MATTER & MIND MATTER *

Tom Birkoben  
Kiel University  
Faculty of Engineering  
Institute for Electrical Engineering and Information Engineering  
Chair of Nanoelectronics  
tobi@tf.uni-kiel.de

Hermann Kohlstedt †  
Kiel University  
Faculty of Engineering  
Institute for Electrical Engineering and Information Engineering  
Chair of Nanoelectronics  
hko@tf.uni-kiel.de

ABSTRACT

As a result of a hundred million years of evolution, living animals have adapted extremely well to their ecological niche. Such adaptation implies species-specific interactions with their immediate environment by processing sensory cues and responding with appropriate behavior. Understanding how living creatures perform pattern recognition and cognitive tasks is of particular importance for computing architectures: by studying these information pathways refined over eons of evolution, researchers may be able to streamline the process of developing more highly advanced, energy efficient autonomous systems.

With the advent of novel electronic and ionic components along with a deeper understanding of information pathways in living species, a plethora of opportunities to develop completely novel information processing avenues are within reach.

Here, we describe the basal information pathways in nervous systems, from the local neuron level to the entire nervous system network. The dual importance of local learning rules is addressed, from spike timing dependent plasticity at the neuron level to the interwoven morphological and dynamical mechanisms of the global network. Basal biological principles are highlighted, including phylogenies, ontogenesis, and homeostasis, with particular emphasis on network topology and dynamics. While in machine learning system training is performed on virgin networks without any a priori knowledge, the approach proposed here distinguishes itself unambiguously by employing growth mechanisms as a guideline to design novel computing architectures. Including fundamental biological information pathways that explore the spatiotemporal fundamentals of nervous systems has untapped potential for the development of entirely novel information processing systems. Finally, a benchmark for neuromorphic systems is suggested.

Keywords Bio-inspired Computing ∙ Phylogenesis ∙ Ontogenesis ∙ Homeostasis ∙ Artificial spatio-temporal networks

*Citation: Authors. Title. Pages.... DOI:000000/11111.
†Corresponding author
1 Introduction

Is it truly possible to implement higher brain functions, such as perception or consciousness, in engineered systems? This question has been frequently raised over the last few decades and has led to distinct views over time, as both neurobiological understanding and available computational capabilities advanced (Churchland and Churchland, 1990; Churchland, 1999; Aleksander, 2001; Hawkins and Blakeslee, 2004; Koch and Tononi, 2008; Dehaene, 2014; Dehaene et al., 2017). The essence of this question goes back to the fundamental relation between matter and mind, which was addressed as early as ancient Greece, and emerged in the principle of “Dualism” most famously defended by the philosopher René Descartes in the sixteen century (Ostenfeld, 2018). Descartes postulated that the body (matter) and the mind are distinct and separate units in human beings because he could not imagine that mental phenomena could be explained by natural mechanisms (Damasio, 2004). However, the invention of electroencephalography (EEG) and imaging techniques, such as functional magnetic resonance imaging (fMRI), enabled the study of inner information processing in the human brain and individuals’ states of consciousness (Varela et al., 2001; Noirhomme and Laureys, 2014; Kriegeskorte and Douglas, 2018; Demertzi et al., 2019). As a result, the strict distinction between matter and mind has become blurry (Storm et al., 2017; Dehaene, 2001). Strong evidence has been found that the inner representation of the human brain (the mind) is related to its neurochemistry (the matter), e.g. the amount and type of neurotransmitters and/or drugs within the nervous system (Tagliazucchi Enzo et al., 2016; Perry et al., 1999). It is therefore worthwhile to reconsider the relationship between mind and matter when engineering artificial systems to exhibit higher brain functions by considering recent progress in nanoelectronics and neurobiology.

This perspective on future computing is motivated by three key aspects. First by the recent, growing movement to reboot the entire field of computing, i.e. how data are processed. Second by state-of-the-art, fundamental progress in neurosciences, including the fields of complex networks and dynamic brain states. Third by advances in materials science and nanoelectronics that have led to, e.g., memristive devices, nanoparticle/nanowire networks, and fluidic memristors, providing new functionality in electronics, such as synaptic-like plasticity or spatio-temporal networks (Xia and Yang, 2019; Bian et al., 2021; Mallinson et al., 2019; Robin et al., 2021; Kuncic and Nakayama, 2021). With the foreseen restrictions on current digital computing, the question “What comes next?” finds its answer in merging novel discoveries made on the nervous system’s information pathways with the development of novel electronic devices, paving the way to an entirely new kind of computing.

In this perspective, we present a concept of an artificial spatio-temporal network which uses temporal and structural mechanisms in nervous systems as guidelines. It addresses the important, interwoven spatiotemporal aspects of information pathways and processing in nervous systems (Beggs and Plenz, 2003; Bullmore and Sporns, 2009; Chialvo, 2010; Sporns, 2011; Fornito et al., 2016; Bassett and Sporns, 2017). The state of nervous system criticality combined with the blooming and pruning of nervous cells during growth might be an interesting guideline to develop new computing principles (Beggs and Plenz, 2003; Kaiser and Hilgetag, 2004; Kinouchi and Copelli, 2006; Chialvo, 2010; Kaiser, 2011; Hütt Marc-Thorsten et al., 2014; Kaiser, 2017; Agi et al., 2020). Components essential for artificial spatio-temporal networks and a pathway to realize it, are presented, including biological fundamentals such as phylogenies, ontogenesis, and homeostasis (Lvtrup, 1987; Torday, 2015). However, these basal biological mechanisms alone might not be sufficient to establish mental functions in artificial systems; we therefore include the temporal binding hypothesis developed in neuroscience as a further essential guideline (Singer and Gray, 1995; Engel et al., 2001).
The synchronized firing of neural ensembles across different brain regions is treated as a fundamental neural mechanism that defines how a hierarchical network structure, such as the brain, can integrate several sensory inputs to determine the unity of an object (for example linking form, color, size, motion, etc., together) (Buzsáki, 2006; Schechter, 1996). Opportunities and possible limitations of this approach towards implementing higher brain functions in artificial systems, such as perception and consciousness, will be discussed. The paper is arranged as follows:

In Chapter 2, the current status of computing architectures is summarized. In Chapter 3, we present a condensed overview of advanced device components, with a focus on memristive switching devices. We subsequently address spatiotemporal information processing in nervous systems, including network structure, network dynamics, and homeostasis in Chapter 4. An artificial spatio-temporal network concept is introduced in Chapter 5, where we hypothesize on which information pathways might lead to higher brain functions in engineered systems based on hardware-oriented electrochemical electronics but also discuss current limitations of this approach. In Chapter 6 a possible benchmark is discussed for bio-inspired systems. Chapter 7 provides a discussion on the practical implementation of an artificial spatio-temporal network, to mimic basal biological information pathways.

2 The current state of information technology

The sixties marked the beginning of a glorious time in information technology as the tremendous opportunities of silicon technology merged with the concept of Boolean computing, resulting in the first digital revolution (Berlin, 2005). This development followed the exponential increase over time of electronic components integration on a chip predicted by Gordon E. Moore, combined with a sequential data processing architecture comprising a central processing unit and memory for data storage, for which Alain Turing and John von Neumann laid the foundation years before (Moore, 1965; Turing, 1937; J. von Neumann, 1993). The tremendous technological and economical success of the digital revolution is still going strong today with seemingly no end in sight. Billions of transistors on a single processor chip, displaying features as small as about 10 nm in size and clock frequencies of a few GHz, are the current standard in CMOS (Complementary Metal Oxide Semiconductor) technology, representing the backbone of today’s semiconductor industry (J. M. Veendrick, 2017; Masuhara, 2016; Kurinec and Walia, 2019). However, during the last couple of years, dark clouds have appeared on the horizon for the semiconductor industry. The envisioned goal of downsizing devices with every new circuit generation to the nm level has created an ongoing need to develop ever more sophisticated and expensive fabrication tools for e.g. lithography, dry-etching, and layer deposition (Dennard et al., 1974; Höflinger, 2016; Radamson et al., 2020). As a result, each new circuit generation entails an increasing economic risk for semiconductor companies. Moreover, over the last few decades, progress in processor core clock rates have overtaken memory access and access times, leading to a cumbersome situation where data transmission between the arithmetic logic unit (ALU) and memories dominates instead of the arithmetic information process itself. This system level-related challenge is called memory latency (or memory gap) and is a consequence of the von Neumann bottleneck, where data is processed sequentially (Backus, 1978; Iniewski, 2010; J. M. Veendrick, 2017). Two major obstacles restrict the further development of information technology, namely limitations in downsizing at the device level, and memory latency on the architecture. Although society is experiencing a second digital revolution via the
resurgence of artificial intelligence (AI) and the Internet of Things (IOT), Moore’s law, which has been driving the computer industry for decades, is becoming outdated as the limits of device integration and/or economical boundaries have now been reached. The incredible advances made by the first digital revolution based on binary “0” and “1” computation combined with the latest achievements in the field of machine learning led to great progress in speech and pattern recognition, while rendering autonomous driving tangible. Yet, additional challenges are growing increasingly problematic behind the scenes. Huge, power consuming hardware systems in the form of cloud servers are now mandatory to support recent advancements in AI and the IOT. This is why global digital players, such as Google, Amazon, and Facebook, as well as bitcoin trading platforms need energy-hungry server farms (Jones, 2018).

On the system level, and in particular since the advent of the internet and the renewed interest in AI, the power consumption of the digital world is growing without limits, in increasing conflict with sustainable and climate-neutral resource management. Moreover, future autonomous electric vehicles require both high recognition capability and low power consumption. It therefore is hardly surprising that the semiconductor world is currently in an era of upheaval, turning a new page on information processing based on novel computing architectures and advanced hardware components.

3 Advanced computing architectures and novel electronic devices

The aim of this section is to give a short survey on novel computing architectures and advanced electronic devices. We do not intend to present a comprehensive overview but instead to give a taste of the developments currently being pursued to overcome the limitations of digital computing and to establish new computing primitives. To simplify access to the different research areas for interested readers, we discuss seminal and overview papers and present recently published pioneering research. Nonetheless, we are aware that the given reference list is far from exhaustive. In addition, this section is critical to understanding the similarities, and most importantly the distinctions, between artificial spatio-temporal networks and standard neuromorphic computation presented in section 5. While traditional von Neumann computing continues to dominate the ICT scene, recent groundbreaking innovations in alternative computing architectures and advanced electronic devices have become hard to ignore (Yang et al., 2012; Schuman et al., 2017; Burr et al., 2017; Merolla et al., 2014; Kendall and Kumar, 2020; Kuncie and Nakayama, 2021).

These developments are threefold. Firstly, somewhat older concepts, such as artificial neural networks (ANN) leading to Deep Learning (DL) systems, have received an impressive performance boost through novel and efficient algorithms paired with more powerful electronics hardware (LeCun et al., 2015). Secondly, new technologies, such as Quantum Computing and Reservoir Computing (RC), have appeared, leading to remarkable results (Mermin, 2007; Arute et al., 2019; Gauthier et al., 2021). Thirdly, in the field of nanoelectronics, a plethora of advanced device structures and novel functional components has led to a rethink of traditional computing architecture, paving the way to in-memory computing that circumvents the von-Neumann bottleneck (Burr et al., 2017; Ielmini and Wong, 2018; Kendall and Kumar, 2020; Kaspar et al., 2021). In Fig. 1 a shamrock-like illustration highlights these three research areas.

The first leaf representing Machine Learning encompasses Artificial Neural Networks (ANN), Spiking Neural Networks (SNN), Reservoir Computing (RC), Long Short Term Memory (LSTM), and Deep Learning (DL) systems (Hinton et al., 2012). The foundations of Neural Networks were laid by McCulloch and Pitts (McCulloch and Pitts, 1943), Rosenblatt’s Perceptron (Rosenblatt, 1958) for ANNs, and von Neumann’s postulate of SNNs in 1956. More recent
Figure 1: A shamrock-like illustration of the three development areas, which characterize the currently expansive development in the field of Artificial Intelligence (AI).

Inventions from Jäger (Reservoir Computing) (Jäger, 2001), Hochreiter & Schmidhuber (Long-/Short-Term Memory) (Hochreiter and Schmidhuber, 1997) and Hinton (DL) (Hinton et al., 2012) have advanced the field one huge step forward and comprise the backbone of today’s AI.

In the second leaf, the field of neuromorphic engineering, initiated by Carver Mead and Mohawa & Rodney Douglas, seeks to mimic the basal mechanisms of information processing in nervous systems via an essentially hardware-oriented approach (Mead, 1989; Mahowald and Douglas, 1991; Mead, 2020). In recent years, great progress has been made in the development of bio-inspired processors. Here, event-based spiking neural networks (SNNs) in the form of either mixed (analog and digital) or strictly digital signal processing provides novel opportunities for low-power data processing (Indiveri et al., 2011; Merolla et al., 2014; Pei et al., 2019; Kendall and Kumar, 2020; Frenkel et al., 2021). Interestingly, some of the spiking neuromorphic circuits work at biologically relevant frequencies, exhibiting low energy consumption. One point of merit for neuromorphic engineering is their energy per synaptic operation (SOP), which is in the pJ to nJ range for neuroprocessors (Frenkel et al., 2021; Kendall and Kumar, 2020; Schuman et al., 2017).

Hence, the incorporation of relatively few basal mechanisms of biological information processing, such as leaky-integrated firing, axon delays, and local learning rules, can lead to significant improvements in resource management.

Recent advances in the field of nanoelectronics devices, such as memristive devices, nanoparticle networks, nanowire networks, or memristive fluids, compose the third leaf of advanced computer architecture. Research in silicon nanoelectronics is dominated by the development of new field effect transistors (FET) (Karbalaei et al., 2021; Radamson et al., 2020) for the next generation of CMOS circuits, as well as entirely novel devices and materials exhibiting advanced functionalities (Sengupta et al., 2016; Zhang et al., 2020; Minnai et al., 2017; Lequeux et al., 2016; Sangwan and Hersam, 2020; Sung et al., 2018; Kaspar et al., 2021). In particular, the memristor (originating from memory and resistor, also called memristive device) is a two terminal device that exhibits attractive features for vari-
ous applications in the post-Moore area, generating considerable interest. Memristive devices were intensively studied in the sixties and seventies (Hickmott, 1962; Argall, 1968; Dearnaley et al., 1970). The field was further propelled forward by the establishment of the theoretical background of memristors by Leon Chua (1971), with the corresponding experimental realization and interpretation by Hewlett-Packard (HP)-Labs (2008) [L. Chua, 1971; Strukov et al., 2008]. Over the years, numerous books and reviews have covered fundamental and practical properties of memristive devices and their related circuits [Tetzlafl, 2014; Ielmini and Waser, 2016; Sung et al., 2018; Xia and Yang, 2019; Li et al., 2021].

So far we have described nanoelectronic devices fabricated using top-down methods, where the layers are deposited on an entire wafer and the devices are patterned by lithography and dry-etching (Pease, 2010; Donnelly and Kornblit, 2013; Oluwatosin Abegunde et al., 2019). In bottom-up approaches, functional materials are deposited or synthesized to obtain networks, such as irregular nanowires and/or 3D textures. Often the self-assembly capabilities of materials are exploited to create complex structures. Top-down and bottom-up approaches are habitually combined to create the electrical connections necessary to characterize the structures [Kronholz et al., 2006]. In the context of bio-inspired computing, we would like to highlight here the work done on nanowire networks [Stieg et al., 2012; Asayesh-Ardakani et al., 2013; Pantone et al., 2018; Hochstetter et al., 2021; Zhu et al., 2021; Loeffler et al., 2020; Mallinson et al., 2019; Pike et al., 2020]. The structure of such networks, and in particular their dynamic properties, reflect basal functionalities as observed in nervous systems, such as small-word connectivity and self-organized criticality (SOC) [Watts and Strogatz, 1998; Beggs and Plenz, 2003]. We would like to emphasize that the three ICT research areas shown in Fig. 1 are not independent from one another: there is considerable overlap between them, which has proven to be mutually beneficial.

### 3.1 Advanced computing architectures

Here we present a few concepts of novel and reconsidered computing architectures. We would like to emphasize that the following four examples were chosen to demonstrate the diversity of the field but are not intended to give a comprehensive overview. The icons in Fig. 2 represent different computing principles.

For concepts other than those shown in Fig. 2, such as quantum computing, cellular automata, and probabilistic computing, we refer to the literature (Mermin, 2007; Serb et al., 2016; Baatar et al., 2016; Zhang et al., 2020; Kari).

We focus on comparing today’s digital computing to in-memory computing, vector matrix multiplication, reservoir computing, oscillatory computing, and bio-inspired computing (see icons in Fig. 2).

In order to overcome the von Neumann bottleneck of digital computing (Fig. 2(a)), near-memory computing was developed in 1990 (D. Patterson et al., 1997). Here, the strict separation of an arithmetic logic unit communicating with several distinct memories was eliminated. Part of the computational tasks was performed within the memory itself, leading to more efficient computing. This development has recently shifted to a higher gear, leading to in-memory computing (Fig. 2(b)) following the invention of memristive crossbar-arrays (Burr et al., 2017; Sebastian et al., 2020). Vector matrix multiplication (Fig. 2 (c)) is considered a key hardware booster in Deep Learning. The time and energy consuming task of vector matrix multiplication is performed in a memristive crossbar-array in which the input and output layer are interconnected by an array of weighted, checkboard arranged memristive devices (Burr et al., 2017; Wang et al., 2020b; Li et al., 2021). Vector matrix multiplication is an example of how Deep Learning may benefit...
from the development of new electronic devices, e.g. memristors. Reservoir Computing (Fig. 2 (b)) was independently invented by Herbert Jäger and Wolfgang Maass and belongs to the general framework of Recurrent Neural Networks (RNN) [Jäger, 2001; Maass et al., 2002]. In RNNs, a backpropagation through-time procedure is typically applied to adjust (train) the weights of the network to desired target functions. Here, a significant amount of time is required, with no certainty that the optimal weights will be set after learning. Thus in RC the reservoir consists of an ensemble of nonlinear elements coupled to one another. The reservoir projects incoming data and time series to a higher dimension that can be easily readout by conventional classifiers, in which the training is executed by means of a linear regression, for example. This reservoir can be either virtual or physical. These aforementioned reservoirs are designed like neural networks in which the connections are randomized but remain fixed during computation. Physical reservoirs are those which rely on natural systems exhibiting nonlinearity [Nakajima, 2020; Gauthier et al., 2021; Milano et al., 2022].

The goal of analog computing is to mimic complex technical systems by means of electronic circuits which represent key system parameters as a set of voltage levels at nodes. Oscillatory computing (Fig. 2 (e)) refers to a subset of analog computing in which the oscillator frequencies and phases enrich the representation of information. Oscillatory systems are omnipresent in nature and engineering [Arenas et al., 2008; Pikovskij et al., 2003; Strogatz, 2001]. Technically, oscillators can be realized in numerous ways, such as in discrete or integrated semiconductor electronics, spin-torque
devices, Josephson junctions, optical devices, or micro electro-mechanical systems (Schneider et al. 2018; Lequeux et al. 2016; Chen et al. 2020; Ignatov et al. 2016; X. Cheng et al. 2021; Feldmann et al. 2019; C. Lenk, L. Seeber, and M. Ziegler 2020) (Schneider et al., 2018; Lequeux et al., 2016; Chen et al., 2020; Ignatov et al., 2016; X. Cheng et al., 2021; Feldmann et al., 2019; Lenk et al., 2020). In general, dynamical systems and their coupled oscillators may offer elegant solutions to compute HP-hard problems. Coupled oscillator networks have been successfully exploited in the field of pattern recognition (Kantner et al., 2015; Hölzel and Krischer, 2011). However, larger systems have not yet been successfully developed due to noise-stability problems and device constraints in the new class of compact oscillators based on VO$_2$ or NbO$_x$, for example (Shamsi et al., 2021; D. Lee et al., 2018).

The term bio-inspired computing (Fig. 2 (f)) is only loosely defined. To a large extent, the computing primitives described above (see Fig. 1 and Fig. 2 (b)-(e)) are more or less biologically motivated. The Perceptron is a crude blueprint of a neuron and is still today at the heart of Deep Learning systems (Rosenblatt, 1958). In-memory computing is a strategy to abrogate the strict separation of the ALU and memory in digital computing, and is derived from biological information processing where logic and memory are blended. Neuromorphic processors contain circuits that can execute the Leaky Integrate-and-Fire dynamics of neurons, including the biologically motivated winner-take-all (WTA) principle, and introduces axon delays (Schuman et al., 2017; Hasler and Mari, 2013). Coupled oscillators imitate the orchestra of neural ensembles, i.e. the communication of separate brain regions which is considered to be the fundamental mechanism that explains perception (Singer and Gray, 1995; Varela et al., 2001; Buzsáki, 2006). Cellular automata, for example, were introduced by John von Neumann to describe self-reproduction in biology (Mange et al., 2004). Probabilistic computing is based on Bayesian inference, which is closely related to the way humans make decisions (Alaghi and Hayes, 2013; Parr et al., 2018). Therefore, it is essential to declare precisely to what extent an artificially built system is bio-inspired and which biological pathway have been applied as design principles (Venkatesan and Williams, 2022).

