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Hardware elementary perceptron based on polyaniline memristive devices

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A B S T R A C T

Elementary perceptron is an artificial neural network with a single layer of adaptive links and one output neuron that can solve simple linearly separable tasks such as invariant pattern recognition, linear approximation, prediction and others. We report on the hardware realization of the elementary perceptron with the use of polyaniline-based memristive devices as the analog link weights. An error correction algorithm was used to get the perceptron to learn the implementation of the NAND and NOR logic functions as examples of linearly separable tasks. The physical realization of an elementary perceptron demonstrates the ability to form the hardware-based neuromorphic networks with the use of organic memristive devices. The results provide a great promise toward new approaches for very compact, low-volatile and high-performance neurochips that could be made for a huge number of intellectual products and applications.

1. Introduction

Perceptron is an artificial neural network capable of supervised learning in a variety of tasks among which there are pattern recognition and classification, approximation, prediction, and others. In many cases these tasks are mathematically ill-posed problems (due to incomplete or distorted input data), solution of which allows to navigate in a real environment. They can be relatively easy solved by human but are quite difficult for resolving by common computers. Perceptron was developed by Rosenblatt in 1957 [1] as a model of brain perception. Historically, single-layer perceptron was represented by three layers of neurons: sensory, associative, and responsive ones. Wherein, only the series of links from the associative to responsive neurons could be trained (varied in the process of the network learning), while the first layer of weights from sensory neurons to associative ones was considered accidentally or deterministically given and remained unchanged in the learning process.

Later on, single-layer perceptron (e.g., in the terminology of Wasserman [2]) became known as a network in which each sensory neuron actually was directly connected to a single neuron of associative layer. Thus, the need to assign a set of sensory neurons disappeared, and the only layer of variable links between associative and responsive neurons was held. Note that the classic single-layer Rosenblatt perceptron is not functionally equivalent to the single layer Wasserman perceptron, just because of the presence of the branch points (sensory neurons) for the input signals. For example, a single-layer perceptron in terms of Rosenblatt is able to solve so-called non-linearly separable problem, and in terms of Wasserman does not. Because of this terminological confusion and also due to the critical book of Minsky and Papert [3] there were some misconceptions concerning the limitations of the classical perceptron. As a result, the research in this area was paused for almost 15 years. Nevertheless, a number of mathematical developments, concerning especially the learning algorithms of a multilayered perceptron (with several layers of associative neurons) [4,5], warmed up the interest in artificial neural networks (ANN) that it is still growing.

In recent years, the development and fabrication of a nanostructured solid-state analog of the synapse, so-called memristor, has become a new factor of growing research intensity in the field of

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ANN hardware implementation. Its main property is changing of its conductivity according to the value of the passed electric charge [6]. Due to the large number of materials which have demonstrated memristive properties and small lateral dimensions of the memristors ($\geqslant$10 nm) there is a perspective for the physical realization of a huge number of neurons associated with each other through the memristive links capable of training. It is expected that characteristics of memristor based ANN architectures would be strongly improved, compared to ANN emulated by software on actual computers [7]. Indeed, ANN is inherently a highly parallel system with distributed processing and information storage units. At the same time, a classical machine with von Neumann architecture is not optimal for the ANN implementation on it. The hardware realization of neurochips using memristors could open the huge market of high-level intelligent devices for the smart household applications as well as for the complex robotic systems.

Pattern classification using a single-layer perceptron network implemented with an inorganic memristive crossbar circuit was demonstrated in [8]. Recently, memory devices with organic or polymer materials were experimentally demonstrated, which have unique advantages over traditional inorganic memory materials, including high flexibility, low cost, solution processability, three-dimensional stacking capability and large-area implementation [9]. Memristive devices based on polyaniline have demonstrated good characteristics in synaptic operations [10]. However, the implementation of even simple networks on organic memristive devices is more challenging and has yet to be reported. Therefore, the purpose of our work is to develop and demonstrate the learning ability of the elementary single-layer (in modern terminology) perceptron fabricated from polyaniline-based memristive devices. The structure, working principles and properties of polyaniline (PANI) memristive devices have been previously investigated [11–14]. We call those PANI elements as memristive devices because they are not fully passive as in the case of the original theoretical memristor [15].

