Chapter

# Optical Soliton Neural Networks

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## Abstract

The chapter describes the realization of photonic integrated circuits based on photorefractive solitonic waveguides. In particular, it has been shown that X-junctions formed by soliton waveguides can learn information by switching their state. X junctions can perform both supervised and unsupervised learning. In doing so, complex networks of interconnected waveguides behave like a biological neural network, where information is stored as preferred trajectories within the network. In this way, it is possible to create "episodic" psycho-memories, able to memorize information bit-by-bit, and subsequently use it to recognize unknown data. Using optical systems, it is also possible to create more advanced dense optical networks, capable of recognizing keywords within information packets (procedural psycho-memory) and possibly comparing them with the stored data (semantic psycho-memory). In this chapter, we shall describe how Solitonic Neural Networks work, showing the close parallel between biological and optical systems.


**Keywords:** Nonlinear optics, photorefractive soliton, solitonic waveguide, supervised learning, unsupervised learning, Machine Learning, biological neural network, Artificial Intelligence, optical psycho-memory, optical neural network, photonics

## 1. Introduction

Software artificial intelligence (AI) and the neuromorphic approach, both electronic and optical, are born to reproduce the learning capacity of the biological neural system. AI software has now proved to be fundamental in many fields, although with the limits imposed by the tools used [1]. These represent the pretext for developing neuromorphic hardware capable of overcoming these limitations [2]. Neuromorphic optics has shown great versatility. However, current technologies reproduce only some aspects of neural biology without grasping the overall view. Works such as [3] implement fundamental units capable of reproducing excitability, or spiking properties, while others are focused on synaptic connections [4]. An overview is missing. The biology of the brain [5] teaches us that it is a system with local properties that can have global effects. In other words, learning is a process that affects entire regions of the neural network and manifests itself through a structural organization of the connections between neurons. In this way, real neural maps are built, whose development includes learning and memorization of information. Soliton neural networks (SNNs), exploiting the typical plasticity of photorefractive materials, are dynamic entities capable of self-modifying to process, learn and memorize information. Furthermore, they are able to do so selectively at the information level, exactly as it happens in the human brain. By physically combining the processing and memory units, SNN networks functionally approach the biological nervous system. Now learning and memorization are two events that occur at the same time through modifications of the spatial geometries.

## 2. Photorefractive solitons and solitonic waveguiding

### 2.1 Spatial solitons

The possibility of a beam becoming self-confining and propagating without diffraction was first studied about 50 years ago by E.T. Chiao, E. Garmire, and C.T. Townes [6] who in that year received the Nobel Prize for his studies on the maser and the laser. So they interpreted the phenomenon: "*We shall discuss here conditions under which an electromagnetic beam can produce its dielectric waveguide and propagate without spreading.*" Eight years later, V. E. Zakharov and A. B. Shabat formulated the theory of solitons [7].

The first experimental verification of self-confined beams arrived 13 years later, in 1985, by A. Bartelemy et al. [8] exploiting the Kerr-type nonlinearity of a liquid $CS_2$ cell and, 5 years later in 1990, within a glass planar waveguide [9].

It was immediately evident that the applicability of Kerr solitons was not simple: in fact, the low values of the nonlinearity of the excitable Kerr type in the glass required either very high intensity ($GW/m^2$) or very long propagations (being cumulative), and only planar geometries (Kerr solitons are stable only in 1D and not in 2D geometries). Over the years, it has been clear that these nonlinearities could be exploited only to realize temporal soliton behaviors (pulses without dispersion) in optical fibers by adopting long propagations but not within the chips.

However, in those years, and in particular in 1992–1996, the very first theoretical and experimental works on the formation of spatial solitons in photorefractive materials came out [10–21]. Only later on, at the beginning of the 2000s, bright solitons have been observed in lithium niobate (LN) [22] the most widely used nonlinear material for integrated devices. Since then, spatial solitons in LN have been largely used as waveguides in devices.

However, the first use of solitons as waveguides started early: in 1991, De la Fuente et al. [23] used Kerr solitons as waveguides. Almost 9 years later, E. Fazio et al repeated the same experiment in a glass chip [24] and used spatial soliton interaction for signal processing [25].

### 2.2 Theory of photorefractivity and solitons

A photorefractive crystal is typically a semiconductor that has a second-order nonlinearity of the electro-optical type, that is, the possibility of varying its refractive index as a function of an applied static electric field. Mathematically this can be represented in terms of the nonlinear polarization intensity vector:

$$\vec{P}(\omega) = \varepsilon_0 \left[ \overleftrightarrow{\chi}^{(1)} \bullet \vec{E}(\omega) + \overleftrightarrow{\chi}^{(2)} : \vec{E}(0)\vec{E}(\omega) \right] \tag{1}$$

where $\vec{E}(\omega)$ represents the electric field associated with the light and $\vec{E}(0)$ the static one. Putting in evidence the light field we obtain

$$\vec{P}(\omega) = \varepsilon_0 \left[ \overleftrightarrow{\chi}^{(1)} + \overleftrightarrow{\chi}^{(2)} \bullet \vec{E}(0) \right] \bullet \vec{E}(\omega) \tag{2}$$

which shows that the electric susceptibility, and consequently the dielectric tensor, gets a linear dependence from the static field:

$$\overleftrightarrow{\varepsilon} = \varepsilon_0 \left[ 1 + \overleftrightarrow{\chi}^{(1)} + \overleftrightarrow{\chi}^{(2)} \bullet \vec{E}(0) \right] \tag{3}$$

for this reason, it is also called the "linear Pockels effect." Typically, the refractive index of crystals is described by an ellipsoid of the type:

$$\frac{x^2}{{n_x}^2} + \frac{y^2}{{n_y}^2} + \frac{z^2}{{n_z}^2} = 1 \tag{4}$$

and, as a consequence, its variation is expressed by the variation of

$$\frac{1}{n^2} \text{ (terms)}$$

$$\Delta\left(\frac{1}{n_i^2}\right) = \sum_j r_{ij} E_j(0) \tag{5}$$

that corresponds to a decrease of the refractive index:

$$n_i[E(0)] = n_{i,0} - \frac{1}{2} \sum_j n_{i0}^3 r_{ij} E_j(0) \tag{6}$$

where $i$ represents one of the crystallographic directions (x,y,z) and $n_{i0}$ describes the linear refractive index along the *i-th* direction.

There are two critical points in the discussion that has followed so far:

1. the local electrostatic field must give a local distribution to induce an electro-optical variation of the refractive index capable of self-confining the laser beam and originating spatial solitons

2. the electro-optical effect decreases the refractive index of the material (see Eq. (6)) while to self-confine the light a waveguide must have a higher refractive index than the surrounding environment.

For these reasons, it is necessary to follow a small procedure, a kind of small trick, to achieve a positive variation of the refractive index capable of self-confining the light: this can be done by applying a bias field to the whole material that lowers its index everywhere, and screening it in a small region where the light is, in order to raise back its value. As a consequence, the bright photorefractive spatial solitons are usually called *screening solitons*. Here is how this happens.

Let us consider a photorefractive medium as a semiconductor doped by a donor medium. Donor states ($N_D$) are usually localized energetically within the energy gap: which means that light can induce electron transitions from the donor states to the conduction bands. Consequently, two charge populations are generated so far: ionized donors, that is holes ($N_D^+$), which are physically localized, that is, are not free of moving because are connected to the physical position of the dopant ions, and electrons, which instead can go everywhere being in delocalized conduction states.