### 3.2 Novel electronic devices

There is an ongoing effort to shrink silicon FETs to feature sizes below 5 nm. The FinFET structure has dominated CMOS technology since its invention in 1989 (Colinge, 2008). Novel designs, such as GAAFET (Gate-All-Around) and MBCFET (Multi-Bridge-Channel), are serious candidates for next generation CMOS chips (see Fig. 3 (a)) (Radamson et al., 2020). Aside from this ongoing improvement of conventional FETs, devices with novel functionalities and materials have been attracting considerable interest to implement novel computing architecture. Magnetic Josephson Junctions, photonic synapses, and bio-organic memories represent only a fraction of current development strategies (Schneider et al., 2018; Feldmann et al., 2019; Robin et al., 2021; Zhang et al., 2020). In Fig. 3 (b) to (d), unconventional nanoelectronics device structures are illustrated. In Fig. 3 (b), a memristive device structure is illustrated, comprising two electrodes separated by a memristive layer. In the same Figure, a qualitative I-V curve of a memristive device is shown alongside a sketch of a biological synapse (see also Fig. 4), highlighting that memristive devices are promising artificial synaptic counterparts due to their capability of presenting variable resistive weights in engineered neural networks (Bian et al., 2021).

One universal property of the memristive device concept is that the memristive state depends on previously induced charge flows, applied currents, or applied electric fields, thus storing a historically-determined resistance state. For
Figure 3: Schematics of four advanced device components. (a) 3D view graph of a GAAFET as applied in today’s latest digital processors (Radamson et al., 2020), (b) sketch of a memristive device including a qualitative I-V curve and illustration of a synapse (Ielmini and Wasner, 2016; Xia and Yang, 2019; Sun et al., 2021), (c) cartoon of a 3D nanowire network (Stieg et al., 2012; Pantone et al., 2018; Minnai et al., 2017; Mallinson et al., 2019; Loeffler et al., 2020; Zhu et al., 2021; Hochstetter et al., 2021; Kuncic and Nakayama, 2021), (d) 3D cross-sectional graph of a fluidic memristive device adapted from (Robin et al., 2021) with permission.

It is this concurrently complex and simple device concept, together with the tremendous predicted potential for breakthrough technologies in areas such as universal memories and novel non-Boolean computing schemes for cognitive electronic systems, that propels the research and development of memristors and memristor-based circuits worldwide. It is important to mention that, in contrast to the theoretically simplistic memristor concept, in practice the realization of memristive devices by modern thin film technology is a task littered with obstacles. Up until now, a huge number of experimental findings on memristor devices consisting of a broad variety of metal/insulator material combinations have been published, all of which show memristive I-V curves (Ielmini and Wasner, 2016; Wang et al., 2020a; Sun et al., 2021). At first glance, it seems that the toolbox of resistive switching devices is ready for nearly any circuit application: simply pick a device concept and follow the extensive materials and methods laid out in the literature. However, a closer look at the fine details casts a dark shadow on this bright research field, leading to a harsh awakening based on hard facts. These “hard facts” are the requirements and boundary conditions set by the envisaged circuit applications, in which memristors must fit technologically, electronically, and economically. Currently, two main development avenues can be explored for memristive devices. The first focuses on resistive random access memories (RRAMs). It is believed that the zoo of today’s existing memory diversity can be replaced by a single (universal) memory concept. RRAMs are considered attractive candidates for universal memories because they: (i) show non-volatile data storage, (ii) can be densely integrated, (iii) are fast, and (iv) are cheap to produce. In particular, such a universal memory might attenuate the problem known as memory latency in modern digital computers (Iniewski, 2010; Banerjee, 2020). Besides the RRAM goal which may be categorized under the label “More Than Moore”, novel and very appealing computer architectures have been proposed in which memristors might play a vital role. Another main focus of possible memristive device applications may be associated with such catchphrases as: non-Boolean computing, bio-inspired information processing, neuromorphic engineering, or cognitive electronics (Zamarreño-Ramos et al., 2011; Ranjan et al., 2017; Huang and Zhu, 2021; Kaspar et al., 2021; Wan et al., 2019). On
the local, synaptic level, learning in nervous systems is explained by Hebb’s learning rule and Spike-timing dependent plasticity (STDP), amongst others (Bi and Poo, 1998). STDP and other memory-related mechanisms observed in nervous systems, such as Long-term Potentiation (LTP) and Long-term Depression (LTD) (Bliss and Lømo, 1973), have been successfully mimicked by memristive devices (Ohno et al., 2011; Winterfeld et al., 2018). Moreover, traditional studies known from behaviorism, such as classical conditioning (e.g. Pavlov’s dog), anticipation, and optical illusions, were successfully realized experimentally by both single and pairs of memristive devices (Pershin and Di Ventra, 2010; Ziegler et al., 2012; Bichler et al., 2013; Ziegler et al., 2014; Ignatov et al., 2016). The extent to which larger networks of memristive devices are able to mimic higher brain functions is still unknown.

In Fig. 3 (c), a sketch of a nanowire network (NWN) is shown. NWNs have been successfully synthesized for various materials, such as metals, oxides, and semiconductors (Huang and Zhu, 2021; Milano et al., 2022). Nanowires show appealing features with respect to bio-inspired computing from the point of structure, topology, and inherent dynamics (Loeffler et al., 2020; Hochstetter et al., 2021; Zhu et al., 2021; Diaz-Alvarez et al., 2019; Pantone et al., 2018). In recent comprehensive reviews by Zhu et al. and Kuncic and Nakayama, hallmarks known from biological systems as small-world connectivity (topology) and self-organized criticality (dynamic) were addressed (Zhu et al., 2021; Kuncic and Nakayama, 2021). Interestingly, brain-like avalanche effects have been observed in NWNs that exhibit dynamic features found in nervous systems (Pike et al., 2020; Hochstetter et al., 2021; Beggs and Plenz, 2003; Chialvo, 2010). Finally, we would like to emphasize that emergent neuromorphic materials and devices are not restricted to the solid state phase. In Fig. 3 (d), a sketch related to a nanofluidic device is shown. Bocquet and co-workers demonstrated by analysis and molecular dynamic simulations that ion transport across quasi–two-dimensional slits under an electric field displays memristive I-V curves, as well as spiking voltage patterns in accordance with the Hodkin-Huxley model of biological neurons (Robin et al., 2021; Hodgkin and Huxley, 1952). We would like to emphasize that while these examples of NWNs and nanofluidics clearly demonstrate that the material “tool box” offers novel opportunities to implement higher brain function, its full potential has yet to be fully explored.

4 Information Processing in Nervous Systems

This perspective explores the role of information processing observed in nervous systems as a basis for the development of energy-efficient technological computing systems, and even the possibility of implementing higher brain functions in engineered systems. Nervous systems offer paradigms to improve energy-efficient artificial information processing units. The exploration of signal pathways in nervous systems shows us how evolution led to extremely energy-efficient signal processing units (nervous systems). For example, the human brain dissipates a power of only roughly 20 W to 25 W. This, in addition to the amazing capabilities of humans’ vision and hearing, reveals fascinating opportunities for autonomous vehicles or speech recognition. Hence, processing sensitive data in server clouds may lead to severe security concerns. The data of millions of cars in motion, including their controllability, falling into the wrong hands could lead to fatal attacks; Local data processing in an autonomous car with low power consumption is preferable.

Creatures are very well adapted to their specific ecological niche, a result of a hundred million years of ongoing evolution and the associated interaction between creatures and their environment throughout their life span (Martinez and Sprecher, 2020; Dobzhansky, 1973; Jacob, 1977). In particular, information pathways in nervous systems are prototypes for engineers to perform cognitive tasks in quasi-real time with extremely low power consumption.
These features alone, and the information processing behind them, represent attractive models for entirely new computing architectures. In sections 4 A. and 4 B., local and global aspects of information processing mechanisms are presented, respectively. Distinct differences between digital computing and information pathways in biological systems are highlighted in the framework of topology and dynamics to motivate the concept of artificial spatio-temporal networks, as subset of the field of bio-inspired information processing. In sections 4 C. (Phylogeny and Ontogenesis) and 4 D. (Homeostasis), we underline important hallmarks of information processing in biological systems which have so far only been partly considered for artificial systems. Note that in chapter 4, we do not address how such mechanisms can be established in electronics: This is the subject of chapter 5, where several approaches are proposed to implement an artificial spatio-temporal network. It is not our goal to develop another pattern recognition system but to address the fundamental question: “To what extent can higher brain functions be reproduced in artificial systems?” We believe that essential information pathways in biology have been to a large extent overlooked, as detailed in this perspective. One important difference between artificial spatio-temporal networks and contemporary AI and neuromorphic engineering is that essential growth mechanisms observed in nervous systems are exploited as a guideline in the former.

4.1 Local Aspects of Information Processing in Nervous Systems

In contrast to current clock-driven Boolean Turing machines, information processing in biological nervous systems is characterized by highly parallel, energy-efficient, and adaptive architecture (Backus, 1978; Turing, 1950; Rueckert, 2016). When it comes to pattern recognition, failure tolerance, and cognitive tasks, even simple creatures outperform supercomputers, in particular regarding power dissipation. Fundamental building blocks leading to such remarkable properties exploit neurons as central processing units, which are interconnected by synapses to form a complex dynamical three-dimensional network, the connectome (Seung, 2012). In Fig. 4, the structure of a neuron is sketched, including the soma, dendrites, the axon, and connections to other neurons by synapses.

Figure 4: Blueprint of a neuron including an enlarged sketch of a synapse and the illustration of a single action potential, a spike.

An action potential (spike) is defined as a sudden transitory and propagating change in the resting potential across a membrane. Action potentials sent from presynaptic neurons are received via the dendrites and synapses of the post-
synaptic neurons. Those signals are integrated within the cell body of the postsynaptic neuron. When a threshold potential is reached, the neuron generates a new spike or a sequence of new spikes at the axon hillock that are transmitted via the axon to a postsynaptic neuron. This entire process is called Leaky Integrate-and-Fire (LIF). The term leaky reflects the fact that the cell membrane is not a perfect electrical insulator. Numerous LIF models, such as the FitzHugh–Nagumo, Morris–Lecar, or Hindmarsh–Rose models, have been developed to address different aspects of the biological substrate (Dayan and Abbott, 2001; Gerstner and Kistler, 2002; Izhikevich, 2003, 2010). Depending on the electrical activity of two connected neurons, the connection strengths (the weights) can become weaker or stronger. This is at the heart of Donald E. Hebb’s learning rule, who first recognized that “Neurons which fire together wire together” (Hebb, 2005). On the biochemical level the variable strength is explained by the amount of neurotransmitters (vesicles) which are released into the synaptic cleft.

From an engineering point of view, nervous systems process information in such a way that silicon technology, the holy grail of modern digital computing strategies, seems to be outmatched. For example, electronic components and circuits, such as transistors, memories and processors, are optimized for small parameter spreads to run at GHz clock frequencies under a precise pulse timing (Iniewski, 2010; J. M. Veendrick, 2017). In particular, they exploit nanosecond signal pulses that travel at nearly the speed of light along well-ordered transmission lines that connect different system parts in an essentially two-dimensional topology. In contrast, information pathways in nervous systems are characterized by highly irregular tissue consisting of neurons, synapses, and axons. Low conduction velocities on the order of several m/s lead to pronounced signal retardation, i.e. delays. In Fig. 5, characteristic timescales of CMOS processors and nervous systems are compared. In digital computing, the pulse duration is below a ns, and the signal transmission velocity is at nearly the speed of light. In nervous systems, the corresponding values are 3.5 ms for the pulse duration of an action potential or spike, and a few tenths of a ms for the transmission of a spike along myelinated axons (Kandel, 2013). Whereas the clock frequency of a modern Si processor is about 5 GHz, human EEG brain waves range from below 1 Hz to a few 100 Hz (He, 2014; Buzsáki and Draguhn, 2004; Buzsáki, 2006). This represents a six orders of magnitude discrepancy between technical and biological parameters. These facts alone point towards fundamental differences between information processing in digital computing and those in natural nervous systems.

4.2 Global Aspects of Information Processing in Nervous Systems

Nervous systems are considered to be time-varying networks in which spike-dynamics and cellular morphology are intricately linked and reciprocally interwoven (Fornito et al., 2016; Martinez and Sprecher, 2020; Winfree, 2001; Thompson, 1992).

Information processing in nervous systems applies a broad range of structurally and temporally related phenomena (Kandel, 2013; Nassim, 2018; Sterling and Laughlin, 2015). At the level of individual synapses, neurons, and axons, the formation and transmission of action potentials (“spikes”) are reasonably well understood. However, a look at the mesoscopic and macroscopic level of the three-dimensional neuronal network leads to an entirely different assessment. Although groundbreaking progress has been reported on in vivo and in vitro techniques over the last decades, the nervous system’s spatiotemporal information processing is still not well understood (Kleinfeld et al., 1988; Kriegeskorte and Douglas, 2018; Schroeter et al., 2015; van den Heuvel and Hulshoff Pol, 2010). The biochemical mechanisms that explain higher brain functions at the cellular level, such as awareness, perception, and in particu-
Figure 5: Comparison between pulse transmission speed, pulse duration, and voltage amplitude in nervous systems and digital computing. The sequence of action potentials were adapted with permission from Fig. 1 of ref. (Izhikevich, 2003).

lar consciousness, remain elusive (Mackey and Glass, 1977; Engel et al., 1999; Dehaene, 2001; Bullmore and Sporns, 2009; Bassett and Gazzaniga, 2011; Melloni et al., 2021). Nonetheless, neuroscientists were able to identify basal mechanisms that define the fundamental platform of the unique and marvelous nervous system’s information processing. Characteristic features, such as STDP (Bi and Poo, 1998; Gerstner and Kistler, 2002; Markram et al., 2012), stochastic firing and bursting of neurons in the hundred Hz range, recurrent network structures, and aspects of oscillatory synchrony in larger neuronal ensembles (Ernst et al., 1995; Hoppensteadt and Izhikevich, 1997; Buzsáki, 2006; Arenas et al., 2008; Galizia and Lledo, 2013; Gerstner et al., 2014; Amil et al., 2015; Strogatz, 2015; Watts and Strogatz, 1998; Uhlhaas et al., 2009) are essential ingredients in biologically-based information processing. Moreover, factors related to the close interaction of a nervous system with its environment, i.e. external stimuli, are of crucial importance (Beer, 2000). Therefore, neuronal design principles provide a model for bio-inspired computing systems, which are diametric to development strategies in present binary IT, including GHz clock frequencies, near-light-speed signal transmission, and clearly separated from logic and memory (Höfflinger, 2016; J. M. Veendrick, 2017).

Beyond that, we would like to emphasize that information-related aspects of nervous systems during evolution (phylogenies), along with their individual development throughout their lifetime (ontogenesis), provide a promising model from which novel electronic architectures may be designed. In the animal kingdom, the intricacy of nervous systems varies tremendously between single- and multi-cellular organisms, and the human brain with its billions of interconnected neurons (Kandel, 1976; Nakagaki et al., 2000; Azevedo et al., 2009; Bosch et al., 2010; Bielecki and Garm, 2012; Naumann et al., 2015; Bosch et al., 2017; Dupre and Yuste, 2017; Giez et al., 2021). For the sake of completeness, we would like to specify that the existence of cognitive functionalities in entities without a nervous system, such as plants or the acellular slime mold Physarum polycephalum, is currently heavily debated. For interested readers, more detailed information can be found in the following references (Vallverdú et al., 2018; Gagliano et al., 2014; Adamatzky, 2017; Stepney and Adamatzky, 2017).
Matter & Mind Matter

Despite their different cognitive capabilities, neurons and nervous systems present many common features in all creature, such as synapses, signal transmission lines (axons), and action potentials (spikes), that act as basic information building blocks. While the term morphology defines the real structure of a nerve net, the topology of a net is more abstract, related to important theoretical graphical parameters that define the connectome of a nervous system (Barabási and Albert, 1999; Barabási, 2013; Bullmore and Sporns, 2009; Fornito et al., 2016). The connectome is considered to be the canonical state describing the cellular wiring diagram of a nerve net. Edges, nodes, cluster coefficients, characteristic path lengths, hubs, and motifs determine the topological quality of a net, for example. An unraveling of the micro- and macro-connectome and nervous system dynamics offer a suitable model for the next generation of bioinspired hardware electronics (Sterling and Laughlin, 2015).

Figure 6: Network cube and complexity: (a) classification of various networks. The dashed blue line illustrates a fictive, guided “walk” through the cube, starting from “S” and ending at the goal “G”. In this way, it will be possible to push the network properties of neuromorphic circuits towards those of cortical maps (see lower right-hand corner in the cube). This approach is part of an artificial spatio-temporal networks. (b) Qualitative illustration of the complexity term. From a spatial (topological) and temporal (dynamical) point-of-view, a complex system is neither completely random nor entirely ordered, but exhibits a state in between. Figures 6 (a) and (b) are adapted with permission from Solé and Valverde 2004 (Solé and Valverde, 2004) and Huberman and Hogg 1986 (Huberman and Hogg, 1986), respectively.

The network cube (Fig. 6 (a)) classifies a number of different nets according to theoretical attributes, including randomness, modularity, and heterogeneity (Solé and Valverde, 2004; Sporns, 2011). Interestingly, in this framework, cortical maps (lower right corner of the cube) extracted from the structural properties of nervous systems are somewhat isolated from all other nets, which are located in the upper left corner of the cube. In Fig. 6 (b), dynamical complexity (y-axis) is described as a state between complete asynchrony, with independent, random firing of the individual oscillators, and complete synchrony, with all oscillators firing in phase (Huberman and Hogg, 1986). Between these two extremes, system dynamics can be characterized by a complex and time-varying interaction of the oscillatory ensemble. This regime exhibits features of self-organized criticality (SOC) typically observed at and near phase transitions and might be identified by avalanches of firing neuron ensembles (Bak et al., 1988; Beggs and Plenz, 2003; Hesse and Gross, 2014; Shew et al., 2015; Mallinson et al., 2019; Cramer et al., 2020). Avalanche behavior is common in many physical phenomena, such as magnetic systems, earthquakes, and brain dynamics at the critical region of phase transitions, and were first described by Bak et al. (Bak et al., 1988). The common feature of all these systems
is slow external driving, causing an intermittent, widely distributed response. Avalanches appear in very different sizes, often distributed in the form of power laws. As known from statistical physics, power laws imply the absence of a characteristic scale, a property observed close to a critical point. When describing the dynamics in a nervous system using the SOC and brain-like avalanches models, the type of phase transition associated to each term must be clearly defined. For example, SOC and brain-like avalanches in NWNs (see section 3 B. and Fig. 3 (c)) are related to non-activity – activity phase transitions. In the context of firing neuron ensembles in a brain, SOC and avalanches may describe a temporal phase transition between the asynchronous and synchronous states (Hesse and Gross, 2014). In other words, a system could be in the supercritical state (above the critical point) in an inactive -active phase transition, while remaining subcritical (below the critical point) with respect to the asynchronous-synchronous phase transition. However, such phase transitions are not necessarily exclusive and might appear simultaneously in the brain, or the mechanisms could even be interwoven. So far, while nanoparticle networks and NWNs have been studied in context with their activity pattern, neuron-like oscillatory components have yet to be considered. The orchestra of firing neuron ensembles is considered a key underlining mechanism in understanding the binding problem, i.e. the capability of the brain to integrate (bind) different sensory inputs. For example, such a process can occur in the visual system when forming a unified perception of the environment (von der Malsburg, 1999; Singer and Gray, 1995; Uhlhaas et al. 2009; Engel et al., 2001; Schechter, 1996; Sheffield and Dombeck, 2015; Engel et al., 1991). Suggestions on ways to include relaxation-type oscillators to mimic the LIF features of biological neurons and the state of SOC are presented in chapter 5. Finally, the topological and temporal dynamics of the regime are extremely sensitive to external distortions (stimuli) at the critical point, allowing the system to respond in numerous ways to external stimuli (Chialvo, 2010, 2006; Kinouchi and Copelli, 2006; Beggs and Plenz, 2003; Shew et al., 2011). In biological terms, this means that the system can easily adapt to risky environmentally-driven situations. The manifold brain states available near the point of criticality offer a wide repertoire of means to react in a reasonable way to external tasks imposed by the environment. In extreme situations, this improves the chances of survival and is of evolutionary importance.

4.3 Phylogenies and Ontogenesis

The origin of bio-inspired computing can be best drawn from the two following neuroscience quotations:

(1) Gilles Laurent pointed out the common evolutionary heritage of living organisms. His contribution “Shall We Even Understand the Fly’s Brain? (see: 23 Problems in Systems Neuroscience edited by J. L. van Hemmen and T. J. Sejnowski, Chapter 1, page 3, (Hemmen and Sejnowski, 2006)) states: “When it comes to computation, integrative principles, or “cognitive” issues such as perception, however, most neuroscientists act as if King Cortex appeared one bright morning out of nowhere, leaving in the mud a zoo of robotic critters, prisoners of their flawed designs and obviously incapable of perception, feeling, pain, sleep, or emotions, to name but a few of their deficiencies.” (Laurent, 2006).