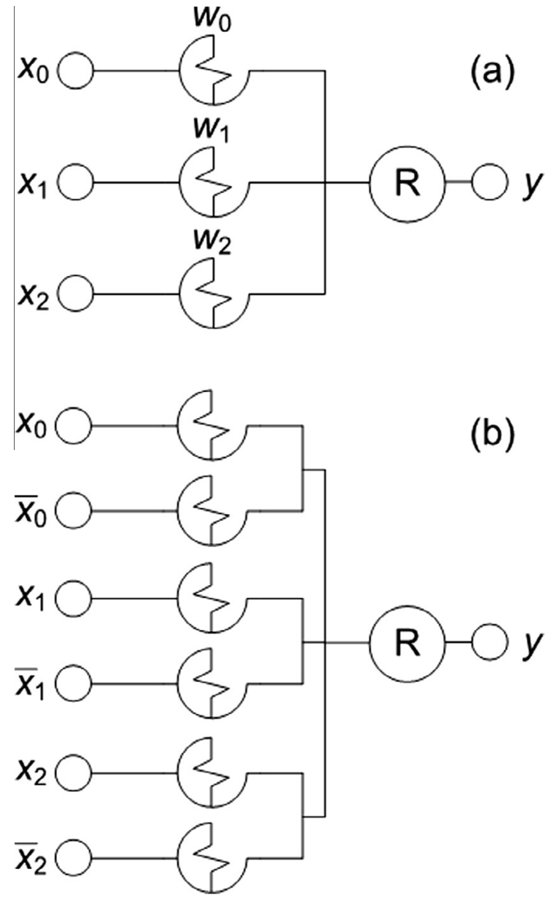

Fig. 1. Scheme of an elementary perceptron based on organic memristors (marked with unclosed circles) with one (a) and two (b) memristors per every link weight. Symbols with bars on top correspond to negation of input signals.

2. Experimental details

PANI based memristive devices were fabricated by the following technique [16]. A solution of PANI (Mw $\approx$ 10,000, Sigma Aldrich) is prepared with a concentration of 0.1 mg mL^{-1} in 1-methyl-2-pyrrolidinone (Sigma Aldrich ACS reagent $\geqslant$99.0%) with the addition of 10% of Toluene (AnalaR NORMAPUR® ACS). This solution is filtered twice and then is deposited onto a glass substrate (1.5×0.5 cm^2) with two Cr electrodes by the Langmuir–Schaefer technique. The PANI conductive channel is formed by depositing 60 layers of polymer in its emeraldine base form and then transforming it in the emeraldine salt conducting form by a doping in the HCl (1 M) solution. Then a stripe of solid electrolyte of about 1 mm in width is deposited on the center of the PANI channel in a crossed configuration and a silver wire (0.05 mm) is connected to the solid electrolyte and works as a reference electrode. The electrolyte is prepared starting from a water solution (20 mg mL^{-1}) of polyethylene oxide with a molecular weight of $8{\cdot}10^6$ Da (PEO) in which a solution of $LiClO_4$ (Sigma) in water is added to reach the concentration of 0.1 M. The final structure is additionally doped in HCl vapor. The application of the voltage cycles and the measurements of the current are performed with a Keithley 236 Source Measure unit and Keithley 6514 system electrometer.

3. Results and discussions

The input layer of the perceptron (Fig. 1(a)) consists of two functional inputs (x_1, x_2) that are coding the features of a recognizable object, and one permanently biased input (x_0 = "1") which is required for the implementation of an origin offset of the linear function $y(\vec{x}) = w_0 + w_1x_1 + w_2x_2$ that separates different classes of recognizable objects. Such network can recognize only two classes of input objects: if the output signal exceeds an *a priori* predetermined value then it corresponds to the class No1, otherwise it is the class No2. For increasing the number of recognizable classes to three or more it is simply necessary to increase the amount of output neurons by providing each of them with its memristive links to inputs.

The implementation of any perceptron linear function $y(\vec{x}) = w_0 + \sum w_ix_i$ requires the negative ANN link weights w_i, along with positive values. In our realization of the perceptron the input signals are voltages, and the output is a current. Therefore, one cannot get the memristive weights of the opposite signs at a fixed sign of the applied voltage. A solution to this problem is to change the sign of the applied voltage, if necessary, during the adaptation of the perceptron weights. Another solution is to use simultaneously two memristors for emulation of one bipolar interneuron link (Fig. 1(b)). In this case, the positive voltage is applied to one of the paired memristors, and the negative voltage of the same magnitude is applied to the other one. During the training procedure the change of the link weight is reached by simultaneous variation of both memristors conductivities.

Another important critical issue is the perceptron learning algorithm. It was chosen the simplest algorithm that was suggested by Rosenblatt. It is a method of error correction [17], wherein the weights of all active connections are changed in the same way in each iteration step depending only on the error sign but not on its magnitude.