The donor rate equation is:

$$\frac{\partial n_D^+}{\partial t} = \sigma F n_D - \gamma n_d^+ n_e \tag{7}$$

where σ is the absorption cross-section, F the photon flux, and γ the relaxation rate. The electron rate equation follows the donor one, with the inclusion of the diffusion-conduction terms:

$$\frac{\partial n_e}{\partial t} = \frac{\partial n_D^+}{\partial t} - \mu \vec{\nabla} \bullet \left( n_e \vec{E} + \frac{k_B T}{q} \vec{\nabla} n_e \right) \tag{8}$$

where μ is the electron mobility, $k_B$ the Boltzmann constant, and T the temperature. Electrons and holes constitute the local charge density ρ:

$$\rho = q\left(n_D^+ - n_e\right) \tag{9}$$

which generates, through Gauss's theorem, a local electric field that screens the applied bias:

$$\varepsilon \vec{\nabla} \bullet \vec{E}_{SC} = \rho \rightarrow \vec{E}_{local} = \vec{E}_{bias} + \vec{E}_{SC} \tag{10}$$

Applying a bias field along the extraordinary $\hat{c}$ the crystallographic direction of a uniaxial photorefractive crystal, the refractive indices get the expressions

$$\begin{cases} n_x = n_y = n_0 \\ n_z = n_e - \dfrac{1}{2} n_e^3 r_{33} E_{z-local} \end{cases} \tag{11}$$

The nonlinear light propagation is then described by the nonlinear wave equation [13]:

$$\left[\frac{\partial}{\partial x} - \frac{i}{2k}\left(\frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial z^2}\right)\right] A(x, y, z) = \frac{ik}{n} \delta n(E_{local}) A(x, y, z) \tag{12}$$

where the field amplitude, in the case of a self-confined solitonic solution, should be factorized into an amplitude, independent from x, and a propagative term as follows:

$$A(x, y, z) = u(y, z) e^{i(\omega t - \Gamma x)} \tag{13}$$

as done for every kind of soliton, not only the photorefractive ones. Many groups have tried to solve analytically Eq. (12) without real success. Semi-analytical solutions are indeed reported in the literature showing that such complex problems can support bright solitons. In order to observe the soliton formation, a numerical integration (*FDTD—Finite Difference in Time Domain*) is performed of all Eqs. (6)–(11). Often, an approximated equation is considered, taking into account the saturable behavior of the nonlinear dielectric constant:

$$\left[\frac{\partial}{\partial x} - \frac{i}{2k}\left(\frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial z^2}\right)\right] A = -\frac{\in_{NL} E_{bias}}{1 + \frac{|A|^2}{|A_{SAT}|^2}} A \tag{14}$$

### 2.3 Experiments on photorefractive solitons

The experimental set-up for spatial solitons is shown in **Figure 1** [22]. A laser beam (soliton beam) is focused down to about 10–12 μm FWHM onto the input face of a

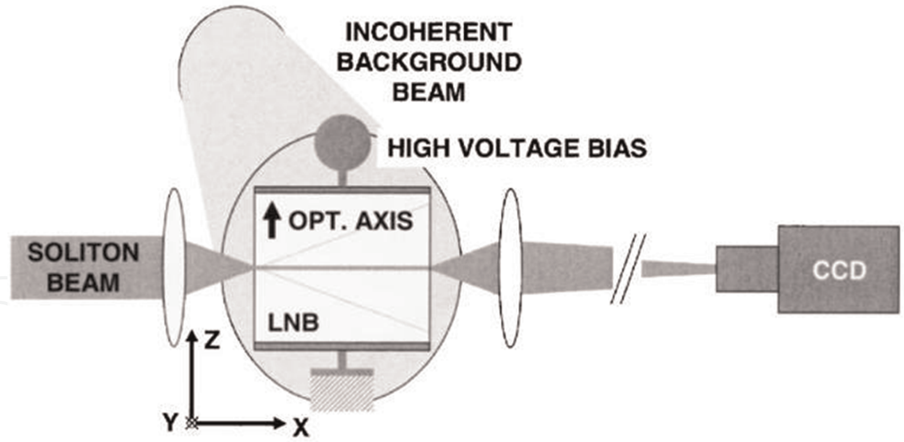


**Figure 1.**
*Experimental set-up for screening photorefractive solitons [22].*

sample. To generate suitable refractive index modulation, the sample must be biased along its optical axis.

The value of the electric field to bias strongly depends on the crystal type and its electro-optic coefficient: for example, using strontium barium niobate crystals (SBN) which have a very high electro-optic coefficient, the electric field ranges from a few hundred V/cm up to some kV/cm [26]; lithium niobate (LN) has a lower electro-optic coefficient and requires several tens of kV/cm [22]; in materials with high optical activity like $Bi_{12}SiO_{20}$ (BSO), the applied bias must be as high as 55 kV/cm or higher to induce the light to reach a nonlinear polarization regime and to self-confine [27–29]. Chauvet et al. [30, 31] proposed an interesting innovative solution for the bias application: induce an internal electric field by applying a thermal gradient and take advantage of the pyroelectric effects that some crystals have, for example, LN. Indeed, this is a major improvement in the technology, as it eliminates any conductive contacts/plates, thus leaving the sample completely free and accessible from all sides for further applications.

Background illumination can be provided also, to stabilize the solitonic beam during propagation (i.e., prevent beam self-deflection [32–35]).

Finally, an optical imaging system is placed after the sample to monitor the output face of the sample using a camera. The typical evolution of the soliton formation is shown in **Figure 2** where the light intensity at the output phase is shown.

A key feature of photorefractive solitons is the very low power required for their writing. Photorefractive solitons require very low powers, of the order of microwatt in continuous [36]. This means that they can be made both with coherent light from continuous or pulsed lasers at the fundamental or second harmonic frequency [37–40], even in the femtosecond regime [41, 42], and with incoherent light from fluorescent bulbs [43] or even ion fluorescence [44].

E. Fazio et al. [22] have shown experimentally that the solitonic solution gives a hyperbolic transverse profile which can be easily identified by plotting the transverse intensity distribution in a semi-log scale (**Figure 3**). A laser beam has usually a Gaussian profile that, in a semi-log plot, gets a negative parabolic shape. As soon as it evolves into a soliton, the Gaussian profile rearranges into a hyperbolic one. This transformation can be monitored in the semi-log graph, where the hyperbolic profile gets a triangular shape (a linear rise and fall tuned together on the vertex).

