Memristive neuromimetic and reservoir computing systems

The development of semiconductor materials and the study of their mechanisms of operation have allowed the creation and development of powerful computer technologies that are the foundation of the information civilization we see today. Analysis and processing of data in the domains of Internet services, finance, autonomous vehicles or intelligent infrastructure based on Internet of Things devices are performed using *machine learning* tools (in addition to classical statistical methods). One of the intensively developed branches of machine learning is artificial neural networks. In their functionality and/or structure they are modeled on biological nervous systems. This is due to the brain's tremendous ability to learn, recognize patterns and classify them. Its abilities are based mainly on highly parallel and iteratively optimized data processing based on a large number of interconnected neurons.

In an attempt to improve the performance of computing devices, intensive research is being conducted using *neuromorphic engineering*. This interdisciplinary field draws inspiration from biology, mathematics, electronic engineering, materials engineering, and computer science where biological neural structures are the main template for computing systems. The use of modern materials technology enables the simulation of neuronal and synaptic functions of varying degrees of complexity, resulting in increased parallelism in areas such as pattern recognition and graph analysis. At the moment, neuromorphic engineering is still in the domain of unconventional computing, but this too is slowly changing. Many research institutes are conducting intensive research drawing inspiration from biological neural structures to achieve more efficient computational systems, potentially of universal applicability.

One of the innovative technologies from the neuromorphic engineering domain are memristive devices. The use of memristive devices makes it possible to delegate some of the computational steps of artificial neural networks so that they are performed *in materia*, based directly on the properties of the device in question. This approach seems to circumvent the von-Neumann bottleneck problem. In classical computing systems, information is stored in memory and all calculations are performed in the microprocessor. The von-Neuman architecture assumes a constant flow of data between these computer components, which in effect slows down computation and consumes energy. Dynamic systems (both semiconductor and wetware) also allow computations to be performed in systems that have memory functions.

In the classical configuration of memristive devices, a capacitive material (e.g., a dielectric or semiconductor) is placed between electrodes with metallic conductivity in a layered arrangement. Memristive devices are characterized by nonlinear current-voltage characteristics, which take the form of a pinched hysteresis loop. For classical memristive devices, two states of resistance (low and high) can be observed. By applying electrical pulses (or alternating-voltage waveforms) with the appropriate amplitude of the electrical potential, materials can be switched to the appropriate conductivity states depending on the type of memristor and its initial state. The variability of operation depending on the frequency of the excitation pulses/scans is another feature of memristive devices. Because of the retention of states observed for memristive elements when the power source is turned off, the effect of resistive switching can be used as a building block for new non-volatile memory.

One of the problems of artificial neural networks is their expensive learning process, especially in the case of recurrent or deep neural networks. All the connection weights between individual neurons, as well as the activation level of a given neuron itself, are subject to optimization. When the network contains recursive connections or multiple layers, each iteration of weight updates prolongs the training of the entire network. To solve this problem, Jaeger and Maas independently proposed the Echo State Network and Liquid State Machine, respectively. In their approach, only the portion of the network sampling the state of the information processing layer is trained. In their work, they pointed out the crucial importance of a multidimensional, rich and dynamic state space of the information processing layer to simplify the training stage of the reading layer as much as possible. Over time, both of these approaches for efficiently training neural networks were subsumed into a common conceptual framework, which was referred to as *reservoir computing*.

To work properly, these unconventional computing systems must have several features, namely, they must exhibit rich internal dynamics, "fleeting" memory, and echo-state property. Reservoir computing circuits are based on: (i) a nonlinear element (e.g., a memristor) that also provides memory functions, (ii) an input layer that provides information/signal for processing, (iii) a readout layer, and optionally (iv) a delayed feedback loop that complements and develops the internal dynamics of the system. A sophisticated artificial neural network is not needed to read the state of the reservoir layer, but simple models such as linear regression or a binary tree will suffice (assuming the reservoir system performs the appropriate signal transformation).

