mach-Zehnder interferometer whose phase in one arm is updated by a microcontroller that drives a thermal phase shifter.

Finally, the authors also numerically analyse the performance of a network involving quantum memristors for tasks such as entanglement detection. They show that the nonlinear behaviour of the quantum memristors allows one to detect entanglement with no human intervention and in a highly efficient way.

The implementation of a quantum memristor in a quantum photonics system opens up an avenue for neuromorphic quantum computing by quantum photonics networks. The combination of quantum coherence (and, therefore, quantum parallelism) with nonlinear behaviour provided by this basic building block, may enable a plethora of applications in machine learning calculations and possibly other fields. Even though it is usually hard to rigorously prove a speedup of a quantum machine learning device with respect to a classical one (just as it is hard to prove a speedup of a classical machine learning system with respect to another one), the field is worth studying, both from a purely fundamental side, and for the promising applications in computing that it could enable. Challenges for the future involve, from the theoretical side, to prove via complexity class techniques that the neuromorphic quantum computing paradigm indeed outperforms classical machine learning protocols when scaling the system up. From the experimental side, further improvements in efficiencies of on-demand deterministic single-photon sources, as well as single-photon detectors, will be required to enable the extension of this technology to a network of many photonic quantum memristors. Should these challenges be solved, among the prospects one may expect are more efficient machine learning calculations, as well as quantum simulations of open quantum systems.

References

[1] Chua, L. *IEEE Transactions on circuit theory* **18**, 507–519 (1971).

[2] Di Ventra, M., Y. V. Pershin, Y. V., & Chua, L.O. *Proceedings of the IEEE* **97**, 1717 – 1724 (2009).

[3] P. Pfeiffer, P., Egusquiza, I. L., Di Ventra, M., Sanz, M., & Solano, E., *Sci. Rep*. **6**, 29507 (2016).

[4] M. Sanz, Lamata, L. & Solano, E. *APL Photonics* **3**, 080801 (2018).

[5] Salmilehto, J., F. Deppe, F., Di Ventra, M., Sanz, M., & Solano, E. *Sci. Rep*. **7**, 42044 (2017).

[6] Spagnolo, M. *et al*., *Nat. Photon.*, xxx, xxx (2022).

[7] O'Brien, J. L., Furusawa, A. & Vučković, J., *Nat Photon*. **3**, 687 (2009).

[8] Lamata, L. *Mach. Learn.: Sci. Technol*. **1**, 033002 (2020).

[9] Biamonte, J., *et al*., *Nature* **549**, 195–202 (2017).

Author information

Affiliations

Departamento de Física Atómica, Molecular y Nuclear, Facultad de Física, Universidad de Sevilla, Apartado 1065, 41080 Sevilla, Spain

Lucas Lamata

llamata@us.es

Ethics declarations

Competing interests

The author declares no competing interests.