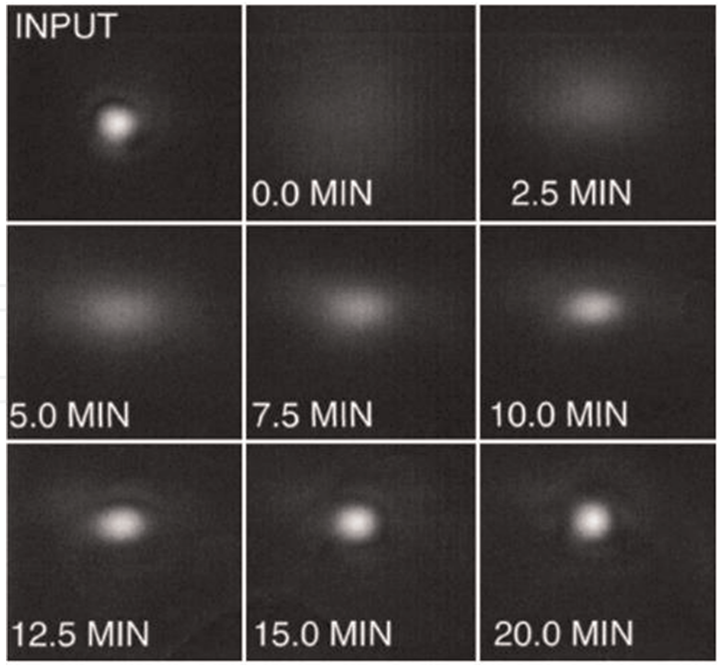


**Figure 2.**
*Experimental images of the soliton formation and stabilization [22].*

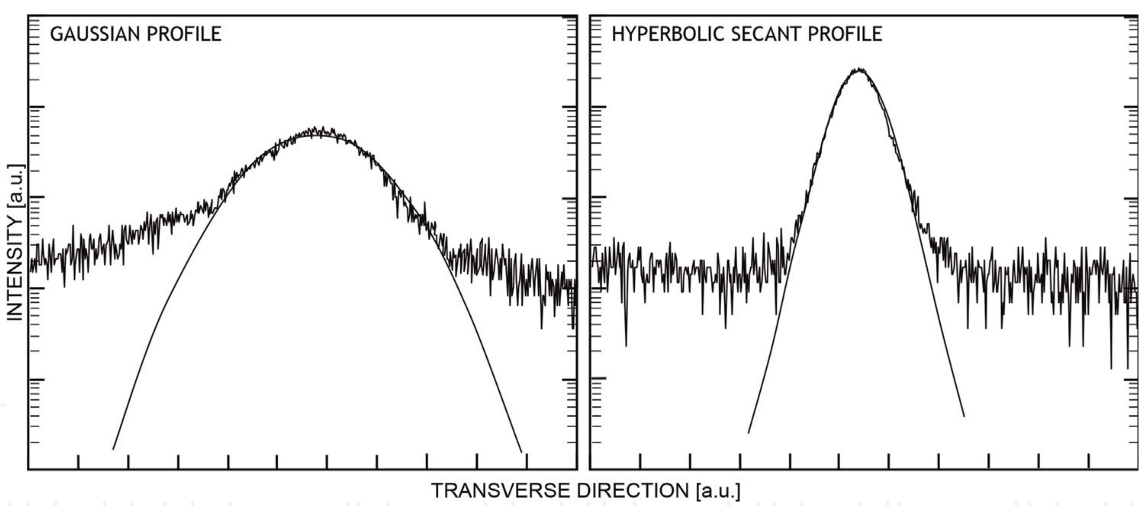


**Figure 3.**
*A Gaussian laser beam modifies into a hyperbolic secant beam when becomes spatial solitons [22].*

### 2.4 Photorefractive soliton waveguiding

Among the possible applications of soliton beams, one of the most important is their use as waveguides. Compared to traditional techniques, writing solitonic waveguides has many advantages in terms of construction costs, 3D geometries, propagation characteristics, and time durations.

Regarding costs, solitonic waveguides can be written with extremely low laser powers and above all in continuous mode: therefore, practically at no cost, since they can also be written by laser diodes for a few euros.

With regard to 3D geometries, a soliton guide can be written in any position within a nonlinear substrate, allowing full exploitation of the entire available volume. This

| | |
|---|---|
| Writing powers | From nW up to mW (typically μW) |
| Full Width Half Maximum | Typically 10–18 μm (min 2–3 μm) |
| Propagation | Measured up to 2–3 cm |
| Refractive index contrast | Typically $10^{-3} \div 10^{-4}$ |
| Refractive index profile | Hyperbolic secant—Gaussian |
| Waveguide modal dispersion | $0.6 \pm 0.2$ fs/mm[1] |
| Lithium Niobate chromatic dispersion | $9.9 \pm 0.2$ fs/mm[2] |
| Waveguide propagation losses | 0.07–0.04 dB/cm |
| Waveguide lifetime | From few ns to months |

*[1]Measured at 800 nm with 75 fs pulses within waveguides written at 514 nm[2]Measured at 800 nm with a CW laser beam*

**Table 1.**
*Performances of typical photorefractive solitonic waveguides.*

was not possible before with traditional waveguide construction techniques, which act mainly on the surface of the substrate or at most by penetrating a few microns.

Regarding the propagative characteristics, the performances of a solitonic guide are amazing, significantly improving the specifications of traditional waveguides.

**Table 1** shows some characteristic values of a soliton guide made of lithium niobate. As you can see, the waveguides are relatively wide and with a rather low refractive index contrast. These factors are related to the applied bias electric field: Low fields originate wide beams with a modest contrast; very high fields can originate narrow beams and, consequently, high refractive index contrasts.

However, the fundamental characteristic of soliton waveguides is linked to the propagative losses, extremely low in the order of 0.07–0.04 dB/cm (limit of measurability), much lower than commercial waveguides (a guide obtained by ion exchange typically has 1 dB/cm as propagative losses). This factor is related to the nature of solitons: unlike traditional guides in which the index profile is made artificially, in this case, it is precisely the light that chooses the best index profile to be able to propagate self-confined, that is, without diffraction. This leads to ultra-very low losses and low modal dispersion (since the guides are almost single-mode).

Another fundamental characteristic of solitonic guides is their transient, permanent or semi-permanent character: using substrates with a very rapid dielectric relaxation and/or using thin films, as soon as the writing light is turned off the associated guide disappears, with times even of a few nanoseconds. By using substrates with extremely slow dielectric relaxations [45, 46], waveguides can survive for a long time, even months. When writing solitons with very intense femtosecond pulses, the material can undergo permanent changes and the waveguides no longer erase.

## 3. Stigmergy, reinforcement learning, and photorefractive plasticity

### 3.1 Stigmergy

Stigmergy was first proposed by French entomologist Pierre-Paul Grassè in the1950s when studying the activities of social insects [47]. The word Stigmergy is a combination of the Greek words ``stigma" (outstanding sign) and ``ergon" (work), signifying that some activities of agents are prompted by external traces, which themselves are generated by the agent's activities [48]. Stigmergy allowed Grassè to explain how insects with fractional intelligence, without obvious communications, can collaboratively engage in complex tasks, such as building a nest simply by following very naive rules. In general, the paradigm of social insect societies is a distributed system that, despite the lack of sophistication of their individuals, offers a highly structured social organization. For instance, as a result of this organization, ant colonies can carry out complex assignments that in some cases are beyond the capacities of a single ant [49]. A study of their behavior indicates that in the heart of their commotional random movements, there can be seen the trace of a series of behaviors that are driven by repeated stimulus-response cycles [50]. For example, when searching for food, ants initially explore the area surrounding their nest randomly and while moving, they leave a chemical pheromone trail on the ground (**Figure 4**). Once an ant finds a food source, it evaluates the quantity and the quality of the food and carries some of it back to the nest [52].

During the return trip, the quantity of pheromone that an ant leaves on the ground may depend on the quantity and quality of the food. The pheromone trails will guide other ants to the food source and subsequently, the shortest path to the food source will be reinforced as the result of a higher probability of feedback concerning the long paths [51]. This environment-intermediated type of communication has captivated researchers in many dissimilar fields. For example, it can be referred to all those protocols for the optimization of multi-variable problems known as genetic algorithms, which exploit the rules of genetics to solve mathematical problems with many independent variables, or neural networks, mathematical systems that base the calculation on a "learning" database that the system has previously prepared. All these typical problems that would require smart signal processing, are called "reinforcement learning" [53]. This expression is commonly used in computer science to describe those algorithms "of machine learning inspired by behaviorist psychology, which is

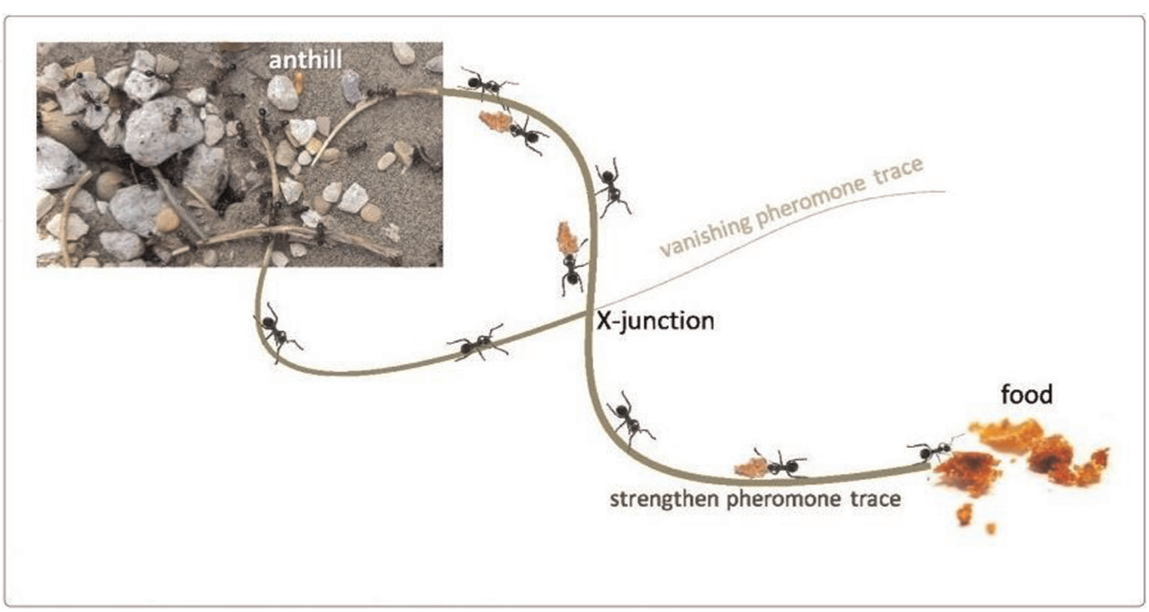


**Figure 4.**
*Basic scheme of the search for food by the ants. The system is based on the two fundamental decision-making principles of following a trace of pheromone and of changing track when a more marked one is met [51].*

connected with how software agents ought to take actions in an environment to amplify some impulse of cumulative reward [54].