(2) Martijn P. van den Heuvel et al., made in “The Neonatal Connectome During Preterm Brain Development” the following statement: “The adult cerebral brain network is the result of a complex developmental trajectory. From the prenatal formation of the first neurons, throughout the first years of life and all the way into late adolescents, the brain undergoes an elaborate developmental trajectory.” (van den Heuvel et al., 2015).
How are these sayings so important for the design of novel bio-inspired computing primitives? The general idea behind these two quotations is the concept of development. Quotation (1) by Gilles Laurent highlights evolutionary development, the phylogenies of species, and their relevance to the emergence of the human cortex. This bottom-up approach favors the study of less complex creatures that appeared early during evolution, laying the foundation for much more complex nervous systems in vertebrates (Naumann et al., 2015). In particular, information processing strategies throughout evolution and in completely different species are astonishingly similar, if not the exact same. For example, the basic ingredients of information processing (neurons, synapses, and action potentials, as described in chapter 3) in the nervous systems of squids and macaques are hardly distinguishable from one another. Although François Jacob addressed the random and playful character of evolution by the phrase “Nature is a tinkerer, not an inventor” (Jacob, 1977), evolution can be somewhat conservative in the sense that similar structural and dynamical features appear in very different species throughout phylogenies. This justifies the investigation of information pathways in simpler, easier-to-understand organisms in order to comprehend higher brain functions in more complex vertebrates. A famous example is the research of Eric Kandel on the snail Aplysia, relating physiological signaling with behavior (Kandel, 1976). Studying the neural design of biological species with only a few hundred or thousands neurons is a fruitful ansatz to develop novel computing primitives (Brenner, 1974; Kaiser and Varier, 2011; Sterling and Laughlin, 2015; Bosch et al., 2017; Dupre and Yuste, 2017; Lovas and Yuste, 2021; Giez et al., 2021). We will come back to this issue in chapter 5.

While phylogenetics addresses the development and evolution of groups of similar species, ontogenesis is the study of how an individual member of a species develops as it ages. In quotation (2), Martijn P. van den Heuvel and coworkers underline the intriguing mechanisms of nervous systems development in humans, from conception to late adolescence. We propose that ontogenesis and their functional ingredients could serve as an essential guideline for novel computing primitives. To support this argument, we describe here the fundamentals of ontogenesis in the human nervous system, including the importance of external stimuli during development. Physiology, neurobiology, and behavioral science provide overwhelming experimental evidence showing that the conditions during the growth and regeneration of neuronal nervous systems under external stimuli are of central importance (Held and Hein, 1963; Huttenlocher, 1990; Dehaene-Lambertz and Spelke, 2015; Kaiser, 2020; Gauthier et al., 2021; Wiesel and Hubel, 1963; Paredes et al., 2016). Both the formation and elimination of nerve cells, synapses, and axonal connections occur frequently during the first stages of brain development, belonging to a very creative process that shapes the nervous system to be well-adapted for future environment-related tasks. In addition to the creation of neurons and axons, pruning (programmed cell death or apoptosis) and axonal rewiring are both essential and expedient mechanisms. Finally, myelination of axons is an essential step to improve the nervous system’s performance by shaping and optimizing the signal transfer time between neurons and distributed brain areas. Gerald Edelman coined the expression “Neuronal Darwinism” to highlight the striking parallels between evolution and brain development (Edelman 1987; Tononi, Sporns, and Edelman 1994; Edelman and Tononi 2001; Van Ooyen and Butz-Ostendorf 2017) (Edelman, 1987; Tononi et al., 1994; Edelman and Tononi, 2001; Van Ooyen and Butz-Ostendorf, 2017). Neurons, synapses, and axonal connections grow lavishly at first, a growth that is controlled by the genome, epigenome, and stochastic factors. Subsequent structural shaping and elimination, often called blooming and pruning, are largely influenced by the interaction of the entire nervous system with environmental stimuli, and the nervous system’s subsequent reaction (Beer, 2000; Huttenlocher, 2002; Hensch, 2005). There have been attempts in the past to design materials and systems that mimic
biological information processing, dubbed “evolvable hardware” and “evolution-in-materio” (Broersma et al., 2012; Stepney and Adamatzky, 2017; Stieg et al., 2012; Miller et al., 2014; Adamatzky, 2017). This work has been recently extended to novel, transistor-based devices by Baek, et al. (Baek et al., 2020). Although the findings are very promising, basal spatiotemporal and topologically-relevant mechanisms have not been reproducible in electronics hardware so far. In both biological and artificial systems, the connection between these mechanisms should be worked out with regard to the required complexity and functionality (see Fig. 6).

Neural network growth in nervous systems has been studied in-depth both theoretically and experimentally (Engert and Bonhoeffer, 1999; Kaiser and Hilgetag, 2004; Kaiser, 2010; Koudier et al., 2013; Hütt Marc-Thorsten et al., 2014; van den Heuvel et al., 2018; Kaiser, 2020; Hiesinger, 2021a,b). In particular, the early stages of nervous system growth under external stimuli is of critical importance for the healthy development of mature creatures (Wiesel and Hubel, 1963; Ardiel and Rankin, 2010; Seung, 2012). It is known that both external stimuli and genetic factors have tremendous impact on the emergence of functional neural circuits that determine behavior during critical periods of cortical region growth (Huttenlocher, 2002; Hensch, 2005; Lohmann and Kessels, 2014; Hiesinger, 2021b). Cell overproduction and subsequent attrition are likewise important for nervous system development (Huttenlocher, 2002; Sanes et al., 2006; Rumpel and Triesch, 2016). Morphological aspects, connectivity, growth, regeneration, and the impact of neuronal activity-related spike-based synchronization mechanisms in neuronal network ensembles serve as models for novel electronics (Faust et al., 2017; Arenas et al., 2008; Uhlhaas et al., 2009; Buzsáki, 2006; Singer, 1998; Buzsáki and Draguhn, 2004; Bassett and Gazzaniga, 2011). Clear evidence of structural dendritic spine plasticity is shown in a series of photographs taken over a few days in Fig. 7, demonstrating that spines grow and shrink depending on external, touch-related stimuli in mice (Holtmaat et al., 2006).

![Figure 7: Structural plasticity.](image)

A look at a few growth parameters underlines the importance of understanding biological networks during development. A two-year-old human toddler exhibits the maximum number of neurons and synapses of our species, roughly a factor of two more than a fully grown adult. If we estimate 170 billion neurons (Huttenlocher, 2002;}

17
Azevedo et al. (2009) with $10^3$ synapses per neuron, a two-year-old human carries $170 \times 10^{12}$ synapses. We assume the total axon length of a toddler to be about 850,000 km (https://aiimpacts.org/transmitting-fibers-in-the-brain-total-length-and-distribution-of-lengths/). The time between egg fertilization to the age of two is 1000 days or $8.64 \times 10^7$ s. This leads to an average net growth of roughly 2000 neuron/s, 2 million synaptic interconnections/s and an axon growth rate of about 10 m/s! These measures alone unambiguously demonstrate the overwhelming significance of network growth in humans, particular during childhood (Kolb and Fantie, 2009; Paredes et al., 2016). Moreover, we believe that such a tremendous development is an interesting template for novel computing architectures. It might be an essential building block to achieve higher brain functionalities in artificial systems, and constitutes a key aspect artificial spatio-temporal networks.

Fig. 8 shows several snapshots taken during human development, where the excessive growth of neurons between the ages of one month to two years is clearly visible. Interestingly, between the ages of two to four years, neuron pruning leads to reduced neuron density. While the net neuron density during adulthood is rather constant, blooming and pruning still continue to occur, albeit at a much lower rate (Van Ooyen and Butz-Ostendorf, 2017).

![Figure 8: Blooming and pruning of nerve cells in young humans](Seung, 2012) and J. Conel, “The Post-Natal Development of the Human Cerebral Cortex,” Harvard University Press, Cambridge, 1939-1967. Adapted from (Seung, 2012).

Figure 8: Blooming and pruning of nerve cells in young humans (Seung, 2012) and J. Conel, “The Post-Natal Development of the Human Cerebral Cortex,” Harvard University Press, Cambridge, 1939-1967. Adapted from (Seung, 2012).

From the postnatal phase up to the age of around two years, our central nervous system is characterized by enormous development and permanent remodeling, while being simultaneously subject to an exuberant amount of external stimuli via our senses (Beer, 2000; Kouider et al., 2013; Hensch, 2005; van den Heuvel et al., 2015). Genetics, stochastics, and external stimuli (in other words nature and nurture) define who we are and strongly influence higher brain function during adulthood, including perception, awareness, and consciousness.

In Fig. 9, windows of plasticity in human brain development are sketched (Hensch, 2005; Hensch and Bilimoria, 2012). Even in much simpler creatures (e.g. the worm C. elegans), external stimuli play an essential role in the healthy development of the nervous system (Ardiel and Rankin, 2010).

These windows for sensing, motor skills, and higher cognition are also called critical periods. They reflect the tremendous rearrangement of the human brain during early childhood, accompanied with enormous learning capabilities. It is interesting to assign the above estimated growth parameters and the appearance of critical periods to human altriciality. Altriciality refers to the way creatures are born completely incapable of caring for themselves (Dunsworth et al. 2012). Hence, at the moment of birth (eye opening), a sudden rush of external stimuli, in particular vision, meets a
Figure 9: Illustration of critical or sensitive periods during the first years after birth for humans. The three periods present (from left to right) the development of sensory pathways, motor skills, and higher cognitive functions. Adapted from (Hensch, 2005; Hensch and Bilimoria, 2012) with permission.

The premature nervous system still under heavy construction, reconstruction, and growth, in the case of humans. The concomitant occurrence of environmental input, nervous system growth, and close interaction between the nervous system and its environment may explain the huge plasticity and learning capabilities during these first years. This development seems to be essential to form higher brain functions (Dehaene-Lambertz and Spelke, 2015; van den Heuvel et al., 2015). Although it might be incredibly difficult to mimic such basal neurobiological mechanisms in engineered systems, nervous system development and growth cannot be neglected in establishing higher brain functions in artificial systems. Attempts to achieve this goal are proposed in chapter 5.

4.4 Homeostasis

As in section 4 C., we begin with the following sequentially-labelled neuroscience quotation: (3) Arjen van Ooyen and Markus Butz-Ostendorf emphasized the role of homeostasis on p.133 of their contribution (see: The Functional Role of Critical Dynamics edited by Nergis Tomen, J. Michael Herrmann, and Udo Ernst (Tomen et al., 2019):

“In conclusion, during development, homeostatic structural plasticity can guide the formation of synaptic connections to create a critical network that has optimal functional properties for information processing in adulthood.”

(Ooyen and Butz-Ostendorf, 2019).

Roughly speaking, is homeostasis a kind of counteracting mechanism to network plasticity, and thus an important factor to ensure network robustness and stability? As will be discussed below in more detail, homeostasis comprises dynamical and morphological components, and is thought to explain how a nervous system stabilizes (itself) near the point of criticality (Brütt and Kaernbach, 2021). In other words, homeostasis addresses the term “self” in SOC. The role of homeostasis as a stabilizing factor in neural networks is amply described in a huge number of publications, with only a few mentioned here (Abbott 2003; Turrigiano 2012; C. Tetzlaff et al. 2010; Stepp, Plenz, and Srinivas 2015; Fauth, Wörgötter, and Tetzlaff 2017; van Ooyen 2017; Ma et al. 2019) (Abbott, 2003; Turrigiano, 2012; Tetzlaff et al. 2010; Stepp et al. 2015; Fauth et al. 2017; van Ooyen and Butz-Ostendorf, 2017; Ma et al. 2019).

In homeostatic structural plasticity, all incoming synapses of a cell are modified to stabilize the neuronal activity around a particular level (set point), and reflect a negative feedback loop between neuronal activity and connectiv-
The fundamental principle of homeostasis is sketched in Fig. 10.

Figure 10: Illustration of homeostasis in a nervous system at the neuron level. Adapted from (Butz-Ostendorf and van Ooyen, 2017) and (Tien and Kerschensteiner, 2018) with permission.

Higher firing (dynamic component) of a neuron results in spine deletion (morphological component), whereas reduced firing supports spine formation, keeping the average electrical activity at a set-point, potentially stabilizing the global activity of the entire neural ensemble near the desired critical state, i.e. the state with the largest dynamic range for information processing (Chialvo, 2006; Kinouchi and Copelli, 2006; Shew et al., 2011; Butz-Ostendorf and van Ooyen, 2017). While this model appears attractive at first glance, it raises a fundamental question in neuroscience: “How can an individual, local neuron in a huge nervous system access the global network state in order to orientate its own activity accordingly?” (Hesse and Gross, 2014; Fornito et al., 2016), or in other words, what defines the activity set-point? This is an example of the poorly understood relation between local, mesoscopic, and global mechanisms in nervous systems.

In chapters 3 and 4, we presented various basal local and global information pathways in nervous systems. In the following chapter, we will suggest a number of strategies with the goal of implementing higher brain functions in artificial systems (Miller et al., 2014).

5 Artificial Spatio-temporal Networks

At this point, an obvious and understandable question might be: Is the goal to achieve higher brain functions in artificial systems possible at all or, more precisely, to what extent can the intriguing and complex biological mechanisms described in Chapters 3 and 4 be merged into a novel computing primitive? How close is neuroscience to understanding higher brain functions and to what extent can the plethora of phenomena set by materials and engineering designs strategies enable mental functions in artificial systems?
Here we discuss possible ways and limitations of using artificial systems to mimic biological fundamentals, including topological and dynamical aspects, such as phylogenies, ontogenies, homeostasis, SOC, memory, oscillatory orchestra (synchrony), and so on. Nonetheless, we are aware that fundamental limits which may impede consciousness in engineered systems. It would be interesting, however, to identify and define those limits.

In Fig. 11, considerations set by materials science and design strategies are illustrated.

Figure 11: Artificial spatio-temporal networks: Materials science considerations and design strategies to generate higher brain function in artificial systems. The proposed system takes basal functionalities of bio-inspired information pathways into account discussed in Chapters 3 and 4. (a) 2D or 3D spatio-temporal materials network. Wires within the network are connected via memristive components. The memristive functionality at cross-sections of the network implements memory and local plasticity in the network. The faded area represents a growing network. In the case of a 2D network structure formed on a planar substrate, network growth might be modified, for example, by pre-pattern substrates, a functionalized surface, additional electrical potentials, optical stimuli, and deposition-related growth parameters (materials, deposition rate, reactive gases, substrate temperature, and so on). A 3D network allows further freedom of design and allows for a nervous system-like connectivity. The 3D network could be in a solid phase, or even multiphase, network, the latter combining materials in the solid, liquid, and gas phase. (b) Representation of a pulse-oscillator ensemble in order to mimic neural spiking activity. The individual oscillators of the ensemble are electrically connected to the network, leading to modifications of the network connectivity by oscillator pulses. Conversely, the network weights in turn influence the dynamic state of the oscillator ensemble via pulse coupling. The oscillatory ensemble allows an input of external stimuli (e.g., touch, vision, and hearing) via fire rate coding. In addition, analyzing the interspike interval (ISI) distributions of the ensemble in quasi-real-time enables permanent monitoring of the dynamic state of individual oscillators, as well as the entire ensemble. (c) Stage to monitor the structure and extract the topology of the network in real time by, for example, optical microscopy, electron microscopy, thermal imaging, or magnetic field distribution detection (similar to MEG (magnetoencephalography)). (d) By monitoring the oscillatory ensemble dynamics (see (b)) and the structural connectivity (see (c)), the spatio-temporal state and its evolution can be analyzed in real-time.
Before describing the interplay between the components sketched in Fig. 11, we should first consider a few aspects of biological information pathways which are obviously implementable by materials science and electronics, and might simplify the execution of the proposed artificial spatio-temporal network. In a human brain, the ability to access, and thus measure, the structural, topological, and dynamical states is hindered by both technological and ethical constraints (Fukushi and Sakura, 2008; Opitz et al., 2017). In contrast, artificial systems should theoretically permit access to all local and global parameters in any conceivable experimental setup. This offers a high degree of freedom in designing artificial systems. In particular, for a system growing in complexity, a designer might decide which segments should be externally controlled and which should develop via self-assembly and self-organization.

Furthermore, the time scales involved in biological information processing may actually facilitate their artificial engineering. In phylogenetic and ontogenetic development, low time scales dominate the scene. Species vary from one generation to the next, with networks growing from days to years. Additionally, nervous system dynamics are in the 100 Hz range, with low transmission velocities on the order of m/s, i.e. the speed of spikes along axons are common. As such, there is no need to build ultrafast artificial systems in order to imitate basal biological information pathway. Indeed, the deposition or synthesis of any material, e.g. nanoparticles or NWNs, is a growing materials network (Fig. 11 (a)), and can be adjusted to low time scales. In addition, low time scales adapt well in many ways to materials transport parameters, including ionic drift, diffusion currents, and mass transport in general. Biological time scales are easily accessible by electronics, facilitating circuit design, and permitting real-time observation of spatio-temporal system development (Figs. 11 (b), (c), (d)). For example, leaky-integrated-firing of a biological neuron can be technically realized by van der Pol (vdP) oscillators (van der Pol, 1926; Pikovskij et al., 2003; Ignatov et al., 2016), compact devices based on VO$_2$ or NbO$_x$, which exhibit a negative differential resistance (NDR) I-V curve (D. Lee et al., 2018; Maffezzoni et al., 2015; Driscoll et al., 2012; Luo et al., 2022), or integrated, mixed-signal circuits (X. Cheng et al., 2021). In general, low time scales known form biological information pathways, including external stimuli that affect them, offer an exploration space attainable by materials-related phenomena, electronics, and parameter monitoring.

How can an artificial spatio-temporal computing system, as sketched in Fig. 11, be practically realized? The goal in a bio-inspired artificial spatiotemporal network is to reach the desired topological and dynamical states simultaneously, in order to mimic the previously discussed characteristic hallmarks of the nervous system. This is handily illustrated in both Fig. 6 (a), where the topological cortical map region is labeled “G” (Goal) in the network cube, and in Fig. 6 (b), where the state of SOC is highlighted as the envisaged dynamical state. The main challenge here is to define the appropriate material network properties and dynamical setting for the entire system that will enable a similar spatiotemporal state to that of a nervous system. This global system state is often said to be structurally complex while being temporally close to the edge of chaos (Skarda and Freeman, 1987; King, 1991; Chialvo, 2010; Strogatz, 2015; Mackey and Glass, 1977; Bullmore and Sporns, 2009; Schroeter et al., 2015). To achieve this goal, we describe the components presented schematically in Fig. 11 and their interactions in accordance to the biological information pathways described in Chapters 3 and 4. The material network template offers manifold opportunities on either a 2D or 3D platform (Fig. 11 (a)). A network growth mimicking ontogenesis can be realized by continuous film deposition, or ongoing material synthesis of, for example, nanoparticle or nanowire networks. Network growth can be influenced in at least three ways, the first of which being the oscillatory ensemble that is electrically connected to the network. Here, external stimuli, e.g., hearing, vision, and touch, are imprinted into the material network growth process via fire rate coding (Fig. 11(b)). Network formation and structure evolution are modified by the additional potential
differences between the oscillator contacts within the network. Second, by integrating additional conductive pads (islands) on a 2D substrate platform, the formation of filaments between the oscillator’s electrodes can be controlled by the islands’ shape, number, size, and/or additional applied bias potential (Fig. 11(a)). The formation of conductive filaments during network growth could also be manipulated via structurally modulated or functionalized surfaces. In this way, not all network pathways are allowed, while others are assisted (D. Michaelis et al., 2021). Biologically, this corresponds to axon growth and guidance (Hiesinger, 2021a). This approach can also apply to 3D structures, which provides an increased degree of freedom and in principle allows nervous system-like connectivity. The materials network, whether 2D or 3D, does not necessarily have to be in the solid state: Electrolytes may be an appropriate fluid which satisfies the aforementioned requirements, including the state of criticality (Fisher, 1994; Robin et al., 2021; Pantone et al., 2018; Aoki et al., 2015; Haugland et al., 2015; Patzauer and Krischer, 2021; Orlik and Orlik, 2012a,b). Third, additional stimuli (Fig. 11(a)) in the form of, e.g. light or temperature, can also modify the spatio-temporal evolution of the functional material network. An imprint of information during network growth is common to all three methods. This distinguishes the artificial spatio-temporal network approach from common AI systems. In the latter, the training or learning sequence is applied after system manufacture. By applying the three methods described above, it might be possible to imprint information in a similar way to that of a human nervous system during ontogenesis (method 1), as well a kind of a-priori knowledge (methods 2 and 3), i.e. phylogenetic factors.