Single Node Echo-State Machine (SNESM) are novel reservoir computing systems that use only one computing node operating in a delayed feedback loop. Essentially, both the signal and the state of the computing node change each time the signal passes through the machine in each successive cycle. The evolution of the signal in the loop can potentially improve the clustering and classification capabilities of a reservoir computing system. The SNESM system has the added benefit of expanding the data set. Each successive epoch of the signal is a slightly different version of the primary signal due to nonlinear transformation and attenuation in the SNESM system. The echo of the primary signal may be easier to classify due to changes in its complexity and the correlation between the parameters describing it.

The dissertation, "Memristive Neuromimetic and Reservoir Computing Systems" includes research on the use of several computational substrates in the domain of unconventional information processing. The work performed was organized to introduce successive elements and concepts of both system design and methods of information processing and analysis, which are finally synthesized in single studies. A review article is presented first, which includes a description of memfractors (a general model that describes memristive devices), simple artificial neural network models, and reservoir computing systems. A mathematical description of delay-based reservoir computing systems is also included. Following, research on photoelectrochemical artificial neuron indicates the possibility of using a simple neuromorphic system for the task of handwriting classification. Measurements were realized based on polymorphic cadmium sulfide, for which spectroscopic characteristics are also presented. The results show an improvement in the separability index of the input data processed by the neuromorphic system relative to the raw data. The paper introduces concepts for the design of an information processing system using a single computational node. Elements of data analysis are also introduced. The computational paradigm of reservoir computing is introduced directly in a study based on a system containing cement doped with semiconductor nanomaterials and metallic particles. The electrical properties of selected samples have been studied by cyclic voltammetry and impedance spectroscopy. The presented system was used to classify electrical signals of simple shapes – sinusoidal, triangular, and rectangular. In addition, one of the complexity parameters of the analyzed signals allows for distinguishing between doping of the sample. The research sustains and complements literature reports on the possibility of implementing reservoir computing on the simplest possible computational substrates for classification tasks. The possibility of using a single computational node in a SNESM system is presented based on a polymer field-effect transistor. The presented SNESM circuit is very close conceptually to the State Weaving Environment Echo Tracker algorithm, in which the reservoir circuit is in direct contact with the analyzed environment. The studied circuit was used to improve the performance of a polymer transistor in the role of an ion sensor. This was done by changing the data representation, made possible by signal transformation (dependent on the concentration of K^+ ions) in the SNESM system. Research on the use of the SNESM reservoir system for analyzing and clustering musical intervals was realized with simulations of a bridge synapse. The bridge synapse consists of four memristors and an operational amplifier. The study presents the generation of higher harmonics in several memristive systems. A comparison of the effects of transforming sinusoidal signals representing musical intervals (from natural scale) with the consonance/sensory dissonance curve and curves determined by the Sethares algorithm is presented. Representation of the data in the space of harmonic component distances allows for partial clustering of musical intervals with respect to their degree of consonance/dissonance. Finally, research is presented on the physical implementation of a bridge synapse (based on semi-commercial KNOWM memristors) in a SNESM reservoir system for epilepsy attack recognition where a simple machine learning algorithm (binary tree) was used to train the model. The analyzed standard data set (downloaded online) was collected using a wearable triaxial accelerometer for simple diagnosis without the need for an EEG system. Complexity parameters of the analyzed signals were used as *features* to train the model. Computations of the complexity parameters were also performed for raw data to compare the effect of the SNESM system on a given signal and its classification quality. The F1-score – a balanced statistical parameter that better reflects the classification ability of the given system than simple *precision* – was used to evaluate the classification accuracy. Results are presented for improving the classification accuracy of signals simulating an epilepsy attack for restrictive conditions (small data sets) where speed and simplicity - thus affecting low cost - of training and testing the final classification model are important. Changes in the distributions of the analyzed parameters and changes in the correlation between them could be the sources of improvement in classification scores. In addition, the ability of the SNESM system to expand the data set has a beneficial effect on resulting classification accuracy.