### 3.2 Reinforcement learning

Reinforcement learning concerns neural networks or artificial intelligence protocols that self-set by reinforcing specific information identified by feedback in the system in order to solve complex problems. This procedure is indeed inspired by nature, adopting its Stigmergy in order to transfer information in decentralized systems, thus realizing distributed cognitive processes through many small, simple elaborations [55]. The basic idea of reinforcement learning is to consider the feedback derived from the dynamic interaction of the learning agent with the surrounding environment. Guiding autonomous agents to act optimally through trial-and-error interaction with the corresponding environment is the primary goal in the field of artificial intelligence and is regarded as one of the most important objectives of reinforcement learning [56]. During the learning process, the adaptive system tries some actions (i.e., output values) on its environment, then, it is reinforced by receiving a scalar evaluation (the reward) of its actions feedback [57]. As a result, the reinforcement learning algorithms selectively retain only the outputs that maximize the received reward because of the higher repetition rate over time [53].

Unfortunately, software-based protocols need solution times that increase exponentially with the size of the problem; after many years of research, no improved algorithm has been found to solve these problems within a polynomial time using a deterministic Turing machine. For this reason, hardware approaches have been proposed in the past [58, 59]. Among all, optical solutions to supercomputing seem to win for versatility [60] in terms of increased fan-in and fan-out, energy consumption, and recursive preprocessing. However, the proposed optical solutions [61, 62] neither reduce the complexity of the problem nor offer technologically efficient procedures without exponentially increasing the demand for physical resources [63].

Very recently, an alternative approach was proposed to realize photonic hardware able to perfectly simulate the Stigmergy processes adopted by ants searching for food. This alternative approach was published in the paper by M. Alonzo et al. entitled "All-Optical Reinforcement Learning in Solitonic X-Junctions [55]." In this work, the pheromone trajectories are represented by paths of the light through a nonlinear photorefractive material and the trajectory of the light is represented as the modified refractive index of the host material. Such modifications behave as induced waveguides, that is, regions that confine optical information which can travel inside them without being dispersed (as signals in optical fibers). The refractive contrast between the induced channel and the surrounding medium depends on the intensity of the writing beam. Consequently, it behaves like the pheromone quantity in the ant's path: it can be strengthened or weakened with the writing light intensity. This decision-making process can be represented by a nonlinear modulation of the crossing point between these paths. The strengthening of one path in an X-crossing point would correspond to making it a preferential trajectory, where the light will be conveyed more easily. It behaves as a channel of water whose banks have been made deeper and therefore more capacious: when two channels meet, more water will flow into the deepest channel rather than inside the shallowest one. Such addressable behavior has been induced into a nonlinear optical X-junction. The junction has been realized by injecting two absorbed beams that cross each other in the middle of the host photorefractive medium. Each beam modulated the refractive index of the host medium according to its intensity. A signal beam (unable to modify the host medium) is injected inside one channel and consequently reaches the X junction. It represents the information that propagates inside the photonic structure. If the writing beams have the same intensities, the junction is perfectly symmetrical, meaning that 50% of the information beam emerges from one channel and 50% from the other one (**Figure 5**). When the writing light is unbalanced or writing feedback is injected from the output, the X-junction switches to an asymmetric behavior, for which 80% of the information beam is now conveyed inside the strengthened channel and the remaining 20% remains in the weaker one.

### 3.3 Photorefractive plasticity

In neuroscience, this phenomenon is the basis of the selective memorizing-forgetting process that characterizes the memory of the events in the brain [64]: information pieces that are no longer reinforced will gradually be lost concerning recently reinforced ones. This capability arises owing to the considerable plasticity of the individual building block of the nervous system which allows animals to adapt to changing internal and external environments. During development, learning, and ongoing behavior, individual neurons, synapses, and circuits form short-term and long-term changes as a result of experience. This is the basis of the learning in a neural network which governs neuroplasticity, that is the ability of a system to modify the synaptic interconnection network according to its own needs, both to carry out "reasoning" and to recover unused areas (e.g., reusing regions that are inhibited due to trauma or injury) [65]. Neuroplasticity occurs at all levels, from the behavior of a single ionic channel to the morphology of neurons and large circuits and over

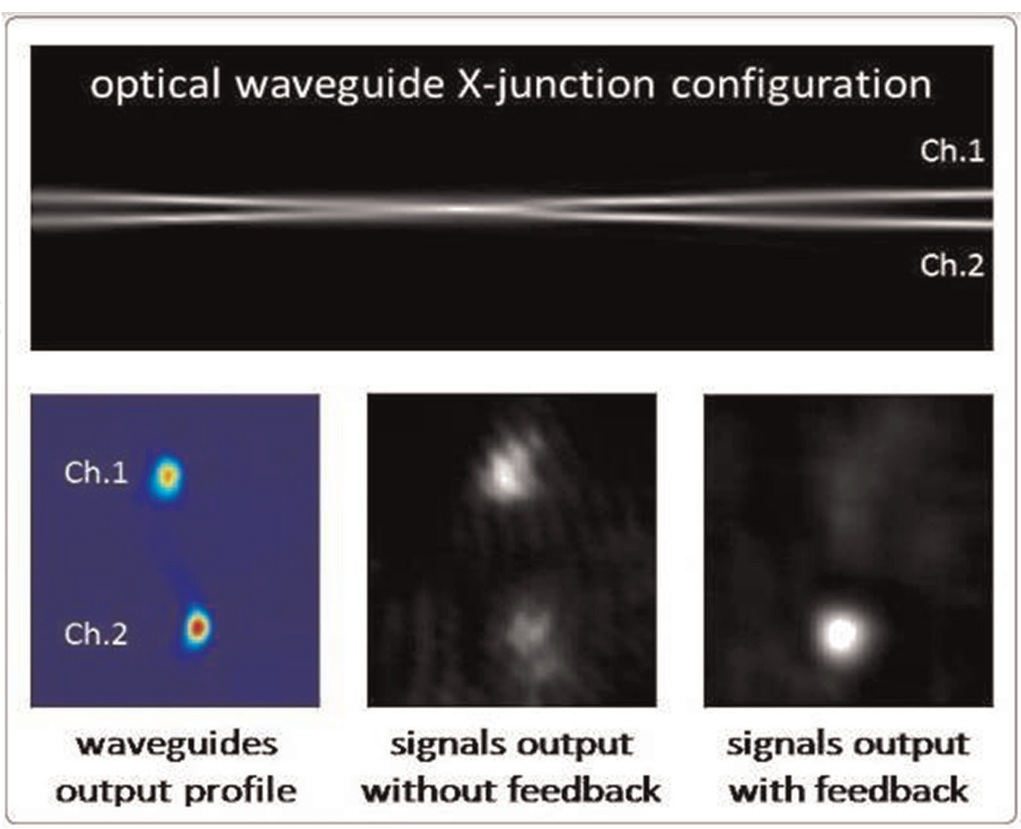


**Figure 5.**
*Numerical simulation (top) and experimental results (below) of a stigmergic photonic x-junction [51].*

timescales ranging from milliseconds to years [66]. Each level of the elementary unit is connected in parallel to each other, which performs simple operations of the storage and processing of information in successive cascading levels. Similar to the performance of the ants in the colony the information processed by a group of neurons is sent to the next level of neurons by opening and/or closing specific synaptic interconnections. In this way, the memory and subsequent reasoning consist of trajectories within the network, the mapping of which represents the set of stored information, which can be kept over time or deleted as needed. This is the way of "learning" and "remembering" a biological neural network. Any further information will follow its path: if the new path coincides with an active trajectory, then the information will be recognized, otherwise, the signal will be blocked, sooner or later, by inactive synaptic interconnections [67].