For the entire system, a simultaneous, in-depth monitoring of network structure during its development and temporal evolution is intended, in accordance with a neuroscience approach to extract the structure and dynamics of complex brain networks (Sporns, 2013; Bullmore and Sporns, 2009). To this end, the spatio-temporal development of time-varying connectivity within the functional materials network (see Fig. 11(a)) will be monitored, for example, by means by optical microscopy, electron microscopy, or the magnetic field distribution in accordance with magnetoencephalography (MEG) (see Fig. 11(c)). This will allow visualization of the time-evolving correlation matrix of the oscillatory ensemble, and the extraction of more theoretical metrics, such as cluster coefficients, characteristic path lengths, motifs, modularity, and hubs (Schroeter et al., 2013; Bullmore and Sporns, 2009; Fornito et al., 2016; Sporns, 2011). In Fig. 6(a), the pale blue dashed line in the cube represents a fictional pathway through the network cube. At first, we assume that the materials network is a topology state labeled “S” (Start). The position “S” within the cube is chosen as an example, but could just as well be any other topological position within the network cube. By constantly monitoring the topology of the system during network growth and intervention via a set of parameters (e.g. added materials, extra potentials, and external stimuli to the oscillatory ensemble), it might be possible to adjust the system to arrive at “G”, defined by a set of characteristic theoretical parameter (hubs, motifs, modularity, cluster coefficient, path length, etc.) (Fornito et al., 2016).

Simultaneously, the ISI distribution and time series of the oscillatory ensemble will be recorded (see Fig. 11(b)) (Kreuz et al., 2007). Spike train distances provide a means of quantifying neuronal variability and the degree of synchrony in and between oscillatory ensembles, and may indicate the rise of oscillatory avalanche firing as one indicator of the SOC (Abbott and Rohrkemper, 2007; Beggs and Plenz, 2003; Scarpetta and de Candia, 2013; Priesemann, 2014; Timme et al., 2016; Milton, 2012; di Santo et al., 2018). SOC is described as a state located somewhere between the random, independent firing of individual oscillators, and complete synchrony, where all oscillators fire in phase with the same frequency (Bottani, 1995; Aoki et al., 2015). Between these two extremes, a system’s dynamics can be characterized by a complex and time-varying interaction of the oscillatory ensemble (see Fig. 6(b)). This
regime exhibits features of criticality typically observed close to phase transitions (Chialvo et al., 2010; Shew et al., 2011; Beggs and Timme, 2012; Srinivasa et al., 2015; Chialvo et al., 2020; Mallinson et al., 2019; Pike et al., 2020). In particular, the topology and temporal dynamics of a system in such a state are extremely sensitive to external distortions (stimuli) and may respond to them in numerous ways.

Practically speaking, we will begin by analyzing coupled nonlinear oscillator network raster plots, phase portraits, phase response curves, bifurcation diagrams, spike distance measurements, and cross-correlation type time-series analysis. Information from these analyses will be subsequently applied to quantify the phase and frequency relationships between network oscillators and their development over time (Kreuz et al., 2009; Hoppensteadt and Peskin, 2012). Finally, we would like to discuss obvious obstacles and challenges. In section 4 D, the rule of homeostasis was highlighted. The concept of homeostasis is of essential importance to stabilize the nervous system dynamics and morphology to a set-point. For the system presented in Fig. 11, homeostasis is not illustrated. It might be possible to reconstruct a feedback parameter from the structural and functional matrices to reduce or enhance, if necessary, the oscillatory activity, or to modify the material growth process. Another challenge might be the implementation of appropriate delay lines to mimic the important signal retardation known from nervous systems (Amil et al., 2015; Mackey and Glass, 1977). Ionic conductors with slow ionic motion in the form of drift or diffusion currents could be a possible solution.

One important issue remains: Picture a fabricated artificial spatio-temporal system as depicted in Fig. 11, that presents all previously discussed biological information pathways. How can we benchmark the system, and determine how it solves tasks set by external stimuli? Certainly, the functional and structural network states reflect the overall system state. As such, one viable approach is to read out the system state and to activate a set of artificial motor neurons to react to an input task. However, this does not accurately represent the process in the human brain, where there is no internal, global system observer to decide on the next step (Damasio, 2004). At this point, we are confronted with a difficult challenge: how can we lead matter to imitate the mind? While the authors can suggest an example system as shown in Fig. 11, this question remains open.

6 Benchmarking for Bio-inspired Computing

Benchmarking in AI is an important approach to measure its performance, and subsequently enable comparisons between different systems. In pattern recognition, for example, MNIS data sets are used, with the recognition rate defining a clear benchmark. While contemporary AI systems show extraordinary capability in performing a single, specific task, their success at task variability is highly limited compared to the nervous system. Nonetheless, a new generation of AI has demonstrated extraordinary capabilities in the field of gaming (Chess and Go), including an aptitude for self-learning (Silver et al., 2018). Yet, it remains unclear how to define a fair and comprehensible benchmarking for neuromorphic systems and bio-inspired computing (Davies, 2019). Computational tasks must be carefully designed in order to assess the overall system’s performance in comparison with human mental capabilities, as previously proposed by Alan Turing in his seminal work on Machinery and Intelligence (Turing, 1950). Bloom’s learning taxonomy, which was developed to hierarchically categorize learning in the classroom, can be helpful in assessing how successfully artificial systems mimic higher brain functions (Adams, 2015). This taxonomy contains six categories of cognitive skills and presents a hierarchy with increasing cognitive functionality from bottom (factual knowledge)...
to top (creation) (see Fig. 12), or in other words, from lower-order skills that require less cognitive processing to higher-order skills that require deeper learning and a greater degree of cognitive processing (Compeau, 2019).

![Bloom's Taxonomy Pyramid](image)

Figure 12: Suggested benchmark for bio-inspired systems based on Bloom’s taxonomy. The pyramid represents increasing cognitive human skills from bottom to top. Fig. 2 from Ref. (Compeau, 2019).

This strategy may serve as a basis for benchmarking in bio-inspired computing systems. However, due to the nervous system’s task variability for each of the six cognitive categories, transparent benchmarks must be developed. This goal is extremely important for future comparisons of bio-inspired systems, which are currently developed on different platforms. In addition, resource-related parameters, such as energy consumption, system weight, and failure tolerance, need to be included.

7 Discussion

This perspective introduces the concept of artificial spatio-temporal networks, which proposes basal hallmarks, such as morphological and dynamical characteristics of nervous systems, to reproduce higher brain functions in artificial systems. In particular, the basal mechanisms known from the growth of nervous systems might play a significant role in their function. This concept will undoubtedly be a way to include biologically-relevant features in future artificial systems. Yet, only the tip of the iceberg has thus far been addressed: to fully realize an artificial spatio-temporal network, several challenges remain unresolved.

In more general terms, artificial spatio-temporal networks again raise the fundamental question: “To what extent can higher brain functions be reproduced in artificial systems?” Seminal books and papers by (Churchland and Churchland, 1990; Churchland, 1995; Aleksander, 2001; Koch and Tononi, 2008; Dehaene et al., 2017; Hiesinger, 2021b; Melloni et al., 2021), and many more address this topic in one way or another. According to the authors, higher brain function can be described on the basis of natural sciences and mathematics, permitting us to view this challenge in another light. On an atomistic level, we find in living nature, and therefore in any nervous system, old and well known friends from the periodic table of the elements, including but not limited to Carbon (C), Sodium (Na), Potassium (K), Chlorine (Cl), Oxygen (O), and Hydrogen (H). Any effort to establish higher brain function in an artificial system, whether in silico (software oriented) or in a material-based substrate, as in the case of artificial spatio-temporal networks, should apply another tool box of elements to establish awareness, perception, or consciousness, e.g. Silicon (Si), Gold (Au), Silver (Ag), Tungsten (W), O, and so on. There is no obvious reason why this strategy should not work, but if it cannot, what are the fundamental limits, and how are they defined? A look at biochemical substrates in...
living species highlights the weaknesses of the simplistic, atomistic viewpoint. There is still unknown genetic information that strongly controls nervous system behavior and function, especially during development, which therefore cannot currently be considered in any artificially-constructed systems. Whether there are shortcuts to bypass the role genes play in neural behavior and development is completely unknown, and might act as a show stopper (Hiesinger, 2021b). On the one hand, it is truly challenging to introduce basal biological functionalities, such as homeostasis, signal delay, growth, and the appropriate states of criticality and topology in an artificial system. On the other hand, the materials tool box may offer plethora of phenomena which have not yet been explored for novel computing architectures (Kaspar et al., 2021; Orlik and Orlik, 2012a,b; Haugland et al., 2015; Patzauer and Krischer, 2021). Hence, these simple questions and views point towards an even more fundamental aspect: in living systems, the separation between matter and information becomes blurred, making it risky to apply these terms without investigating living and artificial systems equally, or precisely clarifying the respective context (Johannsen, 2016).

8 Conclusion

In this perspective, we addressed fundamental limits of current ICT and briefly summarized the state-of-the-art. Today’s digital electronics work with clock rates in the GHz range, utilizing ns pulses and signal transmissions at nearly light speed in a vacuum. Meanwhile, nervous systems exhibit numerous remarkable and fascinating features, including anticipation, awareness, perception, and consciousness. The associated action potential spikes are 6 orders of magnitude longer, and travel with a velocity 6 orders of magnitude lower, than their electronic analogs, while dissipating only a couple of Watts of power. We touched on the fundamentals of information processing in biological (nervous) and engineered systems. Specifically, we highlighted the dynamical and morphological properties exhibited by nervous systems using the human brain as an example. The exceptional topology of the human cortex in comparison to other biological and technical networks, in addition to the state of SOC, served as guidelines to develop artificial spatio-temporal systems. A pathway to realize artificial spatio-temporal systems in a hardware-orientated system was presented, aiming to emulate higher brain functions in an artificial system. The role of ontogenesis was discussed, revealing that the mechanism of neural network growth provides crucial information useful in designing novel artificial computing systems, which have yet to be addressed in great detail.

Neural network growth illustrates how important the ongoing interaction between the internal and external world is when artificially creating the basic structures that provide the ability to learn specific functions. In our opinion, this emphasizes the importance of basal properties which, while beginning to be applied systems in artificial, have yet to be fully implemented. These properties include individual autonomous dynamic units, time-variable coupling between them, and both positive and negative connection growth. With respect to time-variability, the research field has shown enormous progress in recent years with the development of memristive systems. Although memristive devices can already replicate the phenomena associated with learning to a certain degree, the question remains whether these devices can suitably reproduce both the necessary processes in their entirety, and global dynamics which are shaped by an overwhelmingly complex network. The last point in particular presents immense challenges for a conservative implementation of memristive devices in large-scale systems. Finally, we discussed possible limitations in implementing higher brain functions in artificial systems. We concluded that genetic information plays a key role in the development of neural nervous systems, knowledge that we are still lacking if we want to fully implement this behavior in artificial
systems, specifically with regards to awareness, perception, and consciousness. The exploration space for implementation is certainly extraordinary large for artificial spatio-temporal systems. This huge parameter space is both curse and blessing: while such a large number of variables must be monitored and controlled, it also allows for greater flexibility and opportunities. One thing is certain in this context: no matter which engineered solution ultimately prevails, humanity will be confronted with a multitude of ambivalent questions and challenges, in which certainly “Matter & Mind Matter”.

Acknowledgments

We thank Nora Kohlstedt for preparing part of the figures. “Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – Project-ID 434434223 – SFB 1461”. The project is entitled SFB 1461 “Neurotronics: Bio-inspired Information Pathways” (see for more details https://www.crc1461-neurotronics.de/index.php/en/). Moreover, the financial support by the DFG via the Research Unit 2093: “Memristive Devices for neural Systems” is acknowledged. We thank Gitanjali Kolhatkar and Shane Scott for carefully reading the manuscript.

References

L.F. Abbott. Balancing homeostasis and learning in neural circuits. *Zoology*, 106(4):365–371, January 2003. ISSN 09442006. doi: 10.1078/0944-2006-00133. URL https://linkinghub.elsevier.com/retrieve/pii/S0944200604701117

L.F. Abbott and R. Rohrkemper. A simple growth model constructs critical avalanche networks. In Paul Cisek, Trevor Drew, and John F. Kalaska, editors, *Progress in Brain Research*, volume 165, pages 13–19. Elsevier, January 2007. ISBN 0079-6123. URL https://www.sciencedirect.com/science/article/pii/S0079612306650024

Andrew Adamatzky, editor. *Advances in unconventional computing*. Number volume 22-23 in Emergence, complexity and computation. Springer, Switzerland, 2017. ISBN 978-3-319-33920-7 978-3-319-33923-8.

Nancy E Adams. Bloom’s taxonomy of cognitive learning objectives. *Journal of the Medical Library Association : JMLA*, 103(3):152–153, July 2015. ISSN 1558-9439. doi: 10.3163/1536-5050.103.3.010. URL https://pubmed.ncbi.nlm.nih.gov/26213509

Egemen Agi, Abhishek Kulkarni, and Peter Robin Hiesinger. Neuronal strategies for meeting the right partner during brain wiring. *Cellular Neuroscience*, 63:1–8, August 2020. ISSN 0959-4388. doi: 10.1016/j.conb.2020.01.002. URL https://www.sciencedirect.com/science/article/pii/S0959438820300039

Armin Alaghi and John P. Hayes. Survey of Stochastic Computing. *ACM Transactions on Embedded Computing Systems*, 12(2s):1–19, May 2013. ISSN 1539-9087, 1558-3465. doi: 10.1145/2465787.2465794. URL https://dl.acm.org/doi/10.1145/2465787.2465794

Igor Aleksander. *How to build a mind: toward machines with imagination*. Maps of the mind. Columbia University Press, New York, 2001. ISBN 978-0-231-12012-8.

Pablo Amil, Cecilia Cabeza, Cristina Masoller, and Arturo C. Martí. Organization and identification of solutions in the time-delayed Mackey-Glass model. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 25(4):043112, April 2015. ISSN 1054-1500. doi: 10.1063/1.4918593. URL http://dx.doi.org/10.1063/1.4918593
Takaaki Aoki, Koichiro Yawata, and Toshio Aoyagi. Self-organization of complex networks as a dynamical system. *Physical Review E*, 91(1):012908, January 2015. URL http://link.aps.org/doi/10.1103/PhysRevE.91.012908

Evan L Ardiel and Catharine H Rankin. The importance of touch in development. *Paediatrics & Child Health*, 15(3):153–156, March 2010. ISSN 1205-7088, 1918-1485. doi: 10.1093/pch/15.3.153. URL https://academic.oup.com/pch/article-lookup/doi/10.1093/pch/15.3.153

Alex Arenas, Albert Díaz-Guilera, Jurgen Kurths, Yamir Moreno, and Changsong Zhou. Synchronization in complex networks. *Physics Reports*, 469(3):93–153, December 2008. ISSN 0370-1573. doi: 10.1016/j.physrep.2008.09.002. URL http://www.sciencedirect.com/science/article/pii/S0370157308003384

F. Argall. Switching phenomena in titanium oxide thin films. *Solid-State Electronics*, 11(5):535–541, May 1968. ISSN 0038-1101. doi: 10.1016/0038-1101(68)90092-0. URL https://www.sciencedirect.com/science/article/pii/0038110168900920

Frank Arute, Kunal Arya, Ryan Babbush, Dave Bacon, Joseph C. Bardin, Rami Barends, Rupak Biswas, Sergio Boixo, Fernando G. S. L. Brandao, David A. Buell, Brian Burkett, Yu Chen, Zijun Chen, Ben Chiaro, Roberto Collins, William Courtney, Andrew Dunsworth, Edward Farhi, Brooks Foxen, Austin Fowler, Craig Girvin, Marissa Giustina, Rob Graff, Keith Guerin, Steve Habegger, Matthew P. Harrigan, Michael J. Hartmann, Alan Ho, Markus Hoffmann, Trent Huang, Travis S. Humble, Sergei V. Isakov, Evan Jeffrey, Zhang Jiang, Dvir Kafri, Kostiantyn Kechedzhi, Julian Kelly, Paul V. Klimov, Sergey Kunysh, Alexander Korotkov, Fedor Kostritsa, David Landsman, Mike Lindmark, Erik Lucero, Dmitry Lyakh, Salvatore Mandrà, Jarrod R. McClean, Matthew McEwen, Anthony Megrant, Xiao Mi, Kristel Michielsen, Masoud Mohseni, Josh Mutus, Ofer Naaman, Matthew Neeley, Charles Neill, Murphy Yuezhen Niu, Eric Ostby, Andre Petukhov, John C. Platt, Chris Quintana, Eleanor G. Rieffel, Pedram Roushan, Nicholas C. Rubin, Daniel Sank, Kevin J. Satzinger, Vadim Smelyanskiy, Kevin J. Sung, Matthew D. Trevithick, Amit Vainsencher, Benjamin Villalonga, Theodore White, Z. Jamie Yao, Ping Yeh, Adam Zalcman, Hartmut Neven, and John M. Martinis. Quantum supremacy using a programmable superconducting processor. *Nature*, 574(7779):505–510, October 2019. ISSN 1476-4687. doi: 10.1038/s41586-019-1666-5. URL https://doi.org/10.1038/s41586-019-1666-5

H. Asayesh-Ardakani, A. Nie, P.M. Marley, A. Stabile, K. Sarkar, S. Banerjee, S. Ganapathy, Z. Yang, R.F. Klie, and R. Shahbazian-Yassar. Atomic Resolution Studies of Metal-Insulator Transition in VO2 Nanowires. *Microscopy and Microanalysis*, 19(S2):492–493, 2013. ISSN 1431-9276. doi: 10.1017/S1431927613004455. URL https://www.cambridge.org/core/article/atomic-resolution-studies-of-metalinsulator-transition-in-vo2

Frederico A.C. Azevedo, Ludmila R.B. Carvalho, Lea T. Grinberg, José Marcelo Farfão, Renata E.L. Ferretti, Renata E.P. Leite, Wilson Jacob Filho, Roberto Lent, and Suzana Herculano-Houzel. Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain. *Journal of Comparative Neurology*, 513(5):532–541, April 2009. ISSN 0021-9967. doi: 10.1002/cne.21974. URL https://doi.org/10.1002/cne.21974

C. Baatar, Wolfgang Porod, and Tamas Roska. *Cellular Nanoscale ensory Wave Computing*. Springer, New York, 2010. ISBN 978-1-4419-1010-3.
J. Backus. Can Programming Be Liberated from the von Neumann Style? A Functional Style and Its Algebra of Programs, 1978.

Eunhye Baek, Nikhil Ranjan Das, Carlo Vittorio Cannistraci, Taiuk Rim, Gilbert Santiago Cañón Bermúdez, Khrystyna Nych, Hyeonsu Cho, Kihyun Kim, Chang-Ki Baek, Denys Makarov, Ronald Tetzlaff, Leon Chua, Larysa Baraban, and Gianaurelio Cuniberti. Intrinsic plasticity of silicon nanowire neurotransistors for dynamic memory and learning functions. *Nature Electronics*, May 2020. ISSN 2520-1131. doi: 10.1038/s41928-020-0412-1. URL http://www.nature.com/articles/s41928-020-0412-1

Per Bak, Chao Tang, and Kurt Wiesenfeld. Self-organized criticality. *Physical Review A*, 38(1):364–374, July 1988. ISSN 0556-2791. doi: 10.1103/PhysRevA.38.364. URL https://link.aps.org/doi/10.1103/PhysRevA.38.364

Writam Banerjee. Challenges and applications of emerging nonvolatile memory devices. *Electronics*, 9(6), 2020. ISSN 2079-9292. doi: 10.3390/electronics9061029. URL https://www.mdpi.com/2079-9292/9/6/1029

Albert-László Barabási. Network science. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 371(1987):20120375, March 2013. ISSN 1364-503X, 1471-2962. doi: 10.1098/rsta.2012.0375. URL https://royalsocietypublishing.org/doi/10.1098/rsta.2012.0375

Albert-László Barabási and Réka Albert. Emergence of Scaling in Random Networks. *Science*, 286(5439):509, October 1999. doi: 10.1126/science.286.5439.509. URL http://science.sciencemag.org/content/286/5439/509.abstract

Danielle S Bassett and Michael S Gazzaniga. Understanding complexity in the human brain. *Trends in cognitive sciences*, 15(5):200–209, May 2011. ISSN 1879-307X. doi: 10.1016/j.tics.2011.03.006. URL https://www.ncbi.nlm.nih.gov/pubmed/21497128

Danielle S Bassett and Olaf Sporns. Network neuroscience. *Nat Neurosci*, 20(3):353–364, March 2017. ISSN 1097-6256. URL http://dx.doi.org/10.1038/nn.4502

Randall D. Beer. Dynamical approaches to cognitive science. *Trends in Cognitive Sciences*, 4(3):91–99, March 2000. ISSN 13646613. doi: 10.1016/S1364-6613(99)01440-0. URL https://linkinghub.elsevier.com/retrieve/pii/S1364661399014400

John M. Beggs and Dietmar Plenz. Neuronal Avalanches in Neocortical Circuits. *The Journal of Neuroscience*, 23(35):11167–11177, December 2003. ISSN 0270-6474, 1529-2401. doi: 10.1523/JNEUROSCI.23-35-11167.2003. URL https://www.jneurosci.org/lookup/doi/10.1523/JNEUROSCI.23-35-11167.2003

John M Beggs and Nicholas Timme. Being critical of criticality in the brain. *Frontiers in physiology*, 3:163, 2012.

Leslie Berlin. *The man behind the microchip: Robert Noyce and the invention of Silicon Valley*. Oxford University Press, Oxford ; New York, 2005. ISBN 978-0-19-516343-8.