In this way, the neural network simultaneously remembers and processes, in a spatial coexistence where, the traditional computers cannot do this: in fact, they are based on the Von Neumann architecture which provides one or more processors connected to various external, separate peripherals, including memory. Whenever the computer needs information, it must access the memory to take and bring data back to the processor. This operation requires machine time and costs, in terms of energy consumption. Whereas, the neuromorphic paradigm, on the other hand, wants to unify the two areas of processing and memory, as happens in the biological field. However, overcoming the dichotomy between processing and memory is possible by creating neuromorphic architectures. By exploiting the typical functional geometries of the nervous system, information can be stored and processed in the same physical location, unifying memory and processor. In 2011, C. David Wright introduced the use of PCM for arithmetic and bio-inspired calculation [68], and provided the principle experimental proof of "processor" based on PCM for the first time, demonstrating the four basic operations of addition, multiplication, division and subtraction, and storing the results at the same time. In the same year, D. Kuzum reported new nanoscale electronic synapses based on PCM for optical data storage and non-volatile storage [69]. Continuous resistance transitions in PCM [70] and saturable absorber composite materials are used to simulate the properties of biological synapses so as to realize synaptic learning rules [71]. In 2017, Alexander N. Tait of Princeton University published a paper referred to neuromorphic silicon photonics, introducing the world's first integrated photonic neural network [72], It uses a neural compiler to program a silicon photonic neural network with 49 nodes, each node operates at a specific wavelength, light from each node is detected and summed before it is fed into the laser, then the output will be feedback to create a feedback loop with nonlinear characteristics. Tait et al. simulated traditional neural networks demonstrated how photonic neural networks can solve differential equations and found that photonic neural networks using silicon photonic platforms can be connected to ultrafast information processing environments for radio control and scientific computation.

It should be noted that most of the platforms that have been introduced as photonic or electronic neural networks are fixed structures that rigidly perform the calculation without the capability of changing the interconnections as requested [73]. This last aspect requires the use of modifiable plastic materials and/or devices, that is, capable of assuming different behaviors depending on the information to be stored. In these structures, the configuration of the neurons and their interconnections are written and predefined. So, they are only capable of doing certain limited functions, whereas the biological neurons can dynamically modify the interconnections in the procedure of training. They can establish new interconnections or if requires they can diminish or strengthen the weight of specific interconnections in synaptic points. Recently, inspired by the biological brain, reinforcement learning methods based on the memory of past experiences have been realized in photonic platforms via solitonic interconnections. Thanks to the plasticity of photorefractive materials, the light beam itself is able to locally vary the refractive index of the host material and create a channel within which it can propagate without diffraction. This solitonic signal will change the refractive index of the medium similar to the pheromone-mediated indirect communication. Obviously, the repetition and intensity profile of the incoming signals will affect the formation of the waveguide channel by exploiting the nonlinearity of the refractive index. This channel can also be used by other beams that recognize it as a waveguide. Also, these interconnections have a specific lifetime and their weight's strength is dependent on the extent of their exploitation. The interconnection's existence and strength is a self-driven process in which the signal itself can reconfigure its pathway by its occurrence redundancy. Consequently, any interconnection which is not activated for a long time will be diminished and taken out of the computation cycle, at the expense of the highly exploited ones. Depending on the material used, this waveguide will then cancel itself completely when the writing light is switched off (rapid dielectric relaxation) or survive for a shorter or longer time (slow dielectric relaxation).

The solitonic guides are, therefore, completely plastic guides, which are induced by a modification of the material and can be suitably shaped by other light passing through them. Now there is no artificial neuroplastic hardware, that its networks be able to reorganize themselves autonomously, although this is the only way to reproduce artificial systems similar to biological ones. An extremely promising way to achieve them is represented by soliton optical neural networks, able to exploit the plasticity of the refractive index to create circuits whose interconnections can be activated or inhibited as required by the information to be stored or processed. In 2018, a collaboration between Sapienza and Nanyang Technological University in Singapore demonstrated that X-junctions formed by soliton waveguides learn information [55]. Recently, it has been shown that X-junctions can perform both supervised and unsupervised learning, behaving as if they were neurons that fully exploit the plasticity of the substrate both to write the circuit and to post-modification based on the evolution of the system [74]. By exploiting the X junctions as elementary units, it is possible to create complex neural networks capable of storing information as specific trajectories within the circuit network [75].

## 4. Solitonic X-junctions as photonic neurons: Supervised and unsupervised learning

The solitonic neuron is a device capable of reproducing the fundamental characteristics of the learning and memorization processes typical of biological neurons. From a biological point of view, the neuron, a fundamental unit of the nervous system, is a dynamic unit capable of self-assembling and self-modifying according to the information that arrives. These structural changes are the mirror of the unfolding of learning and memorization [76]. The capacity for self-organization is not local, that is, it does not affect the individual units independently as if they were non-communicating structures. Whenever a certain type of information presents itself at the gates of the nervous system, through the different types of receptors of which it is composed, an enlarged (global) mechanism is set in motion, influencing pathways within the nerve mapping, affecting neurons through connections both in parallel and in series. This characteristic interconnectedness underlies the functional complexity of the nervous system and at the same time represents its strength. This is why an event, at a precise point on the neural map, can trigger a succession of changes culminating in a complete reorganization of entire neural regions. One of the properties we have already talked about previously but that needs to be brought to attention perhaps with greater energy is the concept of plasticity. This is a key feature for various reasons. A good approximation of the concept of plasticity can be defined through the expression "dynamic self-organization" [44]. It is typical of systems that do not remain identical to themselves neither at the functional nor at the structural level [77]. More precisely plastic hardware overlaps these two nuances: function becomes synonymous with structure. This is one of the fundamental properties of biological neural tissue. Conceiving the implementation of an artificial hardware neuron that works on the biological model, there are therefore some characteristics that should be kept in mind. First of all, it must have a dynamic structure that is able to adapt to the evolution of the environment and provide a response to it in a nonlinear way. Furthermore, it is necessary to keep the chronology of the information processed at the same time as the analysis and learning operations. A schematic of the functional blocks which characterize the "*modus conoscendi*" of a neuron is shown in **Figure 6a**.

We can highlight a tripartite structure: the neuron receives signals through the dendrites, small branches acting as input channels. The information is collected through these and conducted to the soma, the central body of the neuron which acts as a real microprocessor. Here the signals are "read" and analyzed through weighing and comparison operations with respect to a threshold value. A signal above the threshold is highly informative so it must be stored and propagated along the neural mapping. On the contrary, a sub-threshold signal is judged not important at the informational level and, therefore, its transmission is stopped [78]. The axon is a long channel with the task of carrying the signal out and distributing it to the neurons that follow through special connections called synapses. These are the basis of the communication between different units and correspond to the entities that allow the realization of complex neural mapping. The soliton photon neuron, which the research group of the

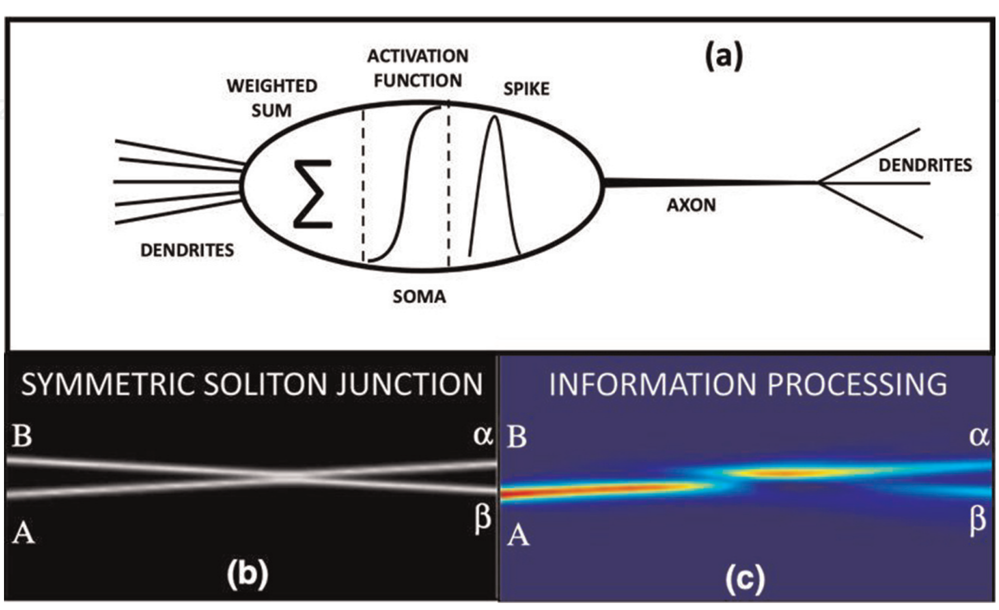


**Figure 6.**
*(a) Fundamental scheme of a biological neuron. (b) the solitonic neuron X-junction structure. (c) Perfectly balanced X-junction.*

Smart and Neuro Photonics Lab has designed and built, has a functional geometry very close to the one just described. A soliton neuron [55] is characterized by an X-junction structure [79], as shown in **Figure 6b** obtained through the intersection of self-written waveguides by two self-confining and non-diffracting laser beams. Using the technology of spatial solitons obtained through the Pockels effect [13, 80], the writing takes place through a local variation of the refractive index induced by the incoherent laser light beams. All materials with a saturating nonlinear electro-optical coefficient can be used. The input channels functionally represent the dendrites that collect the input signals. The soliton soma coincides with the region in which the two laser beams progressively approach until they overlap. It is in this region, which by assonance with the ML models we call the solitonic node, that the nonlinear energy transfer between the channels takes place which, as we will see shortly, allows the learning process. The output channels, which allow a subsequent redistribution of the propagated signal, replicate the functional action of the axon. In order for the soliton soma to form and be active at a functional level, it is necessary that the laser beams arrive at the input face of the crystal at an extremely small angle with respect to the normal, between 0.8° and 1°. For different angles, the node is characterized by an area that is too limited which determines a low coupling between the waveguides. The soliton neuron can perform supervised and unsupervised learning tasks [55, 74]. From a theoretical point of view, supervised learning is performed using a fundamental truth, or in other words, there is prior knowledge of what the output values to learn should be [81–83]. If the learning is unsupervised, on the contrary, there is no a priori knowledge of the desired output, which is identified at the same time as learning [84, 85]. The substantial difference lies in the way in which the already written waveguide structure is modified. In the supervised case, indeed, it is necessary to know the target and therefore to guide the learning. The X junction is modified using a feedback system that locally alters the refractive index contrast, depending on the information received, through successive cycles (**Figure 7**). This mechanism is fully

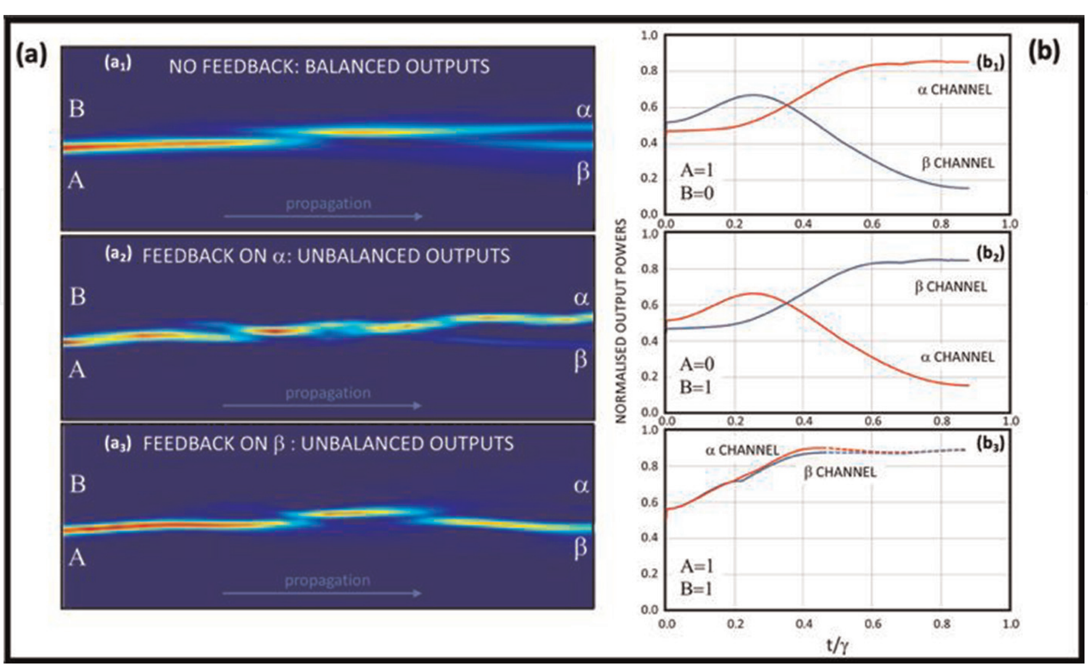


**Figure 7.**
*The X-junction neuron switches from the balanced outputs (a) to the unbalanced behaviors, either due to feedback on the alpha channel (b) or due to feedback on the beta channel (c). Learning dynamics of the solitonic junction: starting from the initial neutral condition 50/50, the junction recognizes the input and switches accordingly.*

explained in [74], where a numerical code FDTD solving the nonlinear equation (Eq. (1)) reported below, shows the morphological evolution of the neuron (see **Figure 7**), index of learning what is happening.

$$\nabla^2 A_i = -\frac{\in_{NL} E_{bias}}{1 + \frac{|A_1|^2 + |A_2|^2}{|A_{SAT}|^2}} A_i \tag{15}$$

where $\varepsilon_{NL}$ is the nonlinear dielectric constant, $E_{bias}$ is the electrostatic bias field that allows the formation of photorefractive solitons and $|A_{SAT}|^2$ the saturation intensity. In this type of learning, only the $A_1$ and $A_2$ beams are able to excite the nonlinearity underlying the index modification. The information signal is indeed represented by a laser with a different wavelength, with respect to which the refractive index is not sensitive. The initial situation is represented by a perfectly balanced X junction, as shown in **Figure 7a$_1$**, which is characterized by a symmetrical structure obtained by using two laser beams at the same power input. The injected signal, having reached the solitonic node, "perceives" the same index and divides itself perfectly 50% into the two output channels. By using different power ratios in the writing phase, it is possible to build asymmetrical structures **Figure 7a$_1$** and **7b$_3$**. In this case, the index will begin to differentiate already within the area of the soliton soma and will result in an unequal division of the input information in the two outputs. However, the soliton neuron is also able to perform unsupervised learning tasks. In this case, the refractive index of the crystal is also sensitive to the wavelength of the signal, which, by propagating within the previously written structure, is able to change it. The information becomes directly responsible for the asymmetrization of the junction. For unsupervised learning, the Helmholtz equation becomes:

$$\nabla^2 A_i = -\frac{\in_{NL} E_{bias}}{1 + \frac{|A_1|^2 + |A_2|^2 + \eta |A_3|^4 \left(1 - e^{-\frac{t}{\gamma}}\right)}{|A_{SAT}|^2}} A_i \tag{16}$$

where $A_3$ represents the information signal and η an efficiency coefficient for the nonlinear process that depends on the wavelength and the material used. These structural variations can be the result of numerous successive propagation cycles or single events characterized by much higher powers. This is another point of similarity with the biological case. The biological signal, called spike, is propagated toward the axon when the combination of input signals is above the threshold. This can occur as a consequence of the accumulation of numerous inputs, spike trains, in a limited time interval, or by virtue of a very intense signal.