Guo-qiang Bi and Mu-ming Poo. Synaptic Modifications in Cultured Hippocampal Neurons: Dependence on Spike Timing, Synaptic Strength, and Postsynaptic Cell Type. *The Journal of Neuroscience*, 18(24):10464, December 1998. doi: 10.1523/JNEUROSCI.18-24-10464.1998. URL http://www.jneurosci.org/content/18/24/10464.abstract
Hongyu Bian, Yi Ying Goh, Yuxia Liu, Haifeng Ling, Linghai Xie, and Xiaogang Liu. Stimuli-Responsive Memristive Materials for Artificial Synapses and Neuromorphic Computing. *Advanced Materials*, 33 (46):2006469, November 2021. ISSN 0935-9648, 1521-4095. doi: 10.1002/adma.202006469. URL https://onlinelibrary.wiley.com/doi/10.1002/adma.202006469

O. Bichler, W. Zhao, F. Alibart, S. Pleutin, S. Lenfant, D. Vuillaume, and C. Gamrat. Pavlov’s dog associative learning demonstrated on synaptic-like organic transistors. *Neural Computation*, 25(2):549–566, February 2013. ISSN 1530-888X. doi: 10.1162/NECO_a_00377.

Jan Bielecki and Anders Garm. *Swim pacemaker response to bath applied neurotransmitters in the box jellyfish Tripedalia cystophora rhopalium*. April 2012.

T. V. P. Bliss and T. Lømo. Long-lasting potentiation of synaptic transmission in the dentate area of the anaesthetized rabbit following stimulation of the perforant path. *The Journal of Physiology*. 232(2):331–356, July 1973. ISSN 00223751. doi: 10.1113/jphysiol.1973.sp010273. URL https://onlinelibrary.wiley.com/doi/10.1113/jphysiol.1973.sp010273

Thomas C. G. Bosch, Friederike Anton-Erxleben, Georg Hemmrich, and Konstantin Khalturin. The Hydra polyp: Nothing but an active stem cell community. *Development, Growth & Differentiation*, 52(1):15–25, January 2010. ISSN 0012-1592. doi: 10.1111/j.1440-169X.2009.01143.x. URL https://doi.org/10.1111/j.1440-169X.2009.01143.x

Thomas C.G. Bosch, Alexander Klimovich, Tomislav Domazet-Lošo, Stefan Gründer, Thomas W. Holstein, Gáspár Jékely, David J. Miller, Andrea P. Murillo-Rincon, Fabian Rentzsch, Gemma S. Richards, Katja Schröder, Ulrich Technau, and Rafael Yuste. Back to the Basics: Cnidarians Start to Fire. *Trends in Neurosciences*, 40(2):92–105, February 2017. ISSN 01662236. doi: 10.1016/j.tins.2016.11.005. URL https://linkinghub.elsevier.com/retrieve/pii/S0166223616301680

Stephano Bottani. Pulse-coupled relaxation oscillators: from biological synchronization to self-organized criticality. *Physical Review Letters*, 74(21):4189, 1995.

S Brenner. The Genetics of CAENORHABDITIS ELEGANS. *Genetics*, 77(1):71–94, May 1974. ISSN 0016-6731. URL http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1213120/

Hajo Broersma, Faustino Gomez, Julian Miller, Michael Petty, and Gunnar Tufte. Nascence Project: Nanoscale Engineering for Novel Computation Using Evolution. *International Journal of Unconventional Computing*, 8:313–317, January 2012.

Maximilian Brütt and Christian Kaernbach. On the Role of the Excitation/Inhibition Balance of Homeostatic Artificial Neural Networks. *Entropy*, 23(12):1681, December 2021. ISSN 1099-4300. doi: 10.3390/e23121681. URL https://www.mdpi.com/1099-4300/23/12/1681

Ed Bullmore and Olaf Sporns. Complex brain networks: graph theoretical analysis of structural and functional systems. *Nat Rev Neurosci*, 10(3):186–198, March 2009. ISSN 1471-003X. doi: 10.1038/nrn2575. URL http://dx.doi.org/10.1038/nrn2575

Geoffrey W. Burr, Robert M. Shelby, Abu Sebastian, Sangbum Kim, Seyoung Kim, Severin Sidler, Kumar Virwani, Masatoshi Ishii, Pritish Narayanan, Alessandro Fumarola, Lucas L. Sanches, Irem Boybat, Manuel Le Gallo, Ki-
bong Moon, Jiyoo Woo, Hyunsang Hwang, and Yusuf Leblebici. Neuromorphic computing using non-volatile memory. *Advances in Physics: X*, 2(1):89–124, January 2017. ISSN 2374-6149. doi: 10.1080/23746149.2016.1259585. URL https://www.tandfonline.com/doi/full/10.1080/23746149.2016.1259585

Markus Butz-Ostendorf and Arjen van Ooyen. Chapter 4 - Is Lesion-Induced Synaptic Rewiring Driven by Activity Homeostasis? In Arjen van Ooyen and Markus Butz-Ostendorf, editors, *The Rewiring Brain*, pages 71–92. Academic Press, San Diego, January 2017. ISBN 978-0-12-803784-3. URL http://www.sciencedirect.com/science/article/pii/B9780128037843000044

G. Buzsáki. *Rhythms of the brain*. Oxford University Press, Oxford ; New York, 2006. ISBN 978-0-19-530106-9 978-0-19-982823-4.

György Buzsáki and Andreas Draguhn. Neuronal Oscillations in Cortical Networks. *Science*, 304(5679):1926, June 2004. doi: 10.1126/science.1099745. URL http://science.sciencemag.org/content/304/5679/1926.abstract

Jen-Ru Chen, Andrew Smith, Eric A. Montoya, Jia G. Lu, and Ilya N. Krivorotov. Spin–orbit torque nano-oscillator with giant magnetoresistance readout. *Communications Physics*, 3(1):187, October 2020. ISSN 2399-3650. doi: 10.1038/s42005-020-00454-7. URL https://doi.org/10.1038/s42005-020-00454-7

Dante R. Chialvo. Are our senses critical? *Nature Physics*, 2(5):301–302, May 2006. ISSN 1745-2481. doi: 10.1038/nphys300. URL https://doi.org/10.1038/nphys300

Dante R. Chialvo. Emergent complex neural dynamics. *Nature Physics*, 6(10):744–750, October 2010. ISSN 1745-2473, 1745-2481. doi: 10.1038/nphys1803. URL http://www.nature.com/articles/nphys1803

Dante R Chialvo, Sergio A Cannas, Tomás S Grigera, Daniel A Martin, and Dietmar Plenz. Controlling a complex system near its critical point via temporal correlations. *Scientific reports*, 10(1):1–7, 2020.

Paul M. Churchland. *The engine of reason, the seat of the soul: a philosophical journey into the brain*. MIT Press, Cambridge, Mass, 1995. ISBN 978-0-262-03224-7.

Paul M Churchland. Densmore and dennett on virtul machines and consciousness. *Philosophy and Phenomenological Research*, 59(3):763–767, 1999.

P.M. Churchland and Pat Churchland. *Could a machine think?* January 1990.

Jean-Pierre Colinge, editor. *FinFETs and other multi-gate transistors*. Series on integrated circuits and systems. Springer, New York, 2008. ISBN 978-0-387-71751-7.

Phillip Compeau. Establishing a computational biology flipped classroom. *PLOS Computational Biology*, 15(5):e1006764, May 2019. ISSN 1553-7358. doi: 10.1371/journal.pcbi.1006764. URL https://dx.plos.org/10.1371/journal.pcbi.1006764

Benjamin Cramer, David Stöckel, Markus Kreft, Michael Wibral, Johannes Schemmel, Karlheinz Meier, and Viola Priesemann. Control of criticality and computation in spiking neuromorphic networks with plasticity. *Nature Communications*, 11(1):2853, December 2020. ISSN 2041-1723. doi: 10.1038/s41467-020-16548-3. URL http://www.nature.com/articles/s41467-020-16548-3
D. Lee, E. Cha, J. Park, C. Sung, K. Moon, S. A. Chekol, and H. Hwang. NbO2-Based Frequency Storable Coupled Oscillators for Associative Memory Application. *IEEE Journal of the Electron Devices Society*, 6:250–253, 2018. ISSN 2168-6734. doi: 10.1109/JEDS.2018.2793342.

D. Michaelis, S. Jenderny, and K. Ochs. A Self-Organizing Gait Pattern Generator Exploiting an Electrical Circuit for Axon Growth. In 2021 *IEEE International Midwest Symposium on Circuits and Systems (MWSCAS)*, pages 166–169, August 2021. ISBN 1558-3899. doi: 10.1109/MWSCAS47672.2021.9531834.

D. Patterson, T. Anderson, N. Cardwell, R. Fromm, K. Keeton, C. Kozyrakis, R. Thomas, and K. Yelick. A case for intelligent RAM. *IEEE Micro*, 17(2):34–44, April 1997. ISSN 1937-4143. doi: 10.1109/40.592312.

Antonio R. Damasio. *Descartes’ error: emotion, reason and the human brain*. Quill, New York, 18. druck edition, 2004. ISBN 978-0-380-72647-9 978-0-399-13894-2.

Mike Davies. Benchmarks for progress in neuromorphic computing. *Nature Machine Intelligence*, 1(9):386–388, September 2019. ISSN 2522-5839. doi: 10.1038/s42256-019-0097-1. URL [http://www.nature.com/articles/s42256-019-0097-1](http://www.nature.com/articles/s42256-019-0097-1).

Peter Dayan and Larry F. Abbott. *Theoretical Neurosciences:computational and mathematical modeling of neuronal systems*. The MIT Press, 2001.

G. Dearnaley, A M Stoneham, and D V Morgan. Electrical phenomena in amorphous oxide films. *Reports on Progress in Physics*, 33(3):1129–1191, September 1970. ISSN 0034-4885. doi: 10.1088/0034-4885/33/3/306. URL [http://dx.doi.org/10.1088/0034-4885/33/3/306](http://dx.doi.org/10.1088/0034-4885/33/3/306).

Stanislas Dehaene, editor. *The cognitive neuroscience of consciousness*. Cognition special issues. MIT Press, Cambridge, Mass, 2001. ISBN 978-0-262-54131-2.

Stanislas Dehaene. *Consciousness and the brain: deciphering how the brain codes our thoughts*. Viking, New York, New York, 2014. ISBN 978-0-670-02543-5.

Stanislas Dehaene, Hakwan Lau, and Sid Kouider. What is consciousness, and could machines have it? page 8, 2017.

G. Dehaene-Lambertz and E.S. Spelke. The Infancy of the Human Brain. *Neuron*, 88(1):93–109, October 2015. ISSN 0896-6273. doi: 10.1016/j.neuron.2015.09.026. URL [http://www.sciencedirect.com/science/article/pii/S0896627315008156](http://www.sciencedirect.com/science/article/pii/S0896627315008156).

A. Demertzì, E. Tagliazucchi, S. Dehaene, G. Deco, P. Bartfeld, F. Raimondo, C. Martial, D. Fernández-Espejo, B. Rohaut, H. U. Voss, N. D. Schiff, A. M. Owen, S. Laureys, L. Naccache, and J. D. Sitt. Human consciousness is supported by dynamic complex patterns of brain signal coordination. *Science Advances*, 5(2):eaat7603, February 2019. ISSN 2375-2548. doi: 10.1126/sciadv.aat7603. URL [https://www.science.org/doi/10.1126/sciadv.aat7603](https://www.science.org/doi/10.1126/sciadv.aat7603).

R.H. Dennard, F.H. Gaensslen, Hwa-Nien Yu, V.L. Rideout, E. Bassous, and A.R. LeBlanc. Design of ion-implanted MOSFET’s with very small physical dimensions. *IEEE Journal of Solid-State Circuits*, 9(5):256–268, October 1974. ISSN 0018-9200, 1558-173X. doi: 10.1109/JSSC.1974.1050511. URL [https://ieeexplore.ieee.org/document/1050511/](https://ieeexplore.ieee.org/document/1050511/).

Serena di Santo, Pablo Villegas, Raffaella Burioni, and Miguel A. Muñoz. Landau–Ginzburg theory of cortex dynamics: Scale-free avalanches emerge at the edge of synchronization. *Proceedings of the National Academy of
Matter & Mind Matter

*Sciences*, 115(7):E1356–E1365, February 2018. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.1712989115. URL [http://www.pnas.org/lookup/doi/10.1073/pnas.1712989115](http://www.pnas.org/lookup/doi/10.1073/pnas.1712989115).

Adrian Diaz-Alvarez, Rintaro Higuchi, Paula Sanz-Leon, Ido Marcus, Yoshitaka Shingaya, Adam Z. Stieg, James K. Gimzewski, Zdenka Kuncic, and Tomonobu Nakayama. Emergent dynamics of neuromorphic nanowire networks. *Scientific Reports*, 9(1):14920, December 2019. ISSN 2045-2322. doi: 10.1038/s41598-019-51330-6. URL [http://www.nature.com/articles/s41598-019-51330-6](http://www.nature.com/articles/s41598-019-51330-6).

Theodosius Dobzhansky. Nothing in Biology Makes Sense except in the Light of Evolution. *The American Biology Teacher*, 35(3):125, March 1973. doi: 10.2307/4444260. URL [http://abt.ucpress.edu/content/35/3/125.abstract](http://abt.ucpress.edu/content/35/3/125.abstract).

Vincent M. Donnelly and Avinoam Kornblit. Plasma etching: Yesterday, today, and tomorrow. *Journal of Vacuum Science & Technology A: Vacuum, Surfaces, and Films*, 31(5):050825, September 2013. ISSN 0734-2101, 1520-8559. doi: 10.1116/1.4819316. URL [http://avs.scitation.org/doi/10.1116/1.4819316](http://avs.scitation.org/doi/10.1116/1.4819316).

Tom Driscoll, Jack Quinn, Massimiliano Di Ventra, Dimitri N. Basov, Giwan Seo, Yong-Wook Lee, Hyun-Tak Kim, and David R. Smith. Current oscillations in vanadium dioxide: Evidence for electrically triggered percolation avalanches. *Physical Review B*, 86(9), September 2012. ISSN 1098-0121, 1550-235X. doi: 10.1103/PhysRevB.86.094203. URL [https://link.aps.org/doi/10.1103/PhysRevB.86.094203](https://link.aps.org/doi/10.1103/PhysRevB.86.094203).

Christophe Dupre and Rafael Yuste. Non-overlapping Neural Networks in Hydra vulgaris. *Current Biology*, 27(8):1085–1097, April 2017. ISSN 09609822. doi: 10.1016/j.cub.2017.02.049. URL [https://linkinghub.elsevier.com/retrieve/pii/S0960982217302208](https://linkinghub.elsevier.com/retrieve/pii/S0960982217302208).

Gerald M. Edelman. *Neural Darwinism: the theory of neuronal group selection*. Basic Books, New York, 1987. ISBN 978-0-465-04934-9.

Gerald M. Edelman and Giulio Tononi. *A universe of consciousness: how matter becomes imagination*. Basic Books, New York, NY, 1. paperback ed., [nachdr.] edition, 2001. ISBN 978-0-465-01377-7.

Andreas K Engel, Peter König, Andreas K Kreiter, and Wolf Singer. Interhemispheric synchronization of oscillatory neuronal responses in cat visual cortex. *Science*, 252(5009):1177–1179, 1991.

Andreas K. Engel, P. Fries, P. Kreiter Konig, M. Brecht, and Wolf Singer. Temporal binding, binocular rivalry, and consciousness. *Consciousness and Cognition*, 8(2), 1999.

Andreas K. Engel, Pascal Fries, and Wolf Singer. Dynamic predictions: Oscillations and synchrony in top–down processing. *Nature Reviews Neuroscience*, 2(10):704–716, October 2001. ISSN 1471-003X, 1471-0048. doi: 10.1038/35094565. URL [http://www.nature.com/articles/35094565](http://www.nature.com/articles/35094565).

Florian Engert and Tobias Bonhoeffer. Dendritic spine changes associated with hippocampal long-term synaptic plasticity. *Nature*, 399(6731):66–70, May 1999. ISSN 0028-0836, 1476-4687. doi: 10.1038/19978. URL [http://www.nature.com/articles/19978](http://www.nature.com/articles/19978).

U. Ernst, K. Pawelzik, and T. Geisel. Synchronization Induced by Temporal Delays in Pulse-Coupled Oscillators. *Physical Review Letters*, 74(9):1570–1573, February 1995. URL [http://link.aps.org/doi/10.1103/PhysRevLett.74.1570](http://link.aps.org/doi/10.1103/PhysRevLett.74.1570).
Michael Fauth, Florentin Wörgötter, and Christian Tetzlaff. Chapter 16 - Long-Term Information Storage by the Interaction of Synaptic and Structural Plasticity. In Arjen van Ooyen and Markus Butz-Ostendorf, editors, The Rewiring Brain, pages 343–360. Academic Press, San Diego, January 2017. ISBN 978-0-12-803784-3. URL http://www.sciencedirect.com/science/article/pii/B9780128037843000160.

J. Feldmann, N. Youngblood, C. D. Wright, H. Bhaskaran, and W. H. P. Pernice. All-optical spiking neurosynaptic networks with self-learning capabilities. Nature, 569(7755):208–214, May 2019. ISSN 1476-4687. doi: 10.1038/s41586-019-1157-8. URL https://doi.org/10.1038/s41586-019-1157-8.

Michael E. Fisher. The story of coulombic criticality. Journal of Statistical Physics, 75(1-2):1–36, April 1994. ISSN 0022-4715, 1572-9613. doi: 10.1007/BF02186278. URL http://link.springer.com/10.1007/BF02186278.

Alex Fornito, Andrew Zalesky, and Edward T. Bullmore. Fundamentals of brain network analysis. Elsevier/Academic Press, Amsterdam ; Boston, 2016. ISBN 978-0-12407908-3.

Charlotte Frenkel, David Bol, and Giacomo Indiveri. Bottom-Up and Top-Down Neural Processing Systems Design: Neurromorphic Intelligence as the Convergence of Natural and Artificial Intelligence. arXiv:2106.01288 [cs], June 2021. URL http://arxiv.org/abs/2106.01288.

Tamami Fukushi and Osamu Sakura. Ethical Challenges and Clinical Implications of Molecular Imaging of Human Consciousness. The American Journal of Bioethics, 8(9):23–24, October 2008. ISSN 1526-5161. doi: 10.1080/15265160802412510. URL https://doi.org/10.1080/15265160802412510.

Monica Gagliano, Michael Renton, Martial Depczynski, and Stefano Mancuso. Experience teaches plants to learn faster and forget slower in environments where it matters. Oecologia, 175(1):63–72, May 2014. ISSN 1432-1939. doi: 10.1007/s00442-013-2873-7. URL https://doi.org/10.1007/s00442-013-2873-7.

C. Giovanni Galizia and Pierre-Marie Lledo, editors. Neurosciences: from molecule to behavior: a university textbook. Springer Spektrum, Heidelberg ; New York, 2013. ISBN 978-3-642-10768-9.

Daniel J. Gauthier, Erik Bollt, Aaron Griffith, and Wendson A. S. Barbosa. Next generation reservoir computing. Nature Communications, 12(1):5564, December 2021. ISSN 2041-1723. doi: 10.1038/s41467-021-25801-2. URL https://www.nature.com/articles/s41467-021-25801-2.

Wulfram Gerstner and Werner M. Kistler. Spiking neuron models: single neurons, populations, plasticity. Cambridge University Press, Cambridge, U.K.; New York, 2002. ISBN 978-0-521-81384-6 978-0-521-89079-3.

Wulfram Gerstner, Werner M. Kistler, Richard Naud, and Liam Paninski. Neuronal dynamics: from single neurons to networks and models of cognition. Cambridge University Press, Cambridge, United Kingdom, 2014. ISBN 978-1-107-06083-8 978-1-107-63519-7.

Christoph Giez, Alexander Klimovich, and Thomas C. G. Bosch. Neurons interact with the microbiome: an evolutionary-informed perspective. Neuroforum, 0(0):000010151520210003, April 2021. ISSN 2363-7013, 0947-0875. doi: 10.1515/nf-2021-0003. URL https://www.degruyter.com/document/doi/10.1515/nf-2021-0003/html.

Jennifer Hasler and Harry Marr. Finding a roadmap to achieve large neuromorphic hardware systems. Frontiers in Neuroscience, 7:118, 2013. ISSN 1662-453X. doi: 10.3389/fnins.2013.00118. URL https://www.frontiersin.org/article/10.3389/fnins.2013.00118.
Sindre W. Haugland, Lennart Schmidt, and Katharina Krischer. Self-organized alternating chimera states in oscillatory media. *Scientific Reports*, 5(1):9883, September 2015. ISSN 2045-2322. doi: 10.1038/srep09883. URL http://www.nature.com/articles/srep09883

Jeff Hawkins and Sandra Blakeslee. *On intelligence*. Times Books, New York, 1st ed edition, 2004. ISBN 978-0-8050-7456-7.