In the solitonic case, learning is, therefore, identified with the process of changing the refractive index and therefore has its own physical translation. What about memory? Many neuromorphic implementations, both in electronics and in optics, have achieved remarkable results in the reproduction of a neural system, however, there is always a great difficulty in defining a memory that is present at the same time as the processing unit. The soliton X junction introduces a new paradigm in the field of neuromorphic research, approaching the nature of biological neurons. The index modification is in general a semi-permanent property with times that depend on the particular material used. The input information is therefore saved in the particular morphological structure obtained during the learning phase. In, the authors show the possibility of building soliton neurons in bulk $LiNbO_3$ crystals. This represents the first supervised realization. The neuron is able to convey information, represented by a signal with a different wavelength, traveling within the waveguides in the directions declared by the local refractive index. Starting from these results and integrating them with the technology of spatial solitons in thin films in lithium niobate [86], in [87] the possibility of implementing soliton neurons in 8 μm films of lithium niobate is demonstrated. This technology brings with it numerous new benefits. First of all, its extreme compactness makes them a useful tool for integration into small devices. Furthermore, the Lithium Niobate layers show focusing dynamics of two orders of magnitude faster than the bulk counterparts. Finally, the films offer greater control over the propagation of the beams within the crystal, ensuring considerable precision which results in greater coupling and, ultimately, in a more performing soliton soma. By virtue of their plastic behavior, soliton X-junction neurons can be interfaced in more complex structures, to give rise to complex neural mappings capable of functionally replicating biological neural tissue. This perspective represents the great innovation of the soliton neuromorphic, which is not limited to reproducing a unity or a connection, as in previous neuromorphic models, but is able to reach a higher and more complete level of complexity, through the realization of a whole neural environment.

## 5. Bit-to-bit data storage and recognition

Solitonic neurons can be interconnected to form complex neural maps, and soliton neural networks (SNNs) [75]. Their functioning is based on the movement of photogenerated electrical charges that assume the same role played by neurotransmitters in biological neural networks (BNN). Both regulate the intensity with which a synaptic connection, solitonic or biological, is built, modified, or destroyed. Furthermore, the solitonic synapse, exactly as in the biological case, is the basis of the memorization processes. The repetition of information results in synaptic strengthening, which is synonymous with information memorization [88]. Therefore, learning and memorization are processes that occur through structural changes. In **Figure 8**, the summary diagram of the functionality of the BNNs and SNNs.

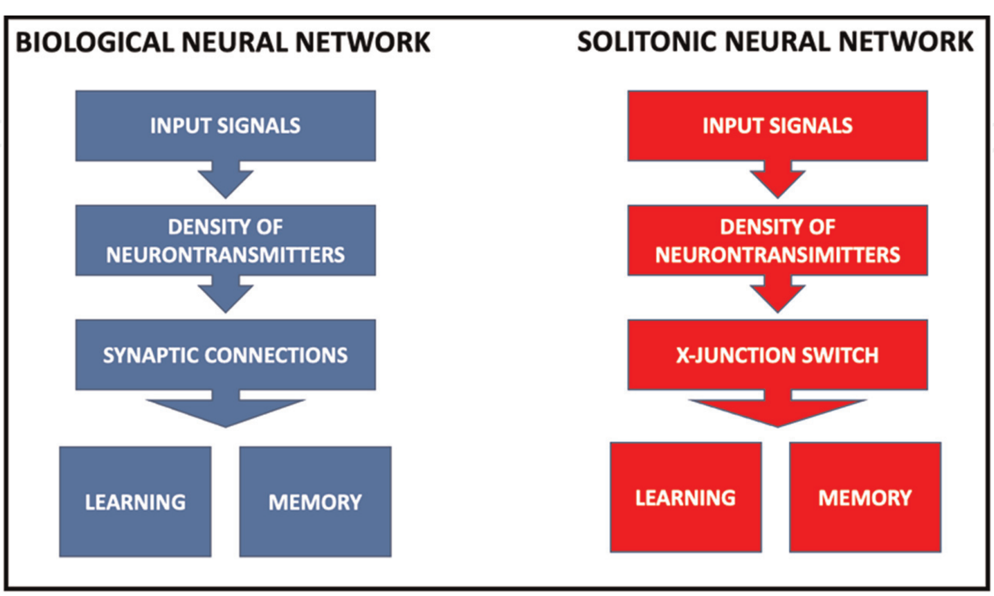


**Figure 8.**
*Functional diagrams on the left of a BNN network and on the right of an SNN network. Both are able to self-modify their structure according to the information signals received to process and store them in precise neural patterns [75].*

Recently, an SNN has been studied which is able to carry out a 4-bit recognition. It is formed by X-Junction channels written with equal power beams in order to create 50–50 junctions. SNNs are divided into successive layers as reported in **Figure 9**.

The first layer corresponds to the input face and is characterized by a number N of channels corresponding to the number of information (bits) to be processed and to the number of incoming laser sources. The SNN exploits the phenomenon of total reflection at the edge in correspondence with the even layers, which are therefore characterized by N/2–2 neural units. While the odd layers are characterized by N/2 fundamental units.

This network is able to learn by switching the propagating signal between the two outputs of each X-Junction. By appropriately increasing the size of the matrix it is possible to obtain the representation of any SNN. Each channel, therefore, has its own weight which is modified over time based on the information received as reported in equation.

$$\underline{Y} = W\left(E_{BIAS}, \underline{X}\right) \cdot \underline{X} \tag{17}$$

For an in-depth analysis of the SNN, we recommend reading [75].

An SNN network, at present, is able to perform an Episodic recognition. This term derives from psychology studies that have made it possible to identify three ways of working with memory, episodic, procedural, and semantic [89]. Memory is of an episodic type if it records an event photographically, that is, it fails to decontextualize the subjects present [90]. Let us consider the picture of a dog running in the mountains. The dog subject is recognized only in that environment, mountains, and in that position, running, if moved then it will be identified as different. Procedural memory, on the other hand, identifies a mechanism and learns its rule. Finally, semantic memory contains these mechanisms within itself, thus reaching abstraction through the analysis of details.

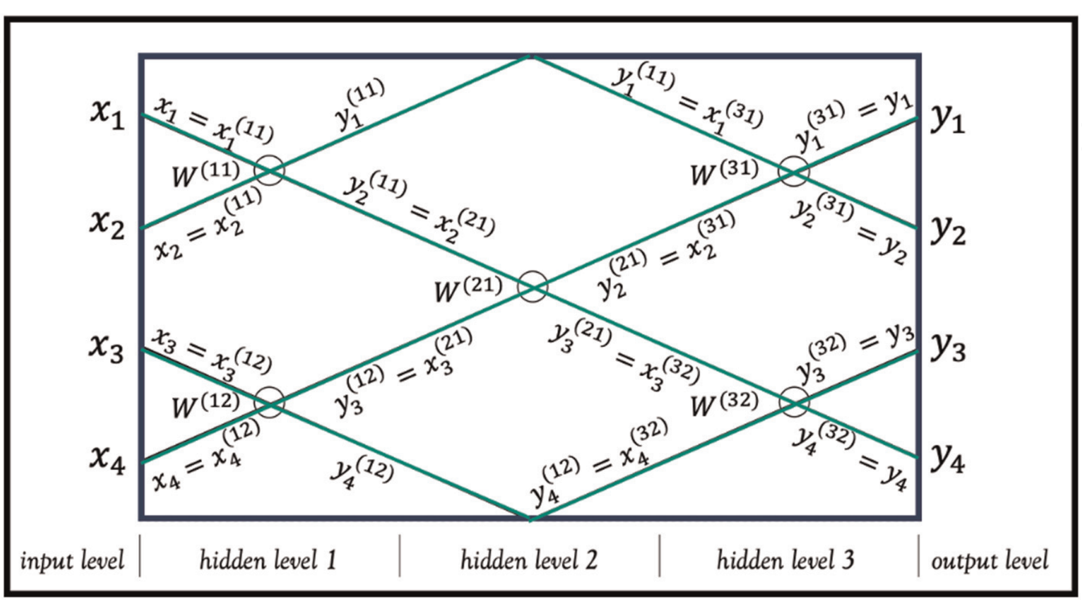


**Figure 9.**
*Structure of a 4-bit SNN network. W is the weight of the junction point. In particular, $W^{(1)}$ is the weight relative to the node of the first solitonic neuron in layer 1, $W^{(2)}$ is the weight relative to the node of the second solitonic neuron in layer 2, and so on. The information inputs are represented by $x_i$ while $y_i$ the processed signals [75].*

The solitonic technology has allowed, until now, to successfully realize an episodic memory able to save information through precise neural mapping. As information flows into the SNN it modifies the refractive index of the network, determining precise paths.

Learning the SNN takes place in two stages. The first phase, defined as Training, consists in administering the information pattern to be learned to the network several times. The network changes morphology accordingly. Then we try to understand how profound the changes have been, or how much the information has been learned and memorized. This phase is called validation. The network acts as a filter letting only the saved information propagate.

**Figure 10** was realized starting from the results proposed by [75]. It shows the learning of 1-bit in four different cases corresponding to the four input channels. In **Figure 10a**, the first line shows the network training with the four 1-digit in each channel while the others are set to 0. The images below report the SNN recognizing process: it uses the stored information to operate the comparison. Therefore, if digit 1

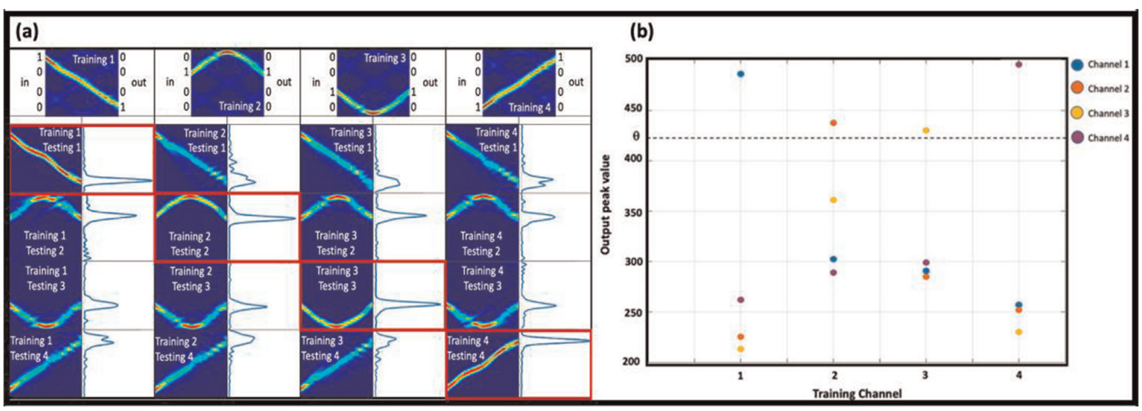

**Figure 10.**
*In (a) training and validation processes of a 4-bit SNN are reported in 1-digit recognition case. The first line is related to the training phase while in the following rows validation steps are reported. In (b) the signal output amplitudes for different training numbers are reported: Only the trained channel is above the threshold (dotted line) [75].*

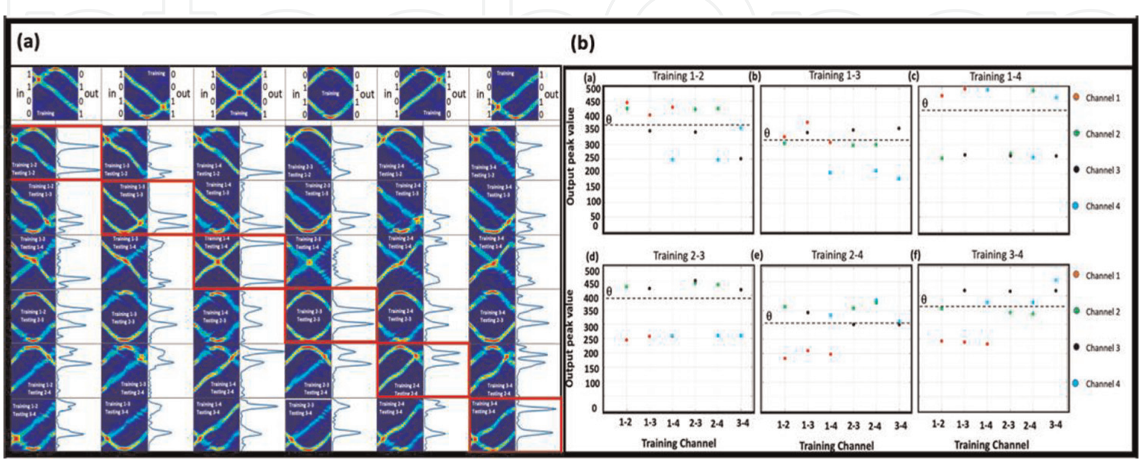

**Figure 11.**
*In (a) training and validation processes of a 4-bit SNN are reported in 2-digit recognition case. The first line is related to the training phase while in the following rows validation steps are reported. In (b) the signal output amplitudes for different training numbers are reported: Only the trained channel is above the threshold (dotted line) [75].*

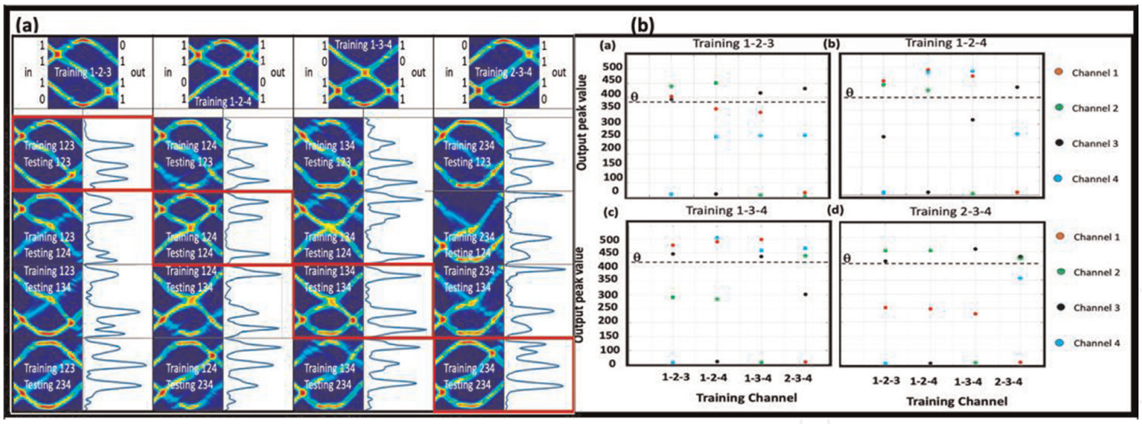


**Figure 12.**
*In (a) training and validation processes of a 4-bit SNN are reported in 3-digit recognition case. The first line is related to the training phase while in the following rows validation steps are reported. In (b) the signal output amplitudes for different training numbers are reported: Only the trained channel is above the threshold (dotted line) [75].*

of the new number corresponds to digit 1 of the training number, the output of the network is high and the information is recognized. Otherwise, the output is low, which means no recognition. **Figures 11** and **12** report the learning cases of 2-digit and 3-digit, following the scheme already illustrated in **Figure 10**.

The SNN recognizes through a threshold process. If the output is higher than a threshold, determined experimentally, then the recognition has occurred. This procedure can be generalized to N bits according to the equation shown below.

$$I_k^{output_i} \geq \theta I_k^{input_i} \tag{18}$$

where θ is the pure number (~0.7).

Therefore, Optical Soliton Neural Networks are systems characterized by a structural dynamism, based on the plasticity of the refractive index, which can self-modify to recognize previously learned or new signals. Learning and memorization occur at the same time as physical evolutions.

## 6. Conclusions

Artificial intelligence is marking a profound innovation in everyday life. To overcome the limitations of AI software, research has developed the neuromorphic approach, which consists in reproducing the functional blocks of the human brain. A first attempt was carried out by electronics, which however suffer from a structural rigidity that does not match neural geometries. One of the fundamental qualities that characterize them is in fact plasticity, that is to say, the ability to self-modify one's units to trap, learning, and memory, in its structure. The solitonic optical approach that we have described in this chapter bases its effectiveness precisely on the concept of plasticity and self-assembly. Compared to other optical technologies, which focus on single neural properties (first of all excitability), soliton networks are able to reproduce complex behavior by exploiting the local differences in refractive indices to build specific trajectories for each information through the propagation of solitons. SNNs are currently able to reproduce a specific type of psycho-memory, episodic memory, in a particularly effective way, that is, with small powers (nW-μW) and with extremely low losses. SNNs capable of reproducing procedural and semantic memories are currently being studied. Once these objectives have been achieved, hardware that is functionally very close to biological neuronal dynamics will be available. In the biological neural system, the synaptic connections are created and deleted following the change in neurotransmitter density, in the soliton paradigm that we propose, the birth and modification of X-junction neurons depends on the density of photo-excited electric charges.

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## Conflict of interest

The authors declare no conflict of interest declaration.

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