Biyu J. He. Scale-free brain activity: past, present, and future. *Trends in Cognitive Sciences*, 18(9):480–487, 2014. ISSN 1364-6613. doi: 10.1016/j.tics.2014.04.003. URL http://dx.doi.org/10.1016/j.tics.2014.04.003

D.O. Hebb. *The Organization of Behavior*. Psychology Press, 0 edition, April 2005. ISBN 978-1-4106-1240-3. URL https://www.taylorfrancis.com/books/9781135631918

Richard Held and Alan Hein. Movement-produced stimulation in the development of visually guided behavior. *Journal of Comparative and Physiological Psychology*, 56(5):872–876, 1963. ISSN 0021-9940. doi: 10.1037/h0040546. URL http://content.apa.org/journals/com/56/5/872

Takao K. Hensch. Critical period plasticity in local cortical circuits. *Nature Reviews Neuroscience*, 6(11):877–888, November 2005. ISSN 1471-0048. doi: 10.1038/nrn1787. URL https://doi.org/10.1038/nrn1787

Takao K Hensch and Parizad M Bilimoria. Re-opening Windows: Manipulating Critical Periods for Brain Development. *Cerebrum : the Dana forum on brain science*, 2012:11–11, July 2012. ISSN 1524-6205. URL https://pubmed.ncbi.nlm.nih.gov/23447797

Janina Hesse and Thilo Gross. Self-organized criticality as a fundamental property of neural systems. *Frontiers in Systems Neuroscience*, 8, September 2014. ISSN 1662-5137. doi: 10.3389/fnsys.2014.00166. URL http://journal.frontiersin.org/article/10.3389/fnsys.2014.00166/abstract

T. W. Hickmott. Low-Frequency Negative Resistance in Thin Anodic Oxide Films. *Journal of Applied Physics*, 33(9):2669–2682, September 1962. ISSN 0021-8979. doi: 10.1063/1.1702530. URL https://doi.org/10.1063/1.1702530

P. Robin Hiesinger. Brain wiring with composite instructions. *BioEssays*, 43(1):2000166, January 2021a. ISSN 0265-9247, 1521-1878. doi: 10.1002/bies.202000166. URL https://onlinelibrary.wiley.com/doi/10.1002/bies.202000166

Peter Robin Hiesinger. *The self-assembling brain: how neural networks grow smarter*. Princeton University Press, Princeton, 2021b. ISBN 978-0-691-18122-6.

Geoffrey Hinton, Li Deng, Dong Yu, George Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara Sainath, and Brian Kingsbury. Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups. *IEEE Signal Processing Magazine*, 29(6):82–97, November 2012. ISSN 1053-5888. doi: 10.1109/MSP.2012.2205597. URL http://ieeexplore.ieee.org/document/6296526/
Sepp Hochreiter and Jürgen Schmidhuber. Long Short-Term Memory. *Neural Computation*, 9(8):1735–1780, November 1997. ISSN 0899-7667, 1530-888X. doi: 10.1162/neco.1997.9.8.1735. URL https://direct.mit.edu/neco/article/9/8/1735-1780/6109

Joel Hochstetter, Ruomin Zhu, Alon Loeffler, Adrian Diaz-Alvarez, Tomonobu Nakayama, and Zdenka Kunic. Avalanches and edge-of-chaos learning in neuromorphic nanowire networks. *Nature Communications*, 12(1):4008, December 2021. ISSN 2041-1723. doi: 10.1038/s41467-021-24260-z. URL http://www.nature.com/articles/s41467-021-24260-z

A L Hodgkin and A F Huxley. A quantitative description of membrane current and its application to conduction and excitation in nerve. *The Journal of physiology*, 117(4):500–544, August 1952. ISSN 0022-3751. doi: 10.1113/jphysiol.1952.sp004764. URL https://pubmed.ncbi.nlm.nih.gov/12991237

Anthony Holtmaat, Linda Wilbrecht, Graham W. Knott, Egbert Welker, and Karel Svoboda. Experience-dependent and cell-type-specific spine growth in the neocortex. *Nature*, 441(7096):979–983, June 2006. ISSN 0028-0836, 1476-4687. doi: 10.1038/nature04783. URL http://www.nature.com/articles/nature04783

Frank C. Hoppensteadt and Eugene M. Izhikevich. *Weakly Connected Neural Networks*, volume Volume 126 of *Applied Mathematical Sciences*. Springer, New York, 1997. ISBN 978-1-4612-7302-8.

Frank C Hoppensteadt and Charles S Peskin. *Modeling and simulation in medicine and the life sciences*, volume 10. Springer Science & Business Media, 2012.

Qijin Huang and Yong Zhu. Patterning of Metal Nanowire Networks: Methods and Applications. *ACS Applied Materials & Interfaces*, 13(51):60736–60762, December 2021. ISSN 1944-8244, 1944-8252. doi: 10.1021/acsami.1c14816. URL https://pubs.acs.org/doi/10.1021/acsami.1c14816

B.A. Huberman and T. Hogg. Complexity and Adaptation. *Physica D: Nonlinear Phenomena*, 22(1-3):376–384, October 1986. ISSN 01672789. doi: 10.1016/0167-2789(86)90308-1. URL https://linkinghub.elsevier.com/retrieve/pii/0167278986903081

Peter R. Huttenlocher. Morphometric study of human cerebral cortex development. *Neuropsychologia*, 28(6):517–527, January 1990. ISSN 0028-3932. doi: 10.1016/0028-3932(90)90031-I. URL http://www.sciencedirect.com/science/article/pii/002839329090031I

Peter R. Huttenlocher. *Neural plasticity: The effects of environment on the development of the cerebral cortex*. Neural plasticity: The effects of environment on the development of the cerebral cortex. Harvard University Press, Cambridge, MA, US, 2002. ISBN 0-674-00743-3 (Hardcover).

Bernd Hofflinger, editor. *New vistas in nanoelectronics*. Number Bernd Hofflinger, editor ; vol. 2 in CHIPS 2020. Springer, Cham Heidelberg New York Dordrecht London, 2016. ISBN 978-3-319-22093-2 978-3-319-22092-5.

R W Hölzel and K Krischer. Pattern recognition with simple oscillating circuits. *New Journal of Physics*, 13(7):073031, July 2011. ISSN 1367-2630. doi: 10.1088/1367-2630/13/7/073031. URL http://dx.doi.org/10.1088/1367-2630/13/7/073031

Hütt Marc-Thorsten, Kaiser Marcus, and Hilgetag Claus C. Perspective: network-guided pattern formation of neural dynamics. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 369(1653):20130522, October 2014. doi: 10.1098/rstb.2013.0522. URL https://doi.org/10.1098/rstb.2013.0522
Daniele Ielmini and Rainer Waser, editors. *Resistive switching: from fundamentals of nanoionic redox processes to memristive device applications*. Wiley-VCH Verlag GmbH & Co. KGaA, Weinheim, 2016. ISBN 978-3-527-33417-9 978-3-527-68093-1 978-3-527-68090-0.

Daniele Ielmini and H.-S. Philip Wong. In-memory computing with resistive switching devices. *Nature Electronics*, 1(6):333–343, June 2018. ISSN 2520-1131. doi: 10.1038/s41928-018-0092-2. URL [https://doi.org/10.1038/s41928-018-0092-2](https://doi.org/10.1038/s41928-018-0092-2)

M. Ignatov, M. Hansen, M. Ziegler, and H. Kohlstedt. Synchronization of two memristively coupled van der Pol oscillators. *Applied Physics Letters*, 108(8):084105, February 2016. ISSN 0003-6951. doi: 10.1063/1.4942832. URL [http://dx.doi.org/10.1063/1.4942832](http://dx.doi.org/10.1063/1.4942832)

Giacomo Indiveri, Bernabe Linares-Barranco, Tara Hamilton, Andre van Schaik, Ralph Etienne-Cummings, Tobi Delbruck, Shih-Chii Liu, Piotr Dudek, Philipp Häfliger, Sylvie Renaud, Johannes Schemmel, Gert Cauwenberghs, John Arthur, Kai Hynna, Fofofolu Folorosole, Sylvain SAIGHI, Teresa Serrano-Gotarredona, Jayawan Wijekoon, Yingxue Wang, and Kwabena Boahen. Neuromorphic Silicon Neuron Circuits. *Frontiers in Neuroscience*, 5:73, 2011. ISSN 1662-453X. doi: 10.3389/fnins.2011.00073. URL [https://www.frontiersin.org/article/10.3389/fnins.2011.00073](https://www.frontiersin.org/article/10.3389/fnins.2011.00073)

Krzysztof Iniewski, editor. *CMOS processors and memories*. Analog circuits and signal processing - ACSP. Springer, Dordrecht, 2010. ISBN 978-90-481-9216-8 978-90-481-9215-1.

E.M. Izhikevich. Simple model of spiking neurons. *IEEE Transactions on Neural Networks*, 14 (6):1569–1572, November 2003. ISSN 1045-9227. doi: 10.1109/TNN.2003.820440. URL [http://ieeexplore.ieee.org/document/1257420/](http://ieeexplore.ieee.org/document/1257420/)

Eugene M Izhikevich. Hybrid spiking models. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 368(1930):5061–5070, 2010.

Harry J. M. Veendrick. *Nanometer CMOS ICs: From Basics to ASICs*. Springer International Publishing : Imprint: Springer, Cham, 2nd ed. 2017 edition, 2017. ISBN 978-3-319-47597-4.

J. von Neumann. First draft of a report on the EDVAC. *IEEE Annals of the History of Computing*, 15(4):27–75, 1993. ISSN 1058-6180. doi: 10.1109/85.238389.

Francois Jacob. Evolution and Tinkering. 196(4295):7, 1977.

Wolfgang Johannsen. *Information und ihre Bedeutung in der Natur: das Leben erfindet die Welt*. Springer, Berlin, 2016. ISBN 978-3-662-50254-9.

Nicola Jones. How to stop data centres from gobbling up the world’s electricity. *Nature*, 561(7722):163–166, September 2018. ISSN 0028-0836, 1476-4687. doi: 10.1038/d41586-018-06610-y. URL [http://www.nature.com/articles/d41586-018-06610-y](http://www.nature.com/articles/d41586-018-06610-y)

Herbert Jäger. The”echo state”approach to analysing and training recurrent neural networks.” (2001). Report Corpus ID: 15467150, Bonn, 2001.

Marcus Kaiser. Hierarchy and dynamics of neural networks. *Frontiers in Neuroinformatics*, 4, 2010. ISSN 16625196. doi: 10.3389/fninf.2010.00112. URL [http://journal.frontiersin.org/article/10.3389/fninf.2010.00112/abstract](http://journal.frontiersin.org/article/10.3389/fninf.2010.00112/abstract)
Marcus Kaiser. Mechanisms of Connectome Development. *Trends in Cognitive Sciences*, 21(9):703–717, September 2017. ISSN 1364-6613. doi: 10.1016/j.tics.2017.05.010. URL http://www.sciencedirect.com/science/article/pii/S1364661317301110

Marcus Kaiser. *Changing connectomes: evolution, development, and dynamics in network neuroscience*. The MIT Press, Cambridge, Massachusetts, 2020. ISBN 978-0-262-04461-5.

Marcus Kaiser and Claus C. Hilgetag. Spatial growth of real-world networks. *Physical Review E*, 69(3):036103, March 2004. doi: 10.1103/PhysRevE.69.036103. URL https://link.aps.org/doi/10.1103/PhysRevE.69.036103

Marcus Kaiser and Sreedevi Varier. Evolution and development of Brain Networks: From Caenorhabditis elegans to Homo sapiens. *Network: Computation in Neural Systems*, 22(1-4):143–147, March 2011. ISSN 0954-898X, 1361-6536. doi: 10.3109/0954898X.2011.638968. URL https://www.tandfonline.com/doi/full/10.3109/0954898X.2011.638968

Eric R. Kandel. *Cellular basis of behavior: an introduction to behavioral neurobiology*. A series of books in psychology. Freeman, San Francisco, 1976. ISBN 978-0-7167-0522-2 978-0-7167-0523-9.

Eric R. Kandel, editor. *Principles of neural science*. McGraw-Hill, New York, 5th ed edition, 2013. ISBN 978-0-07-139011-8.

Markus Kantner, Eckehard Schöll, and Serhiy Yanchuk. Delay-induced patterns in a two-dimensional lattice of coupled oscillators. *Scientific Reports*, 5:8522, February 2015. URL http://dx.doi.org/10.1038/srep08522

Mohammad Karbalaei, Daryoosh Dideban, and Hadi Heidari. A sectorial scheme of gate-all-around field effect transistor with improved electrical characteristics. *Ain Shams Engineering Journal*, 12(1):755–760, March 2021. ISSN 20904479. doi: 10.1016/j.asej.2020.04.015. URL https://linkinghub.elsevier.com/retrieve/pii/S209044792030099X

Sadra Rahimi Kari. Principles of Stochastic Computing: Fundamental Concepts and Applications. page 11.

C. Kaspar, B. J. Ravoo, W. G. van der Wiel, S. V. Wegner, and W. H. P. Pernice. The rise of intelligent matter. *Nature*, 594(7863):345–355, June 2021. ISSN 0028-0836, 1476-4687. doi: 10.1038/s41586-021-03453-y. URL http://www.nature.com/articles/s41586-021-03453-y

Vassilis Kehayas and Anthony Holtmaat. Structural plasticity and cortical connectivity. In *The Rewiring Brain*, pages 3–26. Elsevier, 2017.

Jack D. Kendall and Suhas Kumar. The building blocks of a brain-inspired computer. *Applied Physics Reviews*, 7(1):011305, March 2020. ISSN 1931-9401. doi: 10.1063/1.5129306. URL http://aip.scitation.org/doi/10.1063/1.5129306

Chris C. King. Fractal and chaotic dynamics in nervous systems. *Progress in Neurobiology*, 36(4):279–308, January 1991. ISSN 0301-0082. doi: 10.1016/0301-0082(91)90003-J. URL https://www.sciencedirect.com/science/article/pii/030100829190003J

Osame Kinouchi and Mauro Copelli. Optimal dynamical range of excitable networks at criticality. *Nature Physics*, 2(5):348–351, May 2006. ISSN 1745-2481. doi: 10.1038/nphys289. URL https://doi.org/10.1038/nphys289
D. Kleinfeld, K. H. Kahler, and P. E. Hockberger. Controlled outgrowth of dissociated neurons on patterned substrates. *Journal of Neuroscience*, 8(11):4098–4120, 1988.

Christof Koch and Giulio Tononi. Can machines be conscious? *IEEE Spectrum*, 45:55–59, 2008.

Bryan Kolb and Bryan D. Fantie. Development of the Child’s Brain and Behavior. In Cecil R Reynolds and Elaine Fletcher-Janzen, editors, *Handbook of Clinical Child Neuropsychology*, pages 19–46. Springer US, Boston, MA, 2009. ISBN 978-0-387-70708-2 978-0-387-78867-8. URL http://link.springer.com/10.1007/978-0-387-78867-8_2

Sid Kouider, Carsten Stahlhut, Sofie V. Gelskov, Leonardo S. Barbosa, Michel Dutat, Vincent de Gardelle, Anne Christophe, Stanislas Dehaene, and Ghislaine Dehaene-Lambertz. A Neural Marker of Perceptual Consciousness in Infants. *Science*, 340(6130):376, April 2013. doi: 10.1126/science.1232509. URL http://science.sciencemag.org/content/340/6130/376.abstract

Thomas Kreuz, Florian Mormann, Ralph G. Andrzejak, Alexander Kraskov, Klaus Lehnertz, and Peter Grassberger. Measuring synchronization in coupled model systems: A comparison of different approaches. *Physica D: Non-linear Phenomena*, 225(1):29–42, January 2007. ISSN 0167-2789. doi: 10.1016/j.physd.2006.09.039. URL http://www.sciencedirect.com/science/article/pii/S0167278906003836

Thomas Kreuz, Daniel Chicharro, Ralph G Andrzejak, Julie S Haas, and Henry DI Abarbanel. Measuring multiple spike train synchrony. *Journal of neuroscience methods*, 183(2):287–299, 2009.

Nikolaus Kriegeskorte and Pamela K. Douglas. Cognitive computational neuroscience. *Nature Neuroscience*, 21(9):1148–1160, September 2018. ISSN 1097-6256, 1546-1726. doi: 10.1038/s41593-018-0210-5. URL http://www.nature.com/articles/s41593-018-0210-5

S. Kronholz, S. Rathgeber, S. Karthäuser, H. Kohlstedt, S. Clemens, and T. Schneller. Self-Assembly of Diblock-Copolymer Micelles for Template-Based Preparation of PbTiO3 Nanograins. *Advanced Functional Materials*, 16(18):2346–2354, December 2006. ISSN 1616301X, 16163028. doi: 10.1002/adfm.200600384. URL http://doi.wiley.com/10.1002/adfm.200600384

Zdenka Kuncic and Tomonobu Nakayama. Neuromorphic nanowire networks: principles, progress and future prospects for neuro-inspired information processing. *Advances in Physics: X*, 6(1):1894234, 2021.

S.K. Kurinec and S. Walia. *Energy Efficient Computing & Electronics: Devices to Systems*. Devices, Circuits, and Systems. CRC Press, 2019. ISBN 978-1-351-77985-2. URL https://books.google.de/books?id=vxaGDwAAQBAJ

L. Chua. Memristor-The missing circuit element. *IEEE Transactions on Circuit Theory*, 18(5):507–519, September 1971. ISSN 2374-9555. doi: 10.1109/TCT.1971.108337.

Mario Lanza, Rainer Waser, Daniele Ielmini, J. Joshua Yang, Ludovic Goux, Jordi Sufè, Anthony Joseph Kenyon, Adnan Mehonic, Sabina Spiga, Vikas Rana, Stefan Wiefels, Stephan Menzel, Ilia Valov, Marco A. Villena, Enrique Miranda, Xu Jing, Francesca Campabadal, Mireia B. Gonzalez, Fernando Aguirre, Felix Palumbo, Kaichen Zhu, Juan Bautista Roldan, Francesco Maria Puglisi, Luca Larcher, Tuo-Hung Hou, Themis Prodromakis, Yuchao Yang, Peng Huang, Tianqing Wan, Yang Chai, Kin Leong Pey, Nagarajan Raghavan, Salvador Dueñas, Tao Wang, Qiangfei Xia, and Sebastian Pazos. Standards for the Characterization of Endurance in Resistive Switching Devices.
Gilles Laurent. Shall We Even Understand the Fly’s Brain? In J. Leo van Hemmen and Terrence J. Sejnowski, editors, 23 Problems in Systems Neuroscience, pages 3–21. Oxford University Press, January 2006. ISBN 978-0-19-514822-0. URL https://oxford.universitypressscholarship.com/view/10.1093/acprof:oso/9780195148220.001.0001/acprof-9780195148220.

Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. Nature, 521(7553):436–444, May 2015. ISSN 0028-0836, 1476-4687. doi: 10.1038/nature14539. URL http://www.nature.com/articles/nature14539.

Claudia Lenk, Lars Seeber, and Martin Ziegler. Tuning acoustic sensing properties of mems cantilever by nonlinear operation. In Mikro-Nano-Integration; 8th GMM-Workshop, pages 1–3. VDE, 2020.

Steven Lequeux, Joao Sampaio, Vincent Cros, Kay Yakushiji, Akio Fukushima, Hitoshi Kubota, Shinji Yuasa, and Julie Grollier. A magnetic synapse: multilevel spin-torque memristor with perpendicular anisotropy. Scientific Reports, 6(1):31510, November 2016. ISSN 2045-2322. doi: 10.1038/srep31510. URL http://www.nature.com/articles/srep31510.

Huihan Li, Shaocong Wang, Xumeng Zhang, Wei Wang, Rui Yang, Zhong Sun, Wanxiang Feng, Peng Lin, Zhongrui Wang, Linfeng Sun, and Yugui Yao. Memristive Crossbar Arrays for Storage and Computing Applications. Advanced Intelligent Systems, 3(9):2100017, September 2021. ISSN 2640-4567, 2640-4567. doi: 10.1002/aisy.2021000017. URL https://onlinelibrary.wiley.com/doi/10.1002/aisy.2021000017.

Christian Lohmann and Helmut W. Kessels. The developmental stages of synaptic plasticity: The developmental stages of synaptic plasticity. The Journal of Physiology, 592(1):13–31, January 2014. ISSN 0022-3751. doi: 10.1113/jphysiol.2012.235119. URL http://doi.wiley.com/10.1113/jphysiol.2012.235119.

Jonathan R. Lovas and Rafael Yuste. Ensemble synchronization in the reassembly of Hydra’s nervous system. Current Biology, 31(17):3784–3796.e3, September 2021. ISSN 09609822. doi: 10.1016/j.cub.2021.06.047. URL https://linkinghub.elsevier.com/retrieve/pii/S09609822221008769.

Ziqing Luo, Yeheng Bo, S. M. Sadaf, and Xinjun Liu. Van der Pol oscillator based on NbO2 volatile memristor: A simulation analysis. Journal of Applied Physics, 131(5):054501, February 2022. ISSN 0021-8979. doi: 10.1063/5.0073285. URL https://doi.org/10.1063/5.0073285.

Soren Lvtrup. Phylogenesis, ontogenesis and evolution. Bolletino di zoologia, 54(3):199–208, January 1987. ISSN 0373-4137. doi: 10.1080/11250008709355584. URL http://www.tandfonline.com/doi/abs/10.1080/11250008709355584.

Zhengyu Ma, Gina G. Turrigiano, Ralf Wessel, and Keith B. Hengen. Cortical Circuit Dynamics Are Homeostatically Tuned to Criticality In Vivo. Neuron, 104(4):655–664.e4, November 2019. ISSN 08966273. doi: 10.1016/j.neuron.2019.08.031. URL https://linkinghub.elsevier.com/retrieve/pii/S0896627319307378.
Wolfgang Maass, Thomas Natschläger, and Henry Markram. Real-Time Computing Without Stable States: A New Framework for Neural Computation Based on Perturbations. *Neural Computation*, 14(11):2531–2560, November 2002. ISSN 0899-7667, 1530-888X. doi: 10.1162/089976602760407955. URL [https://direct.mit.edu/neco/article/14/11/2531-2560/6650](https://direct.mit.edu/neco/article/14/11/2531-2560/6650).

MC Mackey and L Glass. Oscillation and chaos in physiological control systems. *Science*, 197(4300):287, July 1977. doi: 10.1126/science.267326. URL [http://science.sciencemag.org/content/197/4300/287.abstract](http://science.sciencemag.org/content/197/4300/287.abstract).

Paolo Maffezzoni, Luca Daniel, Nikhil Shukla, Suman Datta, and Arijit Raychowdhury. Modeling and Simulation of Vanadium Dioxide Relaxation Oscillators. *IEEE Transactions on Circuits and Systems I: Regular Papers*, 62(9):2207–2215, September 2015. ISSN 1549-8328, 1558-0806. doi: 10.1109/TCSI.2015.2452332. URL [http://ieeexplore.ieee.org/document/7229386/](http://ieeexplore.ieee.org/document/7229386/).

Misha Mahowald and Rodney Douglas. A silicon neuron. *Nature*, 354:515, December 1991. URL [http://dx.doi.org/10.1038/354515a0](http://dx.doi.org/10.1038/354515a0).

J. B. Mallinson, S. Shirai, S. K. Acharya, S. K. Bose, E. Galli, and S. A. Brown. Avalanches and criticality in self-organized nanoscale networks. *Science Advances*, 5(11):eaaw8438, November 2019. ISSN 2375-2548. doi: 10.1126/sciadv.aaw8438. URL [https://www.science.org/doi/10.1126/sciadv.aaw8438](https://www.science.org/doi/10.1126/sciadv.aaw8438).

Daniel Mange, André Stauffer, Enrico Petraglio, and Gianluca Tempesta. Self-replicating loop with universal construction. *Physica D: Nonlinear Phenomena*, 191(1-2):178–192, 2004.

H. Markram, W. Gerstner, and P. J. Sjöström. Spike-Timing-Dependent Plasticity: A Comprehensive Overview. *Frontiers in Synaptic Neuroscience*, 4, 2012. ISSN 1663-3563. doi: 10.3389/fnsyn.2012.00002. URL [http://journal.frontiersin.org/article/10.3389/fnsyn.2012.00002/abstract](http://journal.frontiersin.org/article/10.3389/fnsyn.2012.00002/abstract).

Pedro Martínez and Simon G. Sprecher. Of Circuits and Brains: The Origin and Diversification of Neural Architectures. *Frontiers in Ecology and Evolution*, 8, March 2020. ISSN 2296-701X. doi: 10.3389/fevo.2020.00082. URL [https://www.frontiersin.org/article/10.3389/fevo.2020.00082/full](https://www.frontiersin.org/article/10.3389/fevo.2020.00082/full).

Toshiaki Masuhara. The Future of Low-Power Electronics. In Bernd Hofflinger, editor, *CHIPS 2020 VOL. 2*, pages 21–50. Springer International Publishing, Cham, 2016. ISBN 978-3-319-22092-5 978-3-319-22093-2. URL [http://link.springer.com/10.1007/978-3-319-22093-2_2](http://link.springer.com/10.1007/978-3-319-22093-2_2).

Warren S McCulloch and Walter Pitts. A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY. page 17.

Carver Mead. *Analog VLSI and neural systems*. Computation and neural systems series. Addison-Wesley, Reading, Mass, 1989. ISBN 978-0-201-05992-2.

Carver Mead. How we created neuromorphic engineering. *Nature Electronics*, 3(7):434–435, July 2020. ISSN 2520-1131. doi: 10.1038/s41928-020-0448-2. URL [http://www.nature.com/articles/s41928-020-0448-2](http://www.nature.com/articles/s41928-020-0448-2).

Lucia Melloni, Liad Mudrik, Michael Pitts, and Christof Koch. Making the hard problem of consciousness easier. *Science*, 372(6545):911–912, May 2021. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.abj3259. URL [https://www.science.org/doi/10.1126/science.abj3259](https://www.science.org/doi/10.1126/science.abj3259).

N. David Mermin. *Quantum computer science: an introduction*. Cambridge University Press, Cambridge, 2007. ISBN 978-0-521-87658-2.
Paul A. Merolla, John V. Arthur, Rodrigo Alvarez-Icaza, Andrew S. Cassidy, Jun Sawada, Filipp Akopyan, Bryan L. Jackson, Nabil Imam, Chen Guo, Yutaka Nakamura, Bernard Brezzo, Ivan Vo, Steven K. Esser, Rathinakumar Appuswamy, Brian Taba, Arnon Amir, Myron D. Fllickner, William P. Risk, Rajit Manohar, and Dharmendra S. Modha. A million spiking-neuron integrated circuit with a scalable communication network and interface. Science, 345(6197):668, August 2014. doi: 10.1126/science.1254642. URL http://science.sciencemag.org/content/345/6197/668.abstract.

Gianluca Milano, Giacomo Pedretti, Kevin Montano, Saverio Ricci, Shahin Hashemkhani, Luca Boarino, Daniele Ielmini, and Carlo Ricciardi. In materia reservoir computing with a fully memristive architecture based on self-organizing nanowire networks. Nature Materials, 21(2):195–202, February 2022. ISSN 1476-1122, 1476-4660. doi: 10.1038/s41563-021-01099-9. URL https://www.nature.com/articles/s41563-021-01099-9.

Julian F. Miller, Simon L. Harding, and Gunnar Tufte. Evolution-in-materio: evolving computation in materials. Evolutionary Intelligence, 7(1):49–67, April 2014. ISSN 1864-5917. doi: 10.1007/s12065-014-0106-6. URL https://doi.org/10.1007/s12065-014-0106-6.

John G. Milton. Neuronal avalanches, epileptic quakes and other transient forms of neurodynamics: Transient neurodynamics. European Journal of Neuroscience, 36(2):2156–2163, July 2012. ISSN 0953816X. doi: 10.1111/j.1460-9568.2012.08102.x. URL https://onlinelibrary.wiley.com/doi/10.1111/j.1460-9568.2012.08102.x.

Chloé Minnai, Andrea Bellacicca, Simon A. Brown, and Paolo Milani. Facile fabrication of complex networks of memristive devices. Scientific Reports, 7(1):7955, August 2017. ISSN 2045-2322. doi: 10.1038/s41598-017-08244-y. URL https://doi.org/10.1038/s41598-017-08244-y.

Gordon E. Moore. Cramming more components onto integrated circuits. McGraw-Hill New York, NY, USA:, 1965.

Toshiyuki Nakagaki, Hiroyasu Yamada, and Ágota Tóth. Maze-solving by an amoeboïd organism. Nature, 407(6803):470–470, September 2000. ISSN 1476-4687. doi: 10.1038/35035159. URL https://doi.org/10.1038/s41598-017-08244-y.

Kohei Nakajima. Physical reservoir computing—an introductory perspective. Japanese Journal of Applied Physics, 59(6):060501, June 2020. ISSN 0021-4922, 1347-4065. doi: 10.35848/1347-4065/ab8d4f. URL https://iopscience.iop.org/article/10.35848/1347-4065/ab8d4f.

Charlotte Nassim. Lessons from the lobster: Eve Marder’s work in neuroscience. The MIT Press, Cambridge, Massachusetts, 2018. ISBN 978-0-262-03778-5.

Robert Naumann, Janie Ondracek, Sam Reiter, Mark Shein-Idelson, Maria Tosches, Tracy M Yamawaki, and Gilles Laurent. The reptilian brain, volume 25. April 2015.

Quentin Noirhomme and Steven Laureys. Consciousness and Unconsciousness: An EEG Perspective. Clinical EEG and Neuroscience, 45(1):4–5, January 2014. ISSN 1550-0594, 2169-5202. doi: 10.1177/1550059413519518. URL http://journals.sagepub.com/doi/10.1177/1550059413519518.

Takeo Ohno, Tsuyoshi Hasegawa, Tohru Tsuruoka, Kazuya Terabe, James K. Gimzewski, and Masakazu Aono. Short-term plasticity and long-term potentiation mimicked in single inorganic synapses. Nature Materials, 10:591, June 2011. URL http://dx.doi.org/10.1038/nmat3054.
Olayinka Oluwatosin Abegunde, Esther Titilayo Akinlabi, Oluseyi Philip Oladijo, Stephen Akinlabi, and Uchenna Ude. Overview of thin film deposition techniques. *AIMS Materials Science*, 6(2):174–199, 2019. ISSN 2372-0484. doi: 10.3934/matersci.2019.2.174. URL http://www.aimspress.com/article/10.3934/matersci.2019.2.174.

Arjen van Ooyen and Markus Butz-Ostendorf. Homeostatic structural plasticity can build critical networks. In *The Functional Role of Critical Dynamics in Neural Systems*, pages 117–137. Springer, 2019.

Alexander Opitz, Arnaud Falchier, Gary S. Linn, Michael P. Milham, and Charles E. Schroeder. Limitations of ex vivo measurements for in vivo neuroscience. *Proceedings of the National Academy of Sciences*, 114(20):5243, May 2017. doi: 10.1073/pnas.1617024114. URL http://www.pnas.org/content/114/20/5243.abstract.

Marek Orlik and Marek Orlik. *General principles of self-organization: temporal Instabilities*. Number I in Self-organization in electrochemical systems / Marek Orlik. Springer, Heidelberg New York Dordrecht London, softcover reprint of the hardcover 1st edition 2012 edition, 2012a. ISBN 978-3-642-43402-0 978-3-642-27673-6.

Marek Orlik and Marek Orlik. *Spatiotemporal patterns and control of chaos*. Number II in Self-organization in electrochemical systems / Marek Orlik. Springer, Heidelberg New York Dordrecht London, softcover reprint of the hardcover 1st edition 2012 edition, 2012b. ISBN 978-3-642-43322-1 978-3-642-27627-9.

Erik Nis Ostenfeld. *Ancient Greek psychology and the modern mind-body debate*. Number Bd. 63 in Academia philosophical studies. Academia Verlag, Baden-Baden, 2nd edition edition, 2018. ISBN 978-3-89665-759-6.

Ross D. Pantone, Jack D. Kendall, and Juan C. Nino. Memristive nanowires exhibit small-world connectivity. *Neural Networks*, 106:144–151, October 2018. ISSN 08936080. doi: 10.1016/j.neunet.2018.07.002. URL https://linkinghub.elsevier.com/retrieve/pii/S0893608018302016.

Mercedes F. Paredes, David James, Sara Gil-Perotin, Hosung Kim, Jennifer A. Cotter, Carissa Ng, Kadellyn Sandoval, David H. Rowitch, Duan Xu, Patrick S. McQuillen, Jose-Manuel Garcia-Verdugo, Eric J. Huang, and Arturo Alvarez-Buylla. Extensive migration of young neurons into the infant human frontal lobe. *Science*, 354(6308):aaf7073, October 2016. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.aaf7073. URL https://www.science.org/doi/10.1126/science.aaf7073.

Thomas Parr, Geraint Rees, and Karl J. Friston. Computational Neuropsychology and Bayesian Inference. *Frontiers in Human Neuroscience*, 12:61, 2018. ISSN 1662-5161. doi: 10.3389/fnhum.2018.00061. URL https://www.frontiersin.org/article/10.3389/fnhum.2018.00061.

Maximilian Patzauer and Katharina Krischer. Self-Organized Multifrequency Clusters in an Oscillating Electrochemical System with Strong Nonlinear Coupling. *Physical Review Letters*, 126(19):194101, May 2021. ISSN 0031-9007, 1079-7114. doi: 10.1103/PhysRevLett.126.194101. URL https://link.aps.org/doi/10.1103/PhysRevLett.126.194101.

R. Fabian Pease. To charge or not to charge: 50 years of lithographic choices. *Journal of Vacuum Science & Technology B, Nanotechnology and Microelectronics: Materials, Processing, Measurement, and Phenomena*, 28(6):C6A1–C6A6, November 2010. ISSN 2166-2746, 2166-2754. doi: 10.1116/1.3517607. URL http://avs.scitation.org/doi/10.1116/1.3517607.
Matter & Mind Matter

Jing Pei, Lei Deng, Sen Song, Mingguo Zhao, Youhui Zhang, Shuang Wu, Guanrui Wang, Zhe Zou, Zhenzhi Wu, Wei He, Feng Chen, Ning Deng, Si Wu, Yu Wang, Yujie Wu, Zheyu Yang, Cheng Ma, Guoqi Li, Wentao Han, Huanglong Li, Huaqiang Wu, Rong Zhao, Yuan Xie, and Luping Shi. Towards artificial general intelligence with hybrid Tianjic chip architecture. *Nature*, 572(7767):106–111, August 2019. ISSN 1476-4687. doi: 10.1038/s41586-019-1424-8. URL https://doi.org/10.1038/s41586-019-1424-8

Elaine Perry, Matthew Walker, Jan Grace, and Robert Perry. Acetylcholine in mind: a neurotransmitter correlate of consciousness? *Trends in Neurosciences*, 22(6):273–280, June 1999. ISSN 01662236. doi: 10.1016/S0166-2236(98)01361-7. URL https://linkinghub.elsevier.com/retrieve/pii/S0166223698013617

Yuriy V. Pershin and Massimiliano Di Ventra. Experimental demonstration of associative memory with memristive neural networks. *Neural Networks*, 23(7):881–886, September 2010. ISSN 0893-6080. doi: 10.1016/j.neunet.2010.05.001. URL https://www.sciencedirect.com/science/article/pii/S0893608010000948

Matthew D. Pike, Saurabh K. Bose, Joshua B. Mallinson, Susant K. Acharya, Shotai Shirai, Edoardo Galli, Stephen J. Weddell, Philip J. Bones, Matthew D. Arnold, and Simon A. Brown. Atomic Scale Dynamics Drive Brain-like Avalanches in Percolating Nanostructured Networks. *Nano Letters*, 20(5):3935–3942, May 2020. ISSN 1530-6984, 1530-6992. doi: 10.1021/acs.nanolett.0c01096. URL https://pubs.acs.org/doi/10.1021/acs.nanolett.0c01096

Arkadij Pikovskij, Michael Rosenblum, and Jürgen Kurths. *Synchronization: a universal concept in nonlinear sciences*. Number 12 in Cambridge nonlinear science series. Cambridge Univ. Press, Cambridge, 1st paperback ed., repr edition, 2003. ISBN 978-0-521-53352-2 978-0-521-59285-7.

Chi-Sang Poon and Kuan Zhou. Neuromorphic Silicon Neurons and Large-Scale Neural Networks: Challenges and Opportunities. *Frontiers in Neuroscience*, 5, 2011. ISSN 1662-4548. doi: 10.3389/fnins.2011.00108. URL http://journal.frontiersin.org/article/10.3389/fnins.2011.00108/abstract

Viola Priesemann. Spike avalanches in vivo suggest a driven, slightly subcritical brain state. *Frontiers in Systems Neuroscience*, 8, 2014. ISSN 16625137. doi: 10.3389/fnsys.2014.00108. URL http://journal.frontiersin.org/article/10.3389/fnsys.2014.00108/abstract

Henry H. Radamson, Huilong Zhu, Zhenhua Wu, Xiaobin He, Hongxiao Lin, Jinbiao Liu, Jinjuan Xiang, Zhenzhen Kong, Wenjuan Xiong, Junjie Li, Hushan Cui, Jianfeng Gao, Hong Yang, Yong Du, Buing Xu, Ben Li, Xuewei Zhao, Jiahun Yu, Yan Dong, and Guilei Wang. State of the Art and Future Perspectives in Advanced CMOS Technology. *Nanomaterials*, 10(8):1555, August 2020. ISSN 2079-4991. doi: 10.3390/nano10081555. URL https://www.mdpi.com/2079-4991/10/8/1555

Rajeev Ranjan, Pablo Mendoza Ponce, Wolf Lukas Hellweg, Alexandros Kyrmakis, Lait Abu Saleh, Dietmar Schroeder, and Wolfgang H. Krautschneider. Integrated Circuit with Memristor Emulator Array and Neuron Circuits for Biologically Inspired Neuromorphic Pattern Recognition. *Journal of Circuits, Systems and Computers*, 26(11):1750183, November 2017. ISSN 0218-1266, 1793-6454. doi: 10.1142/S0218126617501833. URL http://www.worldscientific.com/doi/abs/10.1142/S0218126617501833

Paul Robin, Nikita Kavokine, and Lydéric Bocquet. Modeling of emergent memory and voltage spiking in ionic transport through angstrom-scale slits. *Science*, 373(6555):687–691, August 2021. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.abf7923. URL https://www.science.org/doi/10.1126/science.abf7923
F. Rosenblatt. The perceptron: A probabilistic model for information storage and organization in the brain. *Psychological Review, 65*(6):386–408, 1958. ISSN 1939-1471(Electronic),0033-295X(Print). doi: 10.1037/h0042519.

Ulrich Rueckert. Brain-Inspired Architectures for Nanoelectronics. In Bernd Höflinger, editor, *CHIPS 2020 VOL. 2*, pages 249–274. Springer International Publishing, Cham, 2016. ISBN 978-3-319-22092-5 978-3-319-22093-2. URL [http://link.springer.com/10.1007/978-3-319-22093-2_18](http://link.springer.com/10.1007/978-3-319-22093-2_18)

Simon Rumpel and Jochen Triesch. Das dynamische Konnektom. *Neuroforum*, 22(3):73–79, September 2016. ISSN 0947-0875, 2363-7013. doi: 10.1007/s12269-016-0048-2. URL [http://link.springer.com/10.1007/s12269-016-0048-2](http://link.springer.com/10.1007/s12269-016-0048-2)

Dan Harvey Sanes, Thomas A. Reh, and William A. Harris. *Development of the nervous system*. Elsevier, Amsterdam; Boston, 2nd ed edition, 2006. ISBN 978-0-12-618621-5.

Vinod K. Sangwan and Mark C. Hersam. Neuromorphic nanoelectronic materials. *Nature Nanotechnology*, 15(7):517–528, July 2020. ISSN 1748-3387, 1748-3395. doi: 10.1038/s41565-020-0647-z. URL [http://www.nature.com/articles/s41565-020-0647-z](http://www.nature.com/articles/s41565-020-0647-z)

Silvia Scarpetta and Antonio de Candia. Neural Avalanches at the Critical Point between Replay and Non-Replay of Spatiotemporal Patterns. *PLoS ONE*, 8(6):e64162, June 2013. ISSN 1932-6203. doi: 10.1371/journal.pone.0064162. URL [https://dx.plos.org/10.1371/journal.pone.0064162](https://dx.plos.org/10.1371/journal.pone.0064162)

Bruce Schechter. How the Brain Gets Rhythm: Distinctive neural oscillations may link separate brain regions that are responding to the same object. Researchers are now identifying the sources of these vibrations. *Science*, 274(5286):339–339, October 1996. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.274.5286.339. URL [https://www.science.org/doi/10.1126/science.274.5286.339](https://www.science.org/doi/10.1126/science.274.5286.339)

Michael L. Schneider, Christine A. Donnelly, Stephen E. Russek, Burm Baek, Matthew R. Pufall, Peter F. Hopkins, Paul D. Dresselhaus, Samuel P. Benz, and William H. Rippard. Ultralow power artificial synapses using nanotextured magnetic Josephson junctions. *Science Advances*, 4(1), January 2018. doi: 10.1126/sciadv.1701329. URL [http://advances.sciencemag.org/content/4/1/e1701329.abstract](http://advances.sciencemag.org/content/4/1/e1701329.abstract)

Manuel S. Schroeter, Paul Charlesworth, Manfred G. Kitzbichler, Ole Paulsen, and Edward T. Bullmore. Emergence of Rich-Club Topology and Coordinated Dynamics in Development of Hippocampal Functional Networks In Vitro. *The Journal of Neuroscience*, 35(14):5459, April 2015. doi: 10.1523/JNEUROSCI.4259-14.2015. URL [http://www.jneurosci.org/content/35/14/5459.abstract](http://www.jneurosci.org/content/35/14/5459.abstract)

Catherine Schuman, Thomas Potok, Robert Patton, J. Birdwell, Mark Dean, Garrett Rose, and James Plank. A Survey of Neuromorphic Computing and Neural Networks in Hardware. May 2017.

Abhronil Sengupta, Priyadarshini Panda, Parami Wijesinghe, Yusung Kim, and Kaushik Roy. Magnetic Tunnel Junction Mimics Stochastic Cortical Spiking Neurons. *Scientific Reports*, 6(1), September 2016. ISSN 2045-2322. doi: 10.1038/srep30039. URL [http://www.nature.com/articles/srep30039](http://www.nature.com/articles/srep30039).
Matter & Mind Matter

Alexander Serb, Johannes Bill, Ali Khiat, Radu Berdan, Robert Legenstein, and Themis Prodromakis. Unsupervised learning in probabilistic neural networks with multi-state metal-oxide memristive synapses. *Nature Communications*, 7(1):12611, September 2016. ISSN 2041-1723. doi: 10.1038/ncomms12611. URL https://www.nature.com/articles/ncomms12611

Sebastian Seung. *Connectome: how the brain’s wiring makes us who we are*. Houghton Mifflin Harcourt, Boston, 2012. ISBN 978-0-547-50818-4.

Jafar Shamsi, María José Avedillo, Bernabé Linares-Barranco, and Teresa Serrano-Gotarredona. Hardware Implementation of Differential Oscillatory Neural Networks Using VO 2-Based Oscillators and Memristor-Bridge Circuits. *Frontiers in Neuroscience*, 15:674567, July 2021. ISSN 1662-453X. doi: 10.3389/fnins.2021.674567. URL https://www.frontiersin.org/articles/10.3389/fnins.2021.674567/full

Mark E J Sheffield and Daniel A Dombeck. The binding solution? *Nature Neuroscience*, 18(8):1060–1062, August 2015. ISSN 1097-6256, 1546-1726. doi: 10.1038/nn.4075. URL http://www.nature.com/articles/nn.4075

W. L. Shew, H. Yang, S. Yu, R. Roy, and D. Plenz. Information Capacity and Transmission Are Maximized in Balanced Cortical Networks with Neuronal Avalanches. *Journal of Neuroscience*, 31(1):55–63, January 2011. ISSN 0270-6474, 1529-2401. doi: 10.1523/JNEUROSCI.4637-10.2011. URL https://www.jneurosci.org/lookup/doi/10.1523/JNEUROSCI.4637-10.2011

Woodrow L. Shew, Wesley P. Clawson, Jeff Pobst, Yahya Karimipanah, Nathaniel C. Wright, and Ralf Wessel. Adaptation to sensory input tunes visual cortex to criticality. *Nature Physics*, 11(8):659–663, August 2015. ISSN 1745-2473, 1745-2481. doi: 10.1038/nphys3370. URL http://www.nature.com/articles/nphys3370

David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, Karen Simonyan, and Demis Hassabis. A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. *Science*, 362(6419):1140–1144, December 2018. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.aar6404. URL https://www.science.org/doi/10.1126/science.aar6404

W. Singer. Consciousness and the structure of neuronal representations. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 353(1377):1829, November 1998. doi: 10.1098/rstb.1998.0335. URL http://rstb.royalsocietypublishing.org/content/353/1377/1829.abstract

W Singer and C M Gray. Visual Feature Integration and the Temporal Correlation Hypothesis. *Annual Review of Neuroscience*, 18(1):555–586, March 1995. ISSN 0147-006X. doi: 10.1146/annurev.ne.18.030195.003011. URL http://dx.doi.org/10.1146/annurev.ne.18.030195.003011

Christine A. Skarda and Walter J. Freeman. How brains make chaos in order to make sense of the world. *Behavioral and Brain Sciences*, 10(2), 1987.

Ricard V. Solé and Sergi Valverde. Information Theory of Complex Networks: On Evolution and Architectural Constraints. In Eli Ben-Naim, Hans Frauenfelder, and Zoltan Toroczkai, editors, *Complex Networks*, volume 650, pages 189–207. Springer Berlin Heidelberg, Berlin, Heidelberg, August 2004. ISBN 978-3-540-22354-2 978-3-540-44485-5. URL http://link.springer.com/10.1007/978-3-540-44485-5_9

Olaf Sporns. *Networks of the brain*. MIT Press, Cambridge, Mass, 2011. ISBN 978-0-262-01469-4.
Olaf Sporns. Structure and function of complex brain networks. *Dialogues in clinical neuroscience*, 15(3):247, 2013.

Narayan Srinivasa, Nigel D Stepp, and Jose Cruz-Albrecht. Criticality as a set-point for adaptive behavior in neuromorphic hardware. *Frontiers in neuroscience*, 9:449, 2015.

Susan Stepney and Andrew Adamatzky. *Inspired by Nature: Essays Presented to Julian F. Miller on the Occasion of His 60th Birthday*, volume 28. Springer, 2017.

Nigel Stepp, Dietmar Plenz, and Narayan Srinivasa. Synaptic Plasticity Enables Adaptive Self-Tuning Critical Networks. *PLOS Computational Biology*, 11(1):e1004043, January 2015. ISSN 1553-7358. doi: 10.1371/journal.pcbi.1004043. URL [https://dx.plos.org/10.1371/journal.pcbi.1004043](https://dx.plos.org/10.1371/journal.pcbi.1004043).

Peter Sterling and Simon Laughlin. *Principles of neural design*. The MIT Press, Cambridge, Massachusetts, 2015. ISBN 978-0-262-02870-7.

Adam Z. Stieg, Audrius V. Avizienis, Henry O. Sillan, Cristina Martin-Olmos, Masakazu Aono, and James K. Gimzewski. Emergent Criticality in Complex Turing B-Type Atomic Switch Networks. *Advanced Materials*, 24(2):286–293, January 2012. ISSN 0935-9648. doi: 10.1002/adma.201103053. URL [https://doi.org/10.1002/adma.201103053](https://doi.org/10.1002/adma.201103053).

Johan F. Storm, Mélanie Boly, Adenauer G. Casali, Marcello Massimini, Umberto Olcese, Cyriel M.A. Pennartz, and Melanie Wilke. Consciousness Regained: Disentangling Mechanisms, Brain Systems, and Behavioral Responses. *The Journal of Neuroscience*, 37(45):10882–10893, November 2017. ISSN 0270-6474, 1529-2401. doi: 10.1523/JNEUROSCI.1838-17.2017. URL [https://www.jneurosci.org/lookup/doi/10.1523/JNEUROSCI.1838-17.2017](https://www.jneurosci.org/lookup/doi/10.1523/JNEUROSCI.1838-17.2017).

Steven H. Strogatz. Exploring complex networks. *Nature*, 410(6825):268–276, March 2001. ISSN 0028-0836. doi: 10.1038/35065725. URL [http://dx.doi.org/10.1038/35065725](http://dx.doi.org/10.1038/35065725).

Steven H. Strogatz. *Nonlinear dynamics and chaos: with applications to physics, biology, chemistry, and engineering*. Westview Press, a member of the Perseus Books Group, Boulder, CO, second edition edition, 2015. ISBN 978-0-8133-4910-7.

Dmitri B. Strukov, Gregory S. Snider, Duncan R. Stewart, and R. Stanley Williams. The missing memristor found. *Nature*, 453(7191):80–83, May 2008. ISSN 1476-4687. doi: 10.1038/nature06932. URL [https://doi.org/10.1038/nature06932](https://doi.org/10.1038/nature06932).

Kaixuan Sun, Jingsheng Chen, and Xiaobing Yan. The Future of Memristors: Materials Engineering and Neural Networks. *Advanced Functional Materials*, 31(8):2006773, February 2021. ISSN 1616-301X, 1616-3028. doi: 10.1002/adfm.202006773. URL [https://onlinelibrary.wiley.com/doi/10.1002/adfm.202006773](https://onlinelibrary.wiley.com/doi/10.1002/adfm.202006773).

Changhyuck Sung, Hyunsang Hwang, and In Kyeong Yoo. Perspective: A review on memristive hardware for neuromorphic computation. *Journal of Applied Physics*, 124(15):151903, October 2018. ISSN 0021-8979. doi: 10.1063/1.5037835. URL [https://aip.scitation.org/doi/10.1063/1.5037835](https://aip.scitation.org/doi/10.1063/1.5037835).

Tagliazucchi Enzo, Chialvo Dante R., Siniatichkin Michael, Amico Enrico, Brichant Jean-Francois, Bonhomme Vincent, Noirhomme Quentin, Laufs Helmut, and Laureys Steven. Large-scale signatures of unconsciousness are consistent with a departure from critical dynamics. *Journal of The Royal Society Interface*, 13(114):20151027, January 2016. doi: 10.1098/rsif.2015.1027. URL [https://doi.org/10.1098/rsif.2015.1027](https://doi.org/10.1098/rsif.2015.1027).
Christian Tetzlaff, Samora Okujeni, Ulrich Egert, Florentin Wörgötter, and Markus Butz. Self-Organized Criticality in Developing Neuronal Networks. *PLoS Computational Biology*, 6(12):e1001013, December 2010. ISSN 1553-7358. doi: 10.1371/journal.pcbi.1001013. URL https://dx.plos.org/10.1371/journal.pcbi.1001013

Ronald Tetzlaff, editor. *Memristors and memristive systems*. Springer, New York, 2014. ISBN 978-1-4614-9067-8.

D’Arcy Wentworth Thompson. *On growth and form*. Dover, New York, 1992. ISBN 978-0-486-67135-2.

Nai-Wen Tien and Daniel Kerschensteiner. Homeostatic plasticity in neural development. *Neural development*, 13(1): 1–7, 2018.

Nicholas M. Timme, Najja J. Marshall, Nicholas Bennett, Monica Ripp, Edward Lautzenhiser, and John M. Beggs. Criticality Maximizes Complexity in Neural Tissue. *Frontiers in Physiology*, 7, September 2016. ISSN 1664-042X. doi: 10.3389/fphys.2016.00425. URL http://journal.frontiersin.org/Article/10.3389/fphys.2016.00425/abstract

Nergis Tomen, J. Michael Herrmann, and Udo Ernst, editors. *The Functional Role of Critical Dynamics in Neural Systems*, volume 11 of *Springer Series on Bio- and Neurosystems*. Springer International Publishing, Cham, 2019. ISBN 978-3-030-20964-3 978-3-030-20965-0. URL http://link.springer.com/10.1007/978-3-030-20965-0

G Tononi, O Sporns, and G M Edelman. A measure for brain complexity: relating functional segregation and integration in the nervous system. *Proceedings of the National Academy of Sciences of the United States of America*, 91 (11):5033–5037, May 1994. ISSN 0027-8424. URL https://www.ncbi.nlm.nih.gov/pubmed/8197179

John Torday. Homeostasis as the Mechanism of Evolution. *Biology*, 4(3):573–590, September 2015. ISSN 2079-7737. doi: 10.3390/biology4030573. URL http://www.mdpi.com/2079-7737/4/3/573

A. M. Turing. On Computable Numbers, with an Application to the Entscheidungsproblem. *Proceedings of the London Mathematical Society*, s2-42(1):230–265, January 1937. ISSN 0024-6115. doi: 10.1112/plms/s2-42.1.230. URL https://doi.org/10.1112/plms/s2-42.1.230

A. M. Turing. I.—COMPUTING MACHINERY AND INTELLIGENCE. *Mind*, LIX(236):433–460, October 1950. ISSN 0026-4423. doi: 10.1093/mind/LIX.236.433. URL http://dx.doi.org/10.1093/mind/LIX.236.433

G. Turrigiano. Homeostatic Synaptic Plasticity: Local and Global Mechanisms for Stabilizing Neuronal Function. *Cold Spring Harbor Perspectives in Biology*, 4(1):a005736–a005736, January 2012. ISSN 1943-0264. doi: 10.1101/cshperspect.a005736. URL http://cshperspectives.cshlp.org/lookup/doi/10.1101/cshperspect.a005736

Peter J Uhlhaas, Gordon Pipa, Bruss Lima, Lucia Melloni, Sergio Neuenschwander, Danko Nikolić, and Wolf Singer. Neural synchrony in cortical networks: history, concept and current status. *Frontiers in integrative neuroscience*, 3:17–17, July 2009. ISSN 1662-5145. doi: 10.3389/neuro.07.017.2009. URL https://www.ncbi.nlm.nih.gov/pubmed/19668703

Jordi Vallverdú, Oscar Castro, Richard Mayne, Max Talanov, Michael Levin, Frantisek Baluška, Yukio Gunji, Audrey Dussutour, Hector Zenil, and Andrew Adamatzky. Slime mould: The fundamental mechanisms of biological cognition. *Biosystems*, 165:57–70, March 2018. ISSN 03032647. doi: 10.1016/j.biosystems.2017.12.011. URL https://linkinghub.elsevier.com/retrieve/pii/S0303264717304574
Martijn P. van den Heuvel and Hilleke E. Hulshoff Pol. Exploring the brain network: A review on resting-state fMRI functional connectivity. *European Neuropsychopharmacology*, 20(8):519–534, August 2010. ISSN 0924-977X. doi: 10.1016/j.euroneuro.2010.03.008. URL [http://www.sciencedirect.com/science/article/pii/S0924977X10000684](http://www.sciencedirect.com/science/article/pii/S0924977X10000684).

Martijn P. van den Heuvel, Karina J. Kersbergen, Marcel A. de Reus, Kristin Keunen, René S. Kahn, Floris Groenendaal, Linda S. de Vries, and Manon J.N.L. Benders. The Neonatal Connectome During Preterm Brain Development. *Cerebral Cortex*, 25(9):3000–3013, September 2015. ISSN 1047-3211, 1460-2199. doi: 10.1093/cercor/bhu095. URL [https://academic.oup.com/cercor/article-lookup/doi/10.1093/cercor/bhu095](https://academic.oup.com/cercor/article-lookup/doi/10.1093/cercor/bhu095).

Balth. van der Pol. LXXXVIII. On “relaxation-oscillations”. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, 2(11):978–992, November 1926. ISSN 1941-5982, 1941-5990. doi: 10.1080/14786442608564127. URL [http://www.tandfonline.com/doi/abs/10.1080/14786442608564127](http://www.tandfonline.com/doi/abs/10.1080/14786442608564127).

Arjen Van Ooyen and Markus Butz-Ostendorf, editors. *The rewiring brain: a computational approach to structural plasticity in the adult brain*. Elsevier, Academic Press, London ; San Diego, CA, 2017. ISBN 978-0-12-803784-3.

Francisco Varela, Jean-Philippe Lachaux, Eugenio Rodriguez, and Jacques Martinerie. The brainweb: Phase synchronization and large-scale integration. *Nat Rev Neurosci*, 2(4):229–239, April 2001. ISSN 1471-003X. doi: 10.1038/35067550. URL [http://dx.doi.org/10.1038/35067550](http://dx.doi.org/10.1038/35067550).

T. Venkatesan and Stan Williams. Brain inspired electronics. *Applied Physics Reviews*, 9(1):010401, March 2022. doi: 10.1063/5.0078798. URL [https://doi.org/10.1063/5.0078798](https://doi.org/10.1063/5.0078798).

Christoph von der Malsburg. The what and why of binding: The modeler’s perspective. *Philosophical Explorations*, 1999.

Qingzhou Wan, Mohammad T. Sharbatì, John R. Erickson, Yanhao Du, and Feng Xiong. Emerging Artificial Synaptic Devices for Neuromorphic Computing. *Advanced Materials Technologies*, 4(4):1900037, April 2019. ISSN 2365-709X, 2365-709X. doi: 10.1002/admt.201900037. URL [https://onlinelibrary.wiley.com/doi/10.1002/admt.201900037](https://onlinelibrary.wiley.com/doi/10.1002/admt.201900037).

Ruopeng Wang, Jia-Qin Yang, Jing-Yu Mao, Zhan-Peng Wang, Shuang Wu, Maojie Zhou, Tianyi Chen, Ye Zhou, and Su-Ting Han. Recent Advances of volatile Memristors: Devices, Mechanisms, and Applications. *Advanced Intelligent Systems*, 2(9):2000055, September 2020a. ISSN 2640-4567, 2640-4567. doi: 10.1002/aisy.202000055. URL [https://onlinelibrary.wiley.com/doi/10.1002/aisy.202000055](https://onlinelibrary.wiley.com/doi/10.1002/aisy.202000055).

Xinxin Wang, Mohammed A. Zidan, and Wei D. Lu. A Crossbar-Based In-Memory Computing Architecture. *IEEE Transactions on Circuits and Systems I: Regular Papers*, 67(12):4224–4232, December 2020b. ISSN 1549-8328, 1558-0806. doi: 10.1109/TCSI.2020.3000468. URL [https://ieeexplore.ieee.org/document/9120335/](https://ieeexplore.ieee.org/document/9120335/).

Duncan J. Watts and Steven H. Strogatz. Collective dynamics of “small-world” networks. *Nature*, 393(6684):440–442, June 1998. ISSN 0028-0836. doi: 10.1038/30918. URL [http://dx.doi.org/10.1038/30918](http://dx.doi.org/10.1038/30918).

Torsten N. Wiesel and David H. Hubel. SINGLE-CELL RESPONSES IN STRIATE CORTEX OF KITTENS DEPRIVED OF VISION IN ONE EYE. *Journal of Neurophysiology*, 26(6):1003–1017, November 1963. ISSN 0022-3077. doi: 10.1152/jn.1963.26.6.1003. URL [https://doi.org/10.1152/jn.1963.26.6.1003](https://doi.org/10.1152/jn.1963.26.6.1003).
Arthur T. Winfree. *The geometry of biological time*. Number v. 12 in Interdisciplinary applied mathematics. Springer, New York, 2nd ed edition, 2001. ISBN 978-0-387-98992-1.

H Winterfeld, M Ziegler, H Hanssen, D Friedrich, W Benecke, and H Kohlstedt. Technology and electrical characterization of MemFlash cells for neuromorphic applications. *Journal of Physics D: Applied Physics*, 51(32):324003, August 2018. ISSN 0022-3727, 1361-6463. doi: 10.1088/1361-6463/aad00b. URL http://stacks.iop.org/0022-3727/51/i=32/a=324003?key=crossref.58be8817b41da948d35d2936de40ab25

X. Cheng, T. Birkoben, H. Kohlstedt, and A. Bahr. A CMOS Integrated Low-Power, Ultra-Low-Frequency Relaxation Oscillator for Neuromorphic Applications. In *2021 IEEE International Midwest Symposium on Circuits and Systems (MWSCAS)*, pages 170–174, August 2021. ISBN 1558-3899. doi: 10.1109/MWSCAS47672.2021.9531896.

Qiangfei Xia and J. Joshua Yang. Memristive crossbar arrays for brain-inspired computing. *Nature Materials*, 18(4):309–323, April 2019. ISSN 1476-1122, 1476-4660. doi: 10.1038/s41563-019-0291-x. URL http://www.nature.com/articles/s41563-019-0291-x

J. Joshua Yang, Dmitri B. Strukov, and Duncan R. Stewart. Memristive devices for computing. *Nature Nanotechnology*, 8:13, December 2012. URL http://dx.doi.org/10.1038/nnano.2012.240

Carlos Zamarreño-Ramos, Luis A. Camuñas-Mesa, Jose A. Pérez-Carrasco, Timothée Masquelier, Teresa Serrano-Gotarredona, and Bernabé Linares-Barranco. On Spike-Timing-Dependent-Plasticity, Memristive Devices, and Building a Self-Learning Visual Cortex. *Frontiers in Neuroscience*, 5, 2011. ISSN 1662-4548. doi: 10.3389/fnins.2011.00026. URL http://journal.frontiersin.org/article/10.3389/fnins.2011.00026/abstract

Hai-Tian Zhang, Priyadarshini Panda, Jerome Lin, Yoav Kalcheim, Kai Wang, John W. Freeland, Dillon D. Fong, Shashank Priya, Ivan K. Schuller, Subramanian K. R. S. Sankaranarayanan, Kaushik Roy, and Shiriram Ramanathan. Organismic materials for beyond von Neumann machines. *Applied Physics Reviews*, 7(1):011309, March 2020. ISSN 1931-9401. doi: 10.1063/1.5113574. URL http://aip.scitation.org/doi/10.1063/1.5113574

Ruomin Zhu, Joel Hochstetter, Alon Loeffler, Adrian Diaz-Alvarez, Tomonobu Nakayama, Joseph T. Lizier, and Zdenka Kuncic. Information dynamics in neuromorphic nanowire networks. *Scientific Reports*, 11(1):13047, December 2021. ISSN 2045-2322. doi: 10.1038/s41598-021-92170-7. URL http://www.nature.com/articles/s41598-021-92170-7

Martin Ziegler, Rohit Soni, Timo Petelczyk, Marina Ignatov, Thorsten Bartsch, Paul Meuffels, and Hermann Kohlstedt. An Electronic Version of Pavlov’s Dog. *Advanced Functional Materials*, 22(13):2744–2749, July 2012. ISSN 1616301X. doi: 10.1002/adfm.201200244. URL http://doi.wiley.com/10.1002/adfm.201200244

Martin Ziegler, Karlheinz Ochs, Mirko Hansen, and Hermann Kohlstedt. An electronic implementation of amoeba anticipation. *Applied Physics A*, 114(2):565–570, February 2014. ISSN 0947-8396, 1432-0630. doi: 10.1007/s00339-013-7615-5. URL http://link.springer.com/10.1007/s00339-013-